

Mid-Point Project Update

The Effect of EU-ETS Carbon-Price Shocks on Green-Energy Equity Performance and Volatility

Aditya Rohatgi — Marco Montenegro — Vicente Puga — Jesse Mason

1. Literature Review

We reviewed 15 peer-reviewed papers (e.g. *Energy Economics*, *Journal of Financial Economics*). Most prior work uses monthly data or focuses only on returns. Few investigate high-frequency shocks or model firm-level heterogeneity with machine learning, establishing our contribution.

2. Data Acquisition & Cleaning

Daily data (2018–2025) gathered and cleaned:

- EU-ETS allowance prices (ICE/Sandbag)
- ETF prices: green (ICLN) and brown (XLE) via Yahoo Finance
- ESG scores and emissions for ETF constituents
- Macro controls: VIX, Brent, TTF gas, CPI
- Timeline of EU carbon-policy events (Web Scraping)

All sets merged in pandas and exported as versioned CSV.

3. Carbon Shock Identification

Daily returns:

$$r_t = \frac{p_t}{p_{t-1}} - 1.$$

AR(5):

$$r_t = \phi_1 r_{t-1} + \dots + \phi_5 r_{t-5} + \varepsilon_t,$$

and residual shocks:

$$Shock_t = \begin{cases} 1 & \text{if } |\varepsilon_t| > \sigma_\varepsilon, \\ 0 & \text{otherwise.} \end{cases}$$

Policy-event dates were matched to the nearest trading day.

4. Return Construction

Log-returns for ICLN and XLE were computed from adjusted closes and merged with shock flags.

5. Impulse-Response Estimation

Local projections (Jordà 2005):

$$R_{t+h} - R_t = \alpha_h + \beta_h Shock_t + \epsilon_{t+h}, \quad h \in \{1, 3, 5, 10, 20\}.$$

Key Findings (Model-Based Shocks)

ETF	Horizon	Beta (%)	SE (%)	<i>p</i> -value	Sig.
ICLN	1d	−0.134	0.156	0.392	n.s.
ICLN	3d	+0.262	0.157	0.096	10%
ICLN	5d	+0.265	0.155	0.087	10%
ICLN	10d	−0.010	0.160	0.949	n.s.
ICLN	20d	−0.045	0.156	0.774	n.s.
XLE	1d	+0.030	0.174	0.864	n.s.
XLE	3d	+0.124	0.177	0.483	n.s.
XLE	5d	+0.336	0.169	0.047	**
XLE	10d	+0.139	0.182	0.445	n.s.
XLE	20d	−0.002	0.172	0.992	n.s.

Table 1: IRF estimates for ETF cumulative returns (** = significant at 5%).

Parameter meanings: *Beta* is the estimated percentage-point change in cumulative return over the horizon per carbon-price shock. *SE* is its standard error. The *p*-value tests $H_0: \beta = 0$; values < 0.05 imply statistical significance.

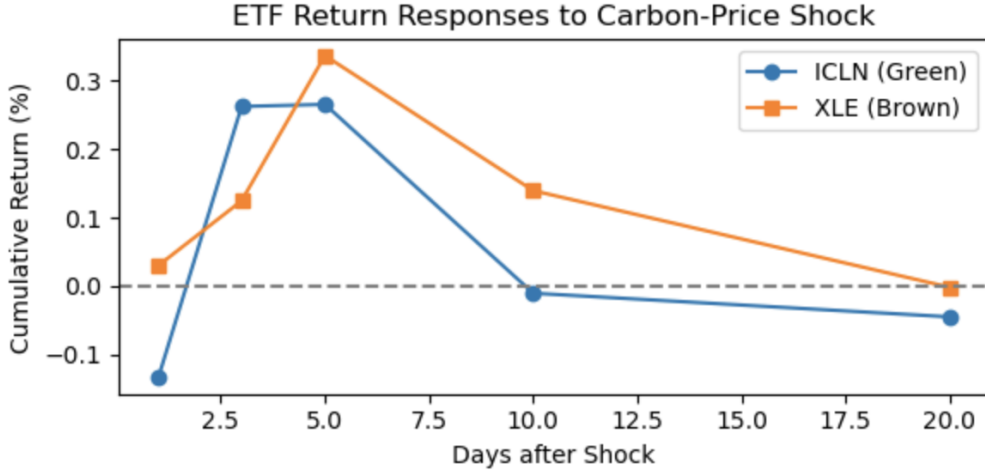


Figure 1: Impulse responses for ICLN vs. XLE.

6. Mathematical Tools & Equations

$$r_t = \frac{p_t}{p_{t-1}} - 1,$$

$$r_t = \phi_1 r_{t-1} + \dots + \phi_5 r_{t-5} + \varepsilon_t,$$

$$\varepsilon_t = r_t - \hat{r}_t,$$

$$Shock_t = \begin{cases} 1 & |\varepsilon_t| > \sigma_\varepsilon, \\ 0 & \text{otherwise,} \end{cases}$$

$$R_{t+h} - R_t = \alpha_h + \beta_h Shock_t + \epsilon_{t+h}.$$

7. Code Infrastructure

1. We developed a full pipeline to analyze how carbon-price shocks affect the performance and volatility of green (ICLN) and brown (XLE) energy ETFs. Using libraries like pandas, numpy, yfinance, statsmodels, matplotlib, and pandas datareader, we automated data collection, cleaning, and transformation for equity returns, carbon futures, macroeconomic indicators (VIX, oil, interest rates), and ESG scores.
2. We implemented a model-based AR(5) framework to identify shock events and estimated impulse response functions (IRFs) using local projection regressions to track return dynamics post-shock. Volatility was modeled through rolling standard deviations (realized) and merged with VIX data (implied). All outputs, including regression tables and visualizations, were generated programmatically, ensuring reproducibility and clarity. Our code also lays the foundation for advanced forecasting with machine learning, including Transformer models to predict volatility patterns beyond traditional econometric models.

8. Challenges Faced

Missing ESG endpoints required manual Sustainalytics scraping; residual fat-tails made the shock threshold sensitive; few policy events reduced causal power, prompting dual shock definitions.

9. Next Steps

1. Test additional historical carbon-price events with extended ETF and futures data to strengthen support for the null hypothesis.
2. Plot IRFs with confidence bands.
3. Estimate event-based IRFs for comparison.
4. Run causal-forest analysis for ESG heterogeneity.
5. Build and benchmark GARCH-MIDAS vs. Transformer volatility forecasts.
6. Draft methodology and results sections for the final report.