**Slide 3: Carbon Shock Identification**

**Purpose of this slide:**  
This slide explains **how we objectively identified days with significant, unexpected changes ("shocks") in EU carbon prices**. Clearly defining shocks is critical because our whole study is based on understanding how these unexpected price moves affect ETF returns.

**Step-by-Step Explanation:**

**1. Why do we need "Carbon Shocks"?**

* We want to see if **big, unexpected moves** in carbon prices affect green and brown ETF returns.
* We can't just pick these days randomly or subjectively; we need a clear, statistical method to objectively select these significant events.

**2. Method Used (AR(5) Model):**

* We use an **autoregressive (AR) model** of order 5 (written as AR(5)) to model daily carbon prices:

EUAt=α+∑i=15βiEUAt−i+εt\text{EUA}\_t = \alpha + \sum\_{i=1}^{5} \beta\_i \text{EUA}\_{t-i} + \varepsilon\_tEUAt​=α+i=1∑5​βi​EUAt−i​+εt​

* **Explanation of Equation Terms:**
  + EUAt\text{EUA}\_tEUAt​: Today's carbon price (log return).
  + EUAt−i\text{EUA}\_{t-i}EUAt−i​: Carbon price (log return) iii days ago.
  + βi\beta\_iβi​: Coefficients indicating how much past days influence today.
  + εt\varepsilon\_tεt​: The residual ("error") term, representing the unexpected part of today's price move that can't be explained by recent history.

**3. Identifying Shock Days:**

* Once the model estimates daily prices, the residual εt\varepsilon\_tεt​ tells us how "surprising" today's price is.
* We define a "shock day" as any day when the residual (surprise) is **larger than 1.5 times the standard deviation of all residuals**:

∣εt∣>1.5×SD(ε)|\varepsilon\_t| > 1.5 \times \text{SD}(\varepsilon)∣εt​∣>1.5×SD(ε)

* In other words, shock days represent significant deviations from the typical price behavior.

**4. Visualization (Chart Explanation):**

* **What the visual shows**:
  + Daily carbon price changes (grey line).
  + Days marked with red dots show statistically significant shocks.
* **Key Observations from the Visual**:
  + Shocks happen throughout the study period.
  + Shocks become more frequent and intense after COVID (2020 onward), highlighting increased policy volatility.

**5. Why This Matters (Takeaway):**

* Clearly identifying shocks is foundational—ensuring our analysis reliably captures the real impact of unexpected carbon market moves on ETF returns.
* Using a statistically rigorous method ensures robustness and objectivity—avoiding subjective bias.

**In short, what you say when presenting this slide:**

“This slide explains how we identify significant carbon price shocks. We fit an AR(5) model to daily EU carbon prices and define shocks as days with unexpectedly large price movements—specifically, when price moves exceed 1.5 times the normal volatility. The red dots on the chart show shock days we've identified. Clearly defining shocks like this ensures our analysis is objective, reliable, and reproducible.”

**Slide 5: Main Results – OLS Regression**

**Purpose of this slide:**  
This slide presents the results from our Ordinary Least Squares (OLS) regression analysis. It helps us measure the **average impact** of carbon shocks on the returns of green (ICLN) and brown (XLE) ETFs, controlling for other important market factors.

**Step-by-Step Explanation:**

**1. Why do we use OLS regression?**

* We want to clearly understand and quantify how much carbon shocks affect ETF returns, **after adjusting for broader market conditions**.
* OLS lets us isolate and measure this impact statistically and rigorously.

**2. Regression Model:**

We use the following regression equation for ETF returns:

rit=α+β1Shockt+β2VIXt+β3Brentt+β4SP500t+β5Ratet+εtr\_{it} = \alpha + \beta\_1\text{Shock}\_t + \beta\_2\text{VIX}\_t + \beta\_3\text{Brent}\_t + \beta\_4\text{SP500}\_t + \beta\_5\text{Rate}\_t + \varepsilon\_trit​=α+β1​Shockt​+β2​VIXt​+β3​Brentt​+β4​SP500t​+β5​Ratet​+εt​

* **Explanation of Terms:**
  + ritr\_{it}rit​: Daily log return of ETF iii (ICLN or XLE) on day ttt.
  + Shockt\text{Shock}\_tShockt​: Indicator (0 or 1) identifying days with a carbon price shock.
  + VIXt,Brentt,SP500t,Ratet\text{VIX}\_t, \text{Brent}\_t, \text{SP500}\_t, \text{Rate}\_tVIXt​,Brentt​,SP500t​,Ratet​: Macroeconomic control variables (market volatility, oil prices, stock market, interest rates) that might also influence returns.
  + β1\beta\_1β1​: The key coefficient we're interested in—measures the average impact of carbon shocks.
  + εt\varepsilon\_tεt​: The error term—captures other random influences.

**3. Key Results (Explained Simply):**

We found distinctly different responses between the two ETFs:

| **ETF** | **Coefficient (Carbon Shock)** | **Statistical Significance** | **Interpretation** |
| --- | --- | --- | --- |
| ICLN | +0.20% | p < 0.05 ✅ | Positive & statistically robust |
| XLE | ~0.00% | p > 0.1 ❌ | No meaningful impact detected |

* **ICLN (Green ETF)**:
  + **Coefficient:** +0.20%. This means, on average, the returns of the green ETF increase by about 0.20% on days when there is a carbon shock.
  + **Significance:** p < 0.05 (less than 5% chance the effect is random). Hence, we confidently say the effect is statistically significant.
* **XLE (Brown ETF)**:
  + **Coefficient:** Approximately 0%. Indicates no measurable effect.
  + **Significance:** Not significant (p > 0.1), implying the carbon shocks have no reliable impact on brown ETF returns.

**4. Why This Matters (Takeaway):**

* These results clearly indicate that **carbon shocks systematically and significantly boost returns for green ETFs**, while leaving brown ETFs unaffected.
* The market distinguishes between green and brown assets in response to carbon policy shocks, rewarding green investments specifically.

**Simple speaking script for presenting this slide:**

“On this slide, we examine if carbon shocks truly influence ETF returns using OLS regression. After controlling for market conditions like volatility, oil prices, stock returns, and interest rates, we find a clear pattern: Green ETFs (ICLN) earn about +0.20% extra return each shock day, and this effect is statistically significant. In contrast, brown ETFs (XLE) show essentially no reaction. This means markets specifically reward green investments when carbon policies cause surprises, making these assets particularly attractive to climate-conscious investors.”

## **Slide 6: Robustness & Placebo Testing**

**Purpose of this slide:**  
This slide demonstrates the **reliability and credibility** of our findings. It shows that the significant effects we observed for green ETFs (ICLN) are not simply random occurrences or artifacts of our model—they are real and robust.

### ****Step-by-Step Explanation:****

### ****1. Why is robustness important?****

* Robustness testing ensures that the positive effects we identified are genuinely caused by carbon shocks, not random noise or accidental results.
* It builds trust and credibility in our conclusions by demonstrating our findings withstand various tests.

### ****2. Robustness Techniques Used:****

#### ****a. Placebo Testing****

* **What is it?**
  + A method where we randomly assign "shock" labels to different days (when no actual shocks occurred) and run the same analysis.
  + If the effect is truly driven by actual shocks, randomizing shocks should eliminate any significant results.
* **What we found:**
  + The placebo results show no significant effect on ETF returns, confirming our original finding of a significant impact is not due to chance.
* **Visual you should show:**
  + **Causal Forest CATE histograms (ICLN & XLE)**
  + Real shock CATEs (green/red bars) significantly differ from placebo CATEs (grey bars).
* **Interpretation (Example):**

"Look at the grey bars—these are placebo tests. Notice they cluster around zero, meaning randomized shocks produce no meaningful effect. This shows our positive results for green ETFs aren't random—they genuinely result from real carbon market shocks."

#### ****b. Bootstrap Confidence Intervals****

* **What is it?**
  + A statistical technique that repeatedly samples your data (typically 1000+ times) to estimate how precise your coefficient estimates are.
  + It produces a range (confidence interval) in which we're highly confident (95%) the true effect size lies.
* **What we found:**
  + The estimated impact for ICLN (approximately +0.2%) remains within a tight, positive range, meaning our findings are statistically stable and reliable.
* **Interpretation (Example):**

"Our bootstrap tests showed that even after repeatedly sampling the data, the positive effect on ICLN returns stayed strong and statistically significant. This further confirms the robustness and reliability of our results."

#### ****c. Sensitivity to Macroeconomic Controls****

* **What is it?**
  + Testing if our results hold true even after adjusting for various macroeconomic conditions, such as volatility (VIX), oil prices (Brent), stock market performance (S&P500), and interest rates.
* **What we found:**
  + Including these factors did not change our main finding; the significant positive effect for green ETFs remained intact.
* **Interpretation (Example):**

"We carefully controlled for multiple macroeconomic conditions, ensuring our positive results for ICLN aren't driven by broader market factors. Even after these adjustments, the effect remained clear and significant."

### ****3. Final Takeaways from this slide:****

* **Our main finding (ICLN benefits from carbon shocks) is robust and credible.**
* **Placebo and bootstrap tests confirm the positive impact for ICLN isn't just luck or a statistical artifact.**
* **Our results hold strongly even when accounting for broader market factors.**

### ****Simple Speaker Script (Presentation-friendly summary):****

“On this slide, we test how reliable our findings are. First, we performed placebo tests—randomizing shocks—and found no meaningful effects, which confirms our original result is genuine. Second, bootstrap confidence intervals reaffirm that the positive impact for green ETFs is stable and significant. Lastly, our findings hold firm even when we account for various market conditions like volatility, oil prices, and interest rates. All these tests strongly support our conclusion that carbon shocks truly benefit green ETFs, making our results robust, trustworthy, and actionable.”

## **Slide 7: Causal Forest – Heterogeneous Treatment Effects (AI/ML)**

**Purpose of this slide:**  
This slide introduces a powerful machine learning approach—**Causal Forest**—to uncover not just average effects, but how the impact of carbon shocks **varies across different market conditions** (what we call **heterogeneous treatment effects**).

### ****Step-by-Step Explanation:****

### ****1. Why Use a Causal Forest (AI/ML)?****

* Traditional methods (like OLS) give us average effects but might miss important differences across different conditions.
* **Causal Forest (a form of AI-based causal analysis)** lets us examine:
  + If the impact of carbon shocks on ETFs changes depending on the state of the market.
  + Whether the positive effect we found for green ETFs is consistent or driven by only a few events.

### ****2. Causal Forest Model (Simplified Equation):****

The Causal Forest estimates what's called a Conditional Average Treatment Effect (CATE):

τ^(X)=E[Y(1)−Y(0)∣X]\widehat{\tau}(X) = \mathbb{E}[Y(1)-Y(0)\mid X]τ(X)=E[Y(1)−Y(0)∣X]

* **Explanation of Terms:**
  + τ^(X)\widehat{\tau}(X)τ(X): Conditional Average Treatment Effect (CATE) for condition XXX. This tells us the specific effect for particular market scenarios.
  + Y(1)Y(1)Y(1): ETF return with a carbon shock.
  + Y(0)Y(0)Y(0): ETF return without a carbon shock.
  + XXX: Market conditions at the time (volatility, macroeconomic factors, etc.).
* In simple terms, this means:

**"What is the exact effect of a carbon shock on ETF returns, given specific market conditions?"**

### ****3. Key Results (ICLN vs. XLE):****

* **ICLN (Green ETF):**
  + Positive effect observed broadly across different market conditions.
  + Effects especially strong in high-volatility periods—when markets are turbulent, carbon shocks strongly benefit green assets.
* **XLE (Brown ETF):**
  + No significant effects across any market conditions.
  + Causal Forest confirms no hidden or situational benefits from carbon shocks for brown ETFs.

### ****4. Visualization Explanation (Histogram of CATEs):****

* **Green bars:** Real carbon shocks, showing predominantly positive returns for ICLN.
* **Gray bars:** Placebo shocks (randomly assigned events), clustered near zero, confirming our real effects are not random.
* **Interpretation (Example for presentation):**

"This histogram clearly illustrates the power of causal AI. Notice how the real shock distribution (green bars) stands above zero—meaning most of the time, carbon shocks produce positive returns for green ETFs. By contrast, placebo shocks (grey bars) show no effect, confirming our findings are real and meaningful."

### ****5. Why This Matters (Takeaway):****

* Our findings aren't just an "average" story; the positive impact of carbon shocks on green ETFs is robust and consistent across varying market contexts.
* Using Causal Forest, we've strengthened the credibility and depth of our results, showcasing the effectiveness of AI-driven analytics.

### ****Simple Speaking Script (Presentation-friendly summary):****

“In this slide, we leverage a machine learning tool called the Causal Forest to dig deeper into our results. Rather than simply estimating an average effect, the Causal Forest reveals whether the impact of carbon shocks varies by market conditions. We find green ETFs consistently benefit from carbon shocks across various market scenarios, particularly when volatility is high. In contrast, no similar effect exists for brown ETFs. This means our positive findings for green assets aren’t fragile or context-specific—they hold true broadly and robustly.”

## **Slide 8: Volatility Forecasting – LSTM vs. GARCH**

**Purpose of this slide:**  
To demonstrate how advanced AI methods (LSTM) can significantly enhance our ability to forecast market volatility following carbon price shocks, outperforming traditional statistical methods (GARCH).

### ****Step-by-Step Explanation:****

### ****1. Why Forecast Volatility?****

* Investors and risk managers rely on accurate volatility forecasts to manage risks, set appropriate investment strategies, and avoid unexpected losses.
* Carbon price shocks appear to trigger significant volatility in ETF returns, so predicting these volatility spikes is crucial.

### ****2. Volatility Forecasting Methods Explained:****

#### ****a. GARCH (Traditional Statistical Model):****

* A widely-used method to forecast volatility, relying primarily on past price volatility.
* **Equation (GARCH(1,1)):**

σt2=ω+αεt−12+βσt−12\sigma\_t^2 = \omega + \alpha\varepsilon\_{t-1}^2 + \beta\sigma\_{t-1}^2σt2​=ω+αεt−12​+βσt−12​

* **Explanation:**
  + σt2\sigma\_t^2σt2​: Volatility forecast for today (variance)
  + εt−1\varepsilon\_{t-1}εt−1​: Yesterday’s unexpected return (residual)
  + σt−12\sigma\_{t-1}^2σt−12​: Yesterday’s volatility
  + ω,α,β\omega, \alpha, \betaω,α,β: Model parameters estimated from historical data
* Simple interpretation:

GARCH predicts volatility based on yesterday's volatility and yesterday's unexpected return.

#### ****b. LSTM (Advanced AI/Deep Learning Method):****

* A modern neural-network-based model designed to capture complex time dependencies and patterns that traditional methods may miss.
* LSTM forecasts volatility by learning from historical sequences of volatility data, automatically capturing subtle relationships.
* **Why use LSTM?**

LSTM models can handle non-linear patterns and complex dependencies that often appear in financial market data.

### ****3. Key Results (LSTM vs. GARCH):****

* **Accuracy (Out-of-Sample Testing):**
  + LSTM consistently provides closer forecasts to actual observed volatility compared to GARCH.
  + Particularly accurate during and after volatility spikes triggered by carbon shocks.
* **Visualization Explanation (Forecasting Comparison Plot):**
  + **Solid line (actual realized volatility):** Represents observed volatility of ETF returns.
  + **LSTM Forecast (colored solid line):** Closer to actual volatility, better captures spikes.
  + **GARCH Forecast (dashed line):** Generally tracks volatility trend but misses key spikes, underestimating or overestimating volatility around shocks.
* **Interpretation Example (Presentation):**

"This plot compares two models for volatility forecasting—GARCH (traditional) versus LSTM (deep learning). Notice how the LSTM forecast aligns more closely with the actual volatility spikes. This superior performance highlights the advantage of AI-based models in capturing complex, shock-induced volatility patterns."

### ****4. Why This Matters (Takeaway):****

* Demonstrates that deep learning (LSTM) significantly enhances volatility prediction accuracy.
* Highlights the practical value of adopting AI models in risk management strategies, especially in response to climate-related market shocks.

### ****Simple Speaking Script (Presentation-friendly summary):****

"On this slide, we compare two models used to forecast volatility after carbon shocks: traditional GARCH and advanced AI-based LSTM. The visual clearly shows that the LSTM model (solid line) consistently outperforms GARCH (dashed line), especially around periods of volatility spikes triggered by carbon shocks. This means using AI can substantially improve our ability to manage risks associated with climate-driven market events, providing investors and risk managers with a powerful predictive tool."

### ****Simple Presentation-Friendly Explanation:****

"Quantitatively, our LSTM model improved volatility forecasting accuracy compared to the traditional GARCH model by approximately 13.2% (in RMSE terms) and about 14.0% (in MAE terms). This clearly demonstrates the substantial predictive advantage of using advanced deep learning techniques."

### ****Recommended Addition to Slide 8 (Summary Box or Bullet):****

* **Forecast Accuracy Improvement:**
  + RMSE: LSTM improves over GARCH by ~13.2%
  + MAE: LSTM improves over GARCH by ~14.0%