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Talking Trump and tanking markets

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ABSTRACT

This study investigates the impact of Trump-related events, measured by the urgency around his mentions in central bank speeches, on volatility in the clean energy market. Using advanced textual analysis, we construct event-related variables and assess their significance through Extreme Bounds Analysis (EBA). Based on the EBA results, we identify Urgency and Commitment as the two key factors, selected from the top and bottom percentiles of robustness rankings. These variables form the basis of an event study framework used to assess the causal impact of policy signals on abnormal market returns This approach enables us to assess not only whether Trump-related policy speeches influence the clean energy market, but also when and under what level of commitment such influence occurs. Importantly, central bank speeches that express high urgency may initially cause uncertainty or caution rather than immediate market action. This delayed response highlights the need to consider both the timing and tone of policy communication when evaluating market reactions.

1. Introduction

Ofer and Siegel (1987) examine how unexpected financial policy announcements induced changes in firm performance. This offers a lens for understanding the possible disconnect between political communication and market behavior, especially in politically charged sectors like clean energy. Recent studies show that energy and policy shocks significantly influence clean energy stocks. We find that oil supply shocks and aggregate demand shocks tend to have a positive effect on clean energy returns, while oil-specific demand shocks and policy uncertainty shocks have a negative impact. These effects are persistent over time. When policy uncertainty is included as an endogenous factor, the influence of oil shocks becomes even stronger. For instance, Trump's tweets have been shown to increase volatility in European stock markets, with the effect intensifying as public attention to his tweets grows. Stock prices typically decline following policy changes, especially when there is elevated uncertainty or a mild recession preceding the change (Zhao, 2020; Pástor and Veronesi, 2012; Nishimura and Sun, 2025). Sposito (2024) examine how authenticity in political speech varies across time and context, measuring it by the frequency of key terms per 1,000 words. Building on this, Sposito (2021) introduce two additional dimensions: commitment and urgency. Commitment refers to the expressed intent to take action, while urgency combines commitment with timing, intensity, and frequency—reflecting how immediate and necessary the message appears to be. Understanding how urgency and commitment shape market responses is essential for interpreting the political influence on clean energy markets.

This study aims to systematically analyze central bankers' speeches related to Trump-era content by leveraging the poldis R package (Sposito, 2021), an advanced language model designed to quantify key dimensions of policy communication. Incorporating

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these policy commitment dimension, we apply Extreme Bounds Analysis (EBA) to identify the two variables most strongly associated with the clean energy market, which are then used to filter the events under investigation. Subsequently, a variety of event type tests are applied.

2. Methodology

2.1. Data collection - Textual analysis

We use the BIS open-source library gingado (Araujo, 2023) to collect central bank speeches mentioning Trump up to April 17, 2025, creating a corpus of 144 speeches. Trump-related content is identified via string matching in the 'text' column.

We chronologically analyze this data using the poldis R package Sposito (2021) to extract five textual variables: Frequency, Timing, Intensity, Commitment, and Urgency.

To evaluate their influence on the clean energy index, we compute daily averages and matched them with the S&P Global Clean Energy Index. Our final dataset contained 101 entries due to missing index values from market holidays or trading halts (Javed Awan et al., 2021; Toms, 2011).

2.2. Data analysis

2.2.1. Variable selection - Extreme bound analysis

To assess statistical significance, we follow the approach by Hlavac (2016), considering variables reliable if their coefficients show at least an 80% probability of being strictly positive or negative. As illustrated in Table 3 and Fig. 6, "Frequency" shows a robust negative relationship while "Commitment" and "Urgency" display stable positive correlations. "Timing" and "Intensity" are less robust, showing symmetric distributions around zero without clear directionality.

We designate the three robust variables as key factors and classify them as Free variables, while the weaker two are categorized as Doubtful variables. Utilizing the flexibility of the EBA framework, Eq. (2) incorporates these classifications, considering combinations of up to two Doubtful variables. The results, shown in Fig. 7 and Table 4, confirm that "Commitment" and "Urgency" remain robust under stricter conditions, while "Frequency" appears less robust.

To enhance model robustness, heteroscedasticity is addressed using robust standard errors (White, 1980), and multicollinearity is controlled using a VIF threshold of 7. LRI weighting further improved model fit (McFadden, 1974). Subsequently, we expand the Doubtful variable set by adding "Frequency", applying flexible combinations with a restriction of $k = 1$ to ensure valid outcomes, as represented in Eq. (3). Outcomes in Fig. 8 and Table 5 confirm that stricter constraints enhance credibility and maintain consistency.

2.2.2. Event identification and metrics construction

As shown in Fig. 8 and Table 5, we identify the most robust variables associated with the clean energy market. Next, we label each event collected from 2.1 based on its "Urgency" and "Commitment" levels. Specifically, if either measure falls within the top 25% of its distribution, the event is classified as "high-Urgency" or "high-Commitment", respectively. This threshold is consistent with the approach used by Patsopoulos et al. (2008), who demonstrated that using the top quartile as a cutoff is both reasonable and effective. In their analysis, applying two different I^2 thresholds (50% and 25%) both led to successful convergence to the pre-specified final I^2 level, supporting the robustness of the top-25% criterion. We retain the events meeting this criterion along with their dates for further analysis, resulting in a total of 35 events spanning from 2015 to the present. Finally, we merge these event dates with the corresponding dates of the clean energy index to facilitate subsequent analysis.

To quantify the market impact, we compute Normal Return using the tidyverse package in R. The analysis is based on daily log returns of the S&P Global Clean Energy Index from 2015 onward. Our other metrics are inspired by the work of Costa et al. (2025) and the relevant formulas will be presented in Appendix B.

2.2.3. Regression models and subgroup (heterogeneity) analysis

Since AAR remains constant across observations, it is excluded from the subsequent regression models. We begin by testing whether there is a statistically significant cumulative market response over the entire event period.

Then we performed regression analyses using both AR and CAR, along with NR, to examine their statistical significance. The results of the regression analyses were presented together in Table 1 for the comparative analysis. In Miller (2023), the x-axis represents event time with job displacement standardized to zero (the "treatment"), and the y-axis shows income relative to a baseline period. Inspired by his approach, we construct Fig. 2.

To further investigate the conditions under which the variables high commitment and high urgency explain the mechanisms underlying abnormal market responses, we conduct a heterogeneity analysis. These two variables, previously identified in Appendix A as significantly positively correlated with market performance, are grouped according to their median values.

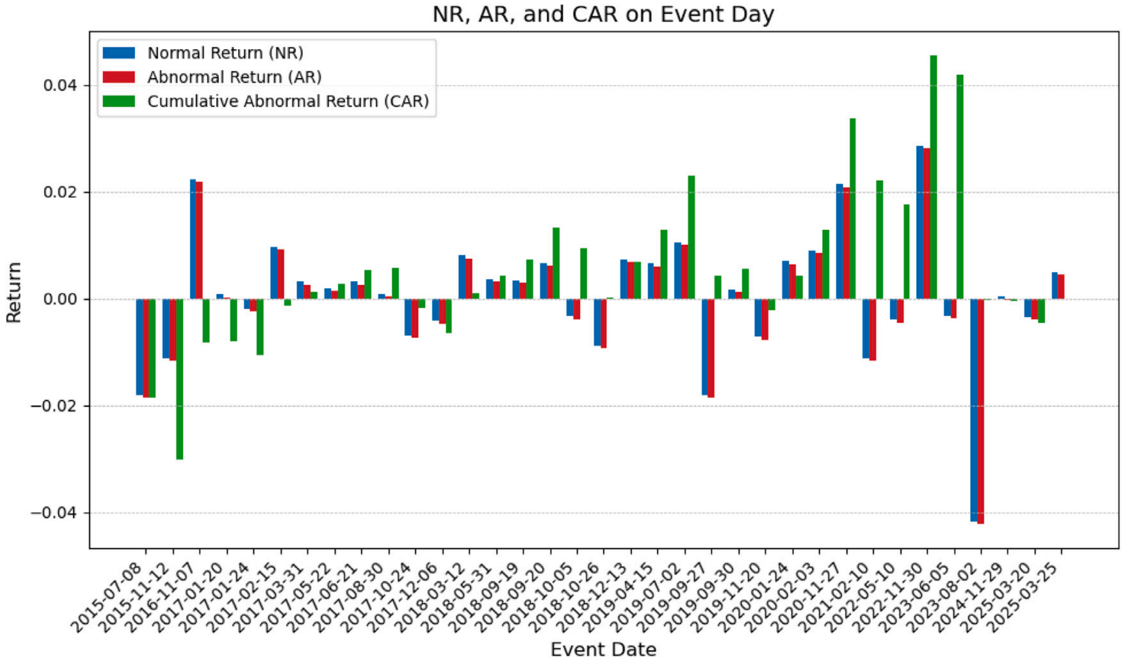


Fig. 1. NR, AR, and CAR on event day.

2.2.4. Event window analysis

To further analyze market fluctuations around the event, we employ the method proposed by Miller (2023), defining an event window that reflects the data's timeframe. Due to the extensive period covered by our dataset, we begin with a wider event window of ±10 trading days, formally expressed in Eq. (9). In Appendix C, we try a ±5-day event window, but the results are not very clear. On the other hand, a longer window makes it difficult to distinguish between consecutive events, as our analysis involves multiple events. As a result, the ±10-day window seems to be the most reasonable choice.

Since our analysis covers multiple events, we calculate the Average Abnormal Returns (AAR) as shown in Eq. (6), along with their cumulative values (CAAR) presented in Eq. (8), for each relative day. Statistical significance tests are conducted daily, with significant results indicated by asterisks (*) in the corresponding graphical representation.

2.2.5. First and latest event analysis

To explore this dynamic, we refine our analysis by selectively focusing on either the first event or the latest event occurring within the full ten-day event window for each observation unit. This approach enables us to investigate whether such alternative specifications enhance the explanatory power of our model. At this stage, unit fixed effects are not included. We note that abnormal returns maybe more intuitively interpretable when examined at the level of individual events rather than through aggregated averages.

Given that the variables "Urgency" and "Commitment" are recorded exclusively on the event day, we do not pursue a heterogeneity analysis based on these factors. Instead, inspired by insights from Miller (2023), we adopt the framework discussed in the "More than One Event Per Unit" section, considering the possibility that an event's impact may depend on the historical context of prior events. For instance, an initial layoff could elicit a significantly different market response compared to subsequent layoffs, either intensifying vulnerability or demonstrating reduced effects due to adaptation or floor effects.

3. Results and discussion

3.1. Event identification and metrics construction

We create bar charts for NR, AR, and CAR according to the timeline before and after the event to visualize the data in Fig. 1. AAR is excluded because it reflects the average value prior to defining the event window.

Fig. 1 illustrates the variation in NR, AR, and CAR with respect to the event timeline. We can observe that market volatility has increased significantly in the recent period, which will be further discussed in 3.4.

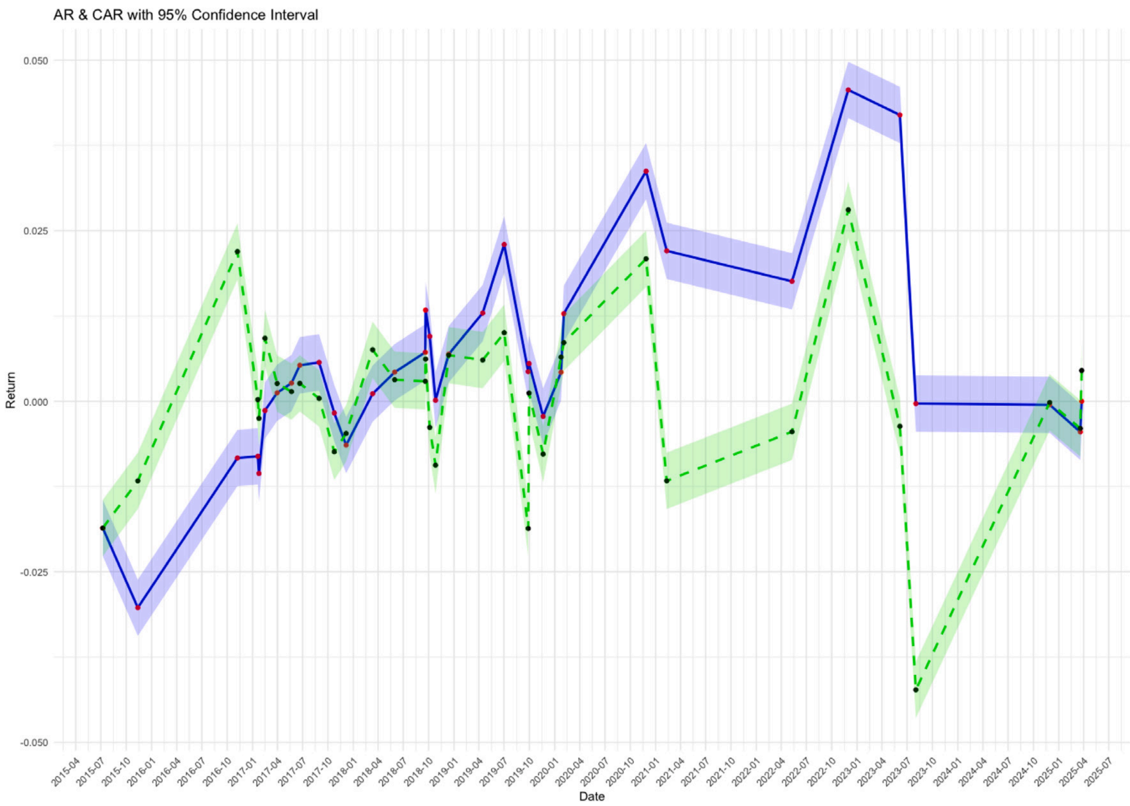


Fig. 2. Event trend.

Table 1
Summary of regression models and subgroup (Heterogeneity) analysis on abnormal returns.

Model	Intercept	daily_return Coefficient	Regression p-value
CAR	0.00513	0.50000	0.0135 *
High Urgency	0.00300	0.59272	0.120
Low Urgency	0.00716	0.47346	0.0354 *
High Commitment	0.00192	1.00161	0.00101 **
Low Commitment	0.00651	0.31099	0.291

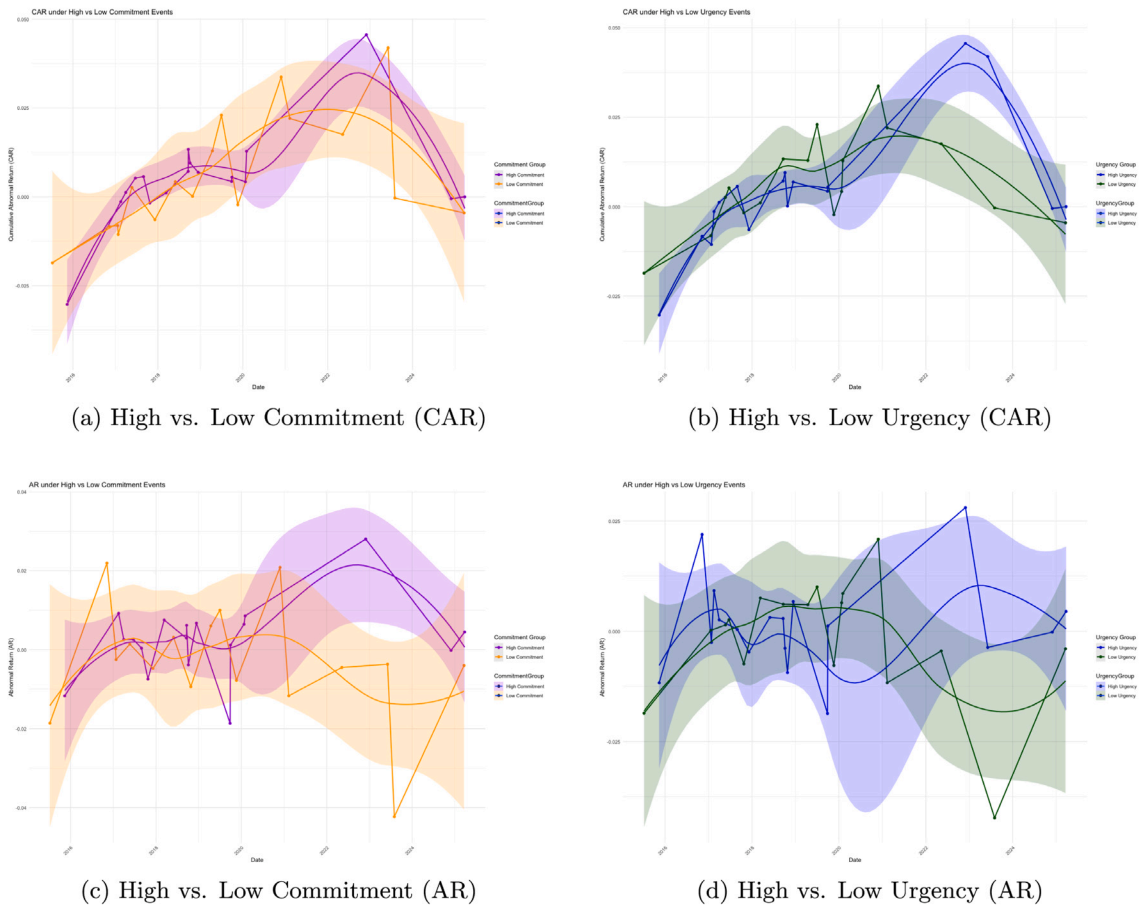
Notes: Regression models are specified as `CAR` and `AR` ∼ `daily_return`.
Significance codes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.
The subgroup regressions focus primarily on CAR, as the p-values associated with AR show limited variation across groups; therefore, the AR results of analysis are omitted from this table. It will be effectively illustrated through visualizations.

3.2. Regression models and subgroup (heterogeneity) analysis

Fig. 2 illustrates the clean energy market response to a series of policy events. The blue line represents the CAR, which shows a clear volatile trend, indicating a sustained abnormal market reaction over time. This trend is reinforced by the 95% confidence bands, which are statistically significant. The green dashed line represents the AR. The events triggered particularly significant market volatility from 2020 to 2025. In particular, AR has experienced increased fluctuations in the most recent period, with a sharp decline observed in the later stage of the event, indicating increased market volatility.

In the regression model, the coefficient for Normal Return in explaining CAR is 0.5, suggesting a positive relationship between daily market trends and cumulative abnormal returns. In the following regressions, we mainly use CAR as the dependent variable, as the preceding results suggest that the impact of policy-related events is clearly associated with this cumulative abnormal effect.

Table 1 shows that cumulative abnormal returns (CAR) are significantly correlated with daily returns, indicating considerable market volatility, Figs. 3(a) and 3(b) illustrate that CAR responds significantly to Trump's policy events, particularly those characterized by a higher level of commitment. While urgency also plays a role, its influence is more stable and statistically stronger when combined with a high degree of commitment. However, CARs for policy events in the low-urgency group exhibit greater significance than those in the high-urgency group. These findings suggest that the "Urgency" indicator which reflects timing effects,



(a) High vs. Low Commitment (CAR)

(b) High vs. Low Urgency (CAR)

(c) High vs. Low Commitment (AR)

(d) High vs. Low Urgency (AR)

Fig. 3. Heterogeneity analysis of AR and CAR by commitment and urgency.

captures a lagged market response, we find that events with lower urgency often lead to stronger abnormal returns than events with high urgency. This seems surprising. One reason may be that low-urgency signals look more careful and believable. In contrast, high-urgency messages may seem like noise or overreaction, especially if they are not clear. This matches ideas from signal clarity and investor attention theories. Markets may react more to clear and focused messages than to strong but confusing ones (Bloom, 1999). As shown in Figs. 3(c) and 3(d), the differences in abnormal returns (AR) are less stable and more volatile, indicating that cumulative effects over time provide clearer evidence of market differentiation in response to commitment and urgency signals.

These findings reinforce the idea that the market responds unevenly to policy signals, with those conveying greater clarity and credibility eliciting stronger reactions. Overall, the results show that market participants respond more actively to events characterized by higher levels of commitment and lower urgency, with "Commitment" exhibiting a more consistent and interpretable effect across various events.

3.3. Event window analysis

As shown in Fig. 4 and Table 2, the CAAR on the event day is not statistically significant, suggesting a relatively muted immediate market response to the event. However, the Average Abnormal Return (AAR) becomes significantly positive seven days after the event, indicating a potential delayed market reaction. This lagged response aligns with findings previously reported in Section 3.2.

3.4. First and latest event analysis

Fig. 5 illustrates that the impact of the first event on the market appears more concentrated, showing a clear short-term negative reaction followed by a rebound. In contrast, abnormal returns around the latest event are more scattered and volatile. This is consistent with the view of Miller (2023), who suggest that subsequent events may either heighten market vulnerability or lead to a diminished response due to increased investor adaptation or the presence of floor effects. Nevertheless, the volatility surrounding the latest event remains considerable, which is related to concerns over tariff policy mentioned in the central bankers' speeches.

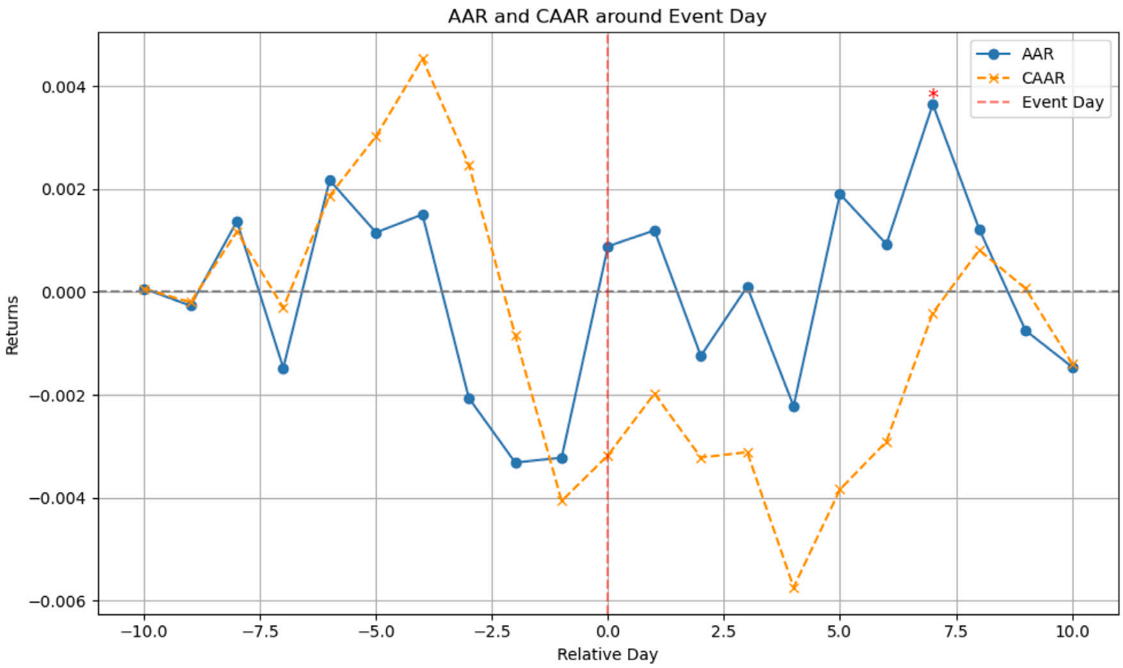


Fig. 4. 10-Day event window.

Table 2
Event study results with ±10-day window.

Relative day	AAR	AAR p-value	AAR Sig.	CAAR	CAAR p-value
−10	−0.000231	0.915775		−0.000231	0.915775
−9	−0.000394	0.737239		−0.000625	0.774338
−8	0.001789	0.252234		0.001164	0.731366
−7	−0.001196	0.334703		−0.000032	0.992421
−6	0.001612	0.175066		0.001580	0.646310
−5	0.001184	0.433188		0.002764	0.405878
−4	−0.001236	0.531824		0.001528	0.419004
−3	−0.002694	0.147566		0.001307	0.754496
−2	−0.002447	0.260734		−0.001139	0.815494
−1	−0.002843	0.206464		−0.003978	0.691521
0	0.001394	0.534947		−0.002593	0.728411
1	0.000697	0.677088		−0.001896	0.791726
2	−0.002031	0.393608		−0.003926	0.633666
3	−0.000546	0.796734		−0.004473	0.587117
4	−0.002201	0.232537		−0.006736	0.439340
5	0.002047	0.220236		−0.004689	0.611935
6	0.000548	0.803715		−0.003719	0.629974
7	0.003830	0.044260	**	0.000111	0.990998
8	0.001013	0.698653		0.001123	0.854308
9	−0.000827	0.590499		0.002968	0.979133
10	−0.000297	0.841836		−0.002342	1.000000

4. Contribution and limitation

4.1. Contribution

Within central bankers' speeches that reference Trump-related content, our Extreme Bounds Analysis (EBA) identifies "Commitment" and "Urgency" as the variables most strongly associated with movements in the clean energy market. These findings indicate that both the intensity of commitment expressed and the perceived urgency of taking action significantly and positively influence market responses. Interestingly, although "Urgency" shows a strong positive relationship in the EBA analysis, our heterogeneity analysis reveals that cumulative abnormal returns (CAR) are significantly higher in cases where urgency is perceived to be lower. This apparent inconsistency may be due to the way markets interpret central bank communication. When central banks express a strong sense of urgency, it may initially generate uncertainty or caution among investors rather than prompt immediate action. In

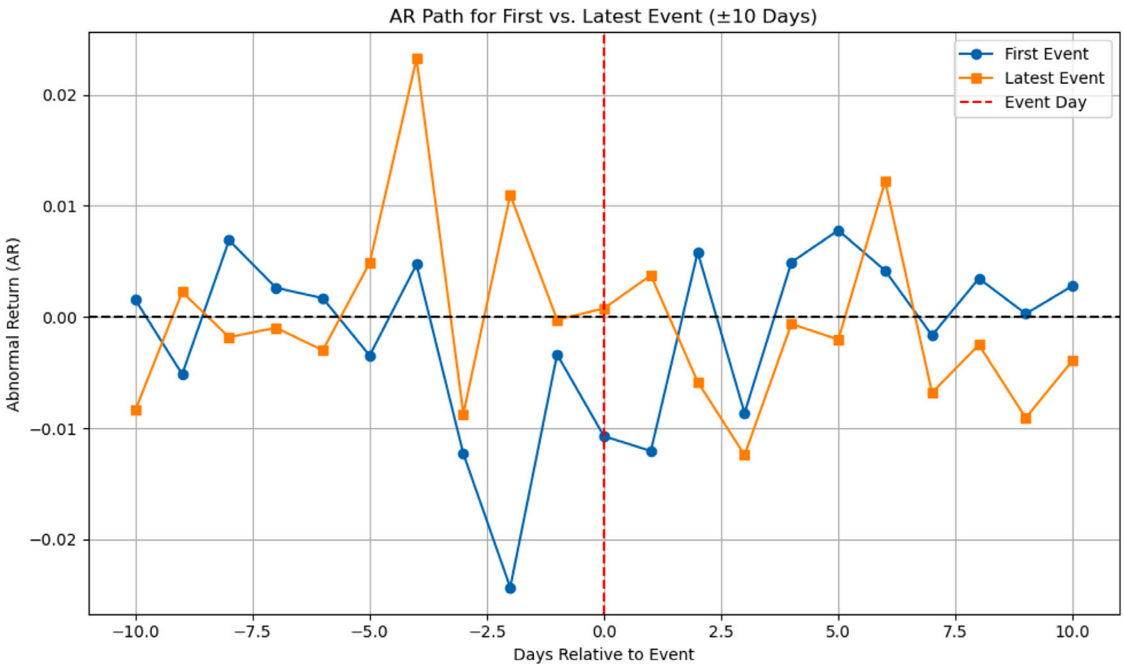


Fig. 5. First and latest trend.

other words, urgent language could be seen as signaling instability or risk, leading to hesitation in the short term. As a result, the market reaction is delayed, which is supported by our finding that the average abnormal return (AAR) becomes significantly positive on day 7 following such events. This suggests that the market may take time to digest and respond to policy signals, particularly during the first week. Recent Trump-related events, especially those mentioned in central bank speeches, seem to increase volatility in the clean energy market. This heightened volatility likely reflects broader policy uncertainty associated with Trump's presidency.

4.2. Limitation and future research

One key limitation textcolorredis we are unable to incorporate relevant control variables for each event. For instance, firm-level and macroeconomic indicators would be valuable control variables in the context of major corporate events, but these are not accessible within the scope of this study. As a result, the explanatory power of our model remains limited. Although we face data limitations, our findings provide meaningful insights and lay the groundwork for future research to explore additional variables and event-specific characteristics.

As the BIS database continues to update, future research could overcome these limitations by including a wider range of relevant events, enabling more precise identification of market response patterns. Such improvements could enhance the predictive accuracy of the analysis and offer investors and financial analysts more actionable and forward-looking insights.

CRediT authorship contribution statement

Yuqi Zheng: Writing – original draft, Formal analysis, Conceptualization. **Brian Lucey:** Writing – review & editing, Project administration, Conceptualization.

Appendix A. Extreme bounds analysis

A.1. All combinations of doubtful variables

After the steps of 2.1, we obtain a dataframe containing the following variables: the S&P Clean Energy Index, "Frequency", "Timing", "Intensity", "Commitment" and "Urgency". Following the experimental procedures outlined in Hlavac (2016), we first conduct the EBA analysis by treating all variables as doubtful, as the focus variables had not yet been identified. The corresponding formulation is presented in Eq. (1).

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon \tag{1}$$

Table 3
Sala-i-Martin's EBA-All combinations of doubtful variables.

Variable	N: CDF($\beta \leq 0$)	N: CDF($\beta > 0$)	G: CDF($\beta \leq 0$)	G: CDF($\beta > 0$)
(Intercept)	0.000	100.000	0.000	100.000
Frequency	90.651	9.349	88.122	11.878
Timing	20.218	79.782	21.702	78.298
Intensity	60.714	39.286	56.808	43.192
Commitment	16.421	83.579	17.397	82.603
Urgency	11.359	88.641	12.667	87.333

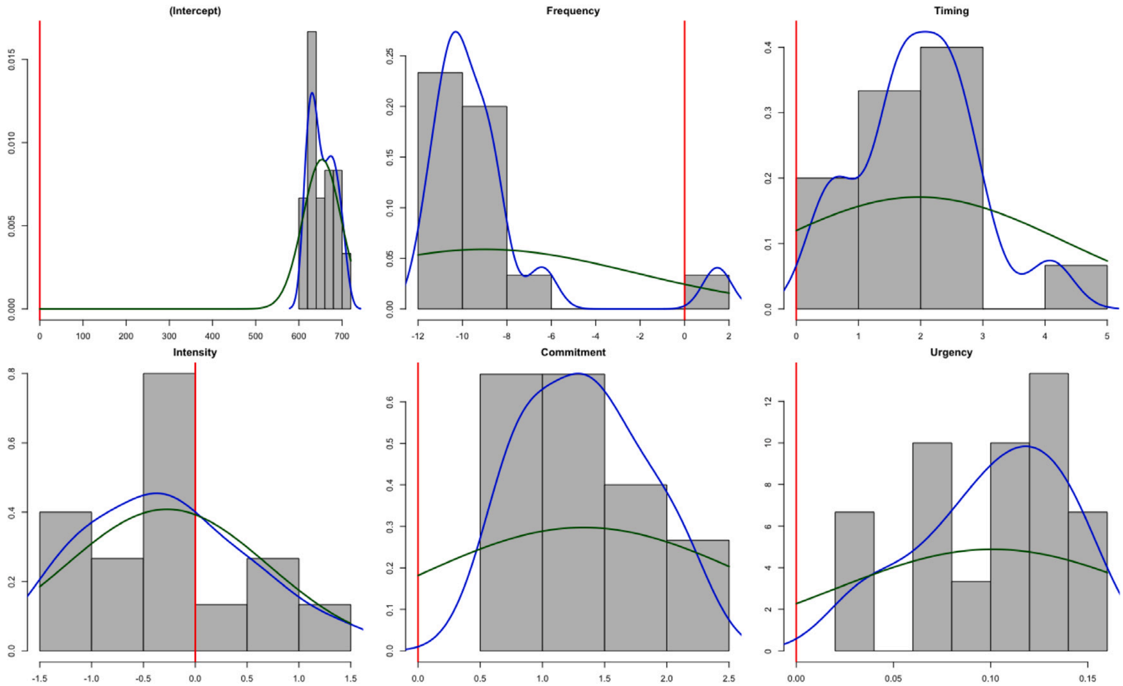


Fig. 6. All combinations of doubtful variables.

Where:

- Y represents the dependent variable S&P Clean Energy Index;
- X_i represents the set of doubtful variables, which include Frequency, Timing, Intensity, Commitment, and Urgency;
- β_0 is the intercept term;
- β_i is the coefficient of the doubtful variables;
- ϵ is the error term.

Thus, we obtained the results shown in Table 3 and Fig. 6.

A.1.1. More sophisticated EBA

$$Y = \beta_0 + \beta_1 \cdot \text{Frequency} + \beta_2 \cdot \text{Commitment} + \beta_3 \cdot \text{Urgency} + \sum_{j=1}^{k} \gamma_j \cdot Z_j + \epsilon \quad (2)$$

Where:

- Y represents the S&P clean energy index;
- Frequency, Commitment, and Urgency are Free variables, included in all model specifications;
- $Z_j \in \{Timing, Intensity\}$ represents the set of Doubtful variables, from which up to $k \leq 2$ variables are selected for each model;
- ϵ is the error term.

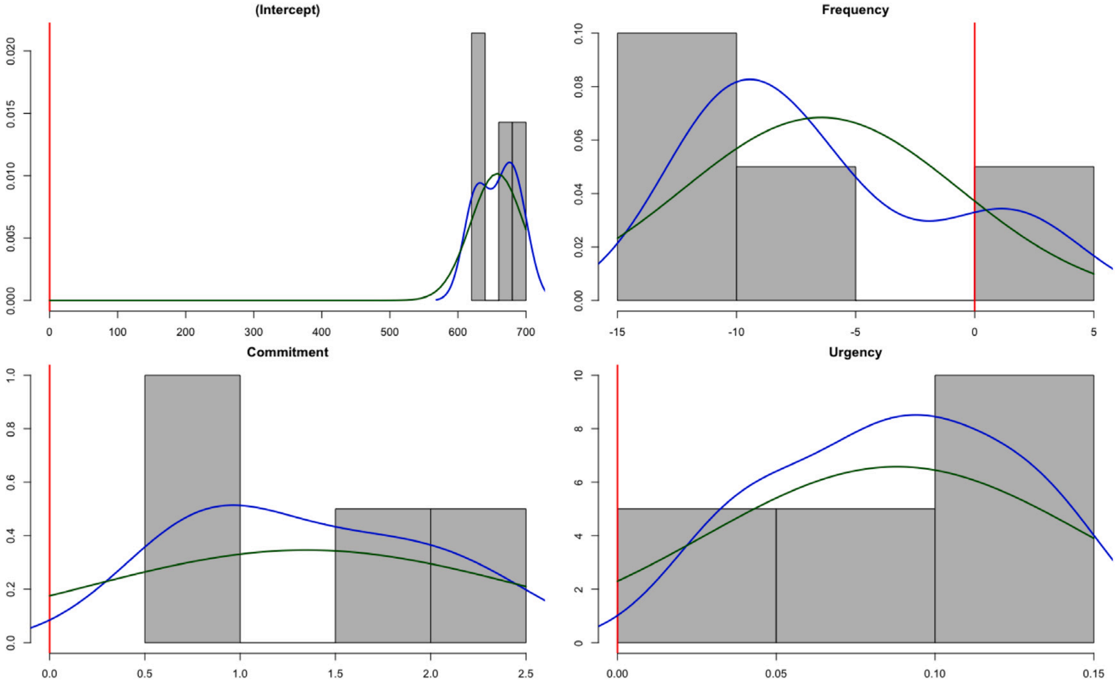


Fig. 7. More sophisticated EBA.

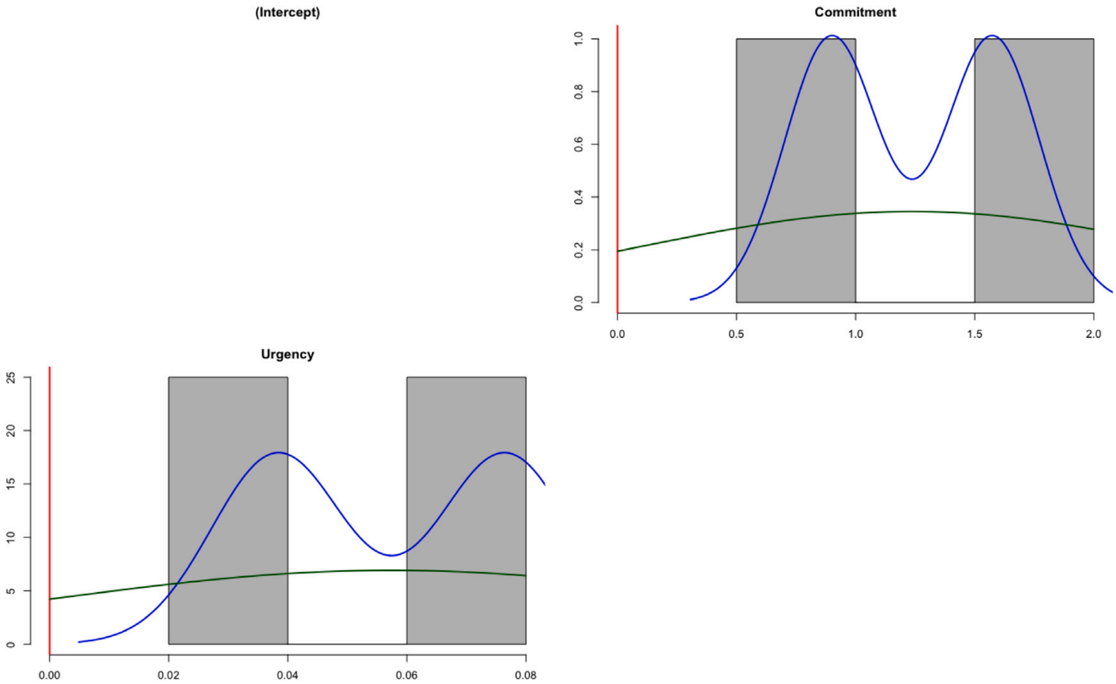


Fig. 8. More robust EBA.

Table 4
Sala-i-Martin's EBA—More sophisticated.

Variable	N: CDF($\beta \leq 0$)	N: CDF($\beta > 0$)	G: CDF($\beta \leq 0$)	G: CDF($\beta > 0$)
(Intercept)	0.000	100.000	0.000	100.000
Frequency	86.370	13.630	78.533	21.467
Commitment	13.082	86.918	15.152	84.848
Urgency	8.227	91.773	10.721	89.279

Table 5
Sala-i-Martin's EBA—More robust.

Variable	N: CDF($\beta \leq 0$)	N: CDF($\beta > 0$)	G: CDF($\beta \leq 0$)	G: CDF($\beta > 0$)
(Intercept)	0.000	100.000	0.000	100.000
Commitment	15.453	84.547	15.400	84.600
Urgency	18.126	81.874	17.177	82.823

A.2. More robust EBA

$$Y = \beta_0 + \beta_1 \cdot \text{Commitment} + \beta_2 \cdot \text{Urgency} + \sum_{j=1}^{k} \gamma_j \cdot Z_j + \epsilon \tag{3}$$

Where:

- Y represents the S&P clean energy index return;
- Commitment and Urgency are Free variables, included in all model specifications;
- $Z_j \in \{Frequency, Timing, Intensity\}$ represents the set of Doubtful variables, from which up to $k = 1$ variable is selected for each model;
- ϵ is the error term;
- Models with a Variance Inflation Factor (VIF) greater than 7 are excluded to mitigate multicollinearity;
- Robust standard errors are computed using the White estimator;
- The results are weighted using the log-likelihood ratio index (LRI) under this EBA framework.

Appendix B. Indicators calculation

Normal Return (NR): The Normal(daily) return is calculated using the logarithmic difference of prices between two consecutive trading days.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{4}$$

Abnormal Return (AR): Defined as the deviation of the normal return from the average daily return.

$$AR_t = R_t - \overline{R} \tag{5}$$

Average Abnormal Return (AAR): Calculated as the mean of abnormal returns across all events on each day in the event window.

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{6}$$

Cumulative Abnormal Return (CAR): The cumulative sum of abnormal returns over time.

$$CAR_t = \sum_{s=1}^{t} AR_s \tag{7}$$

Where R_t represents the return on day t, and P_t, P_{t-1} are the asset's closing prices on day t and day $t-1$, respectively.

Cumulative Average Abnormal Return (CAAR): Reflecting the overall abnormal performance during the event window.

$$\text{CAAR}_t = \frac{1}{N}\sum_{i=1}^{N} \text{CAR}_{i,t} \tag{8}$$

Where:

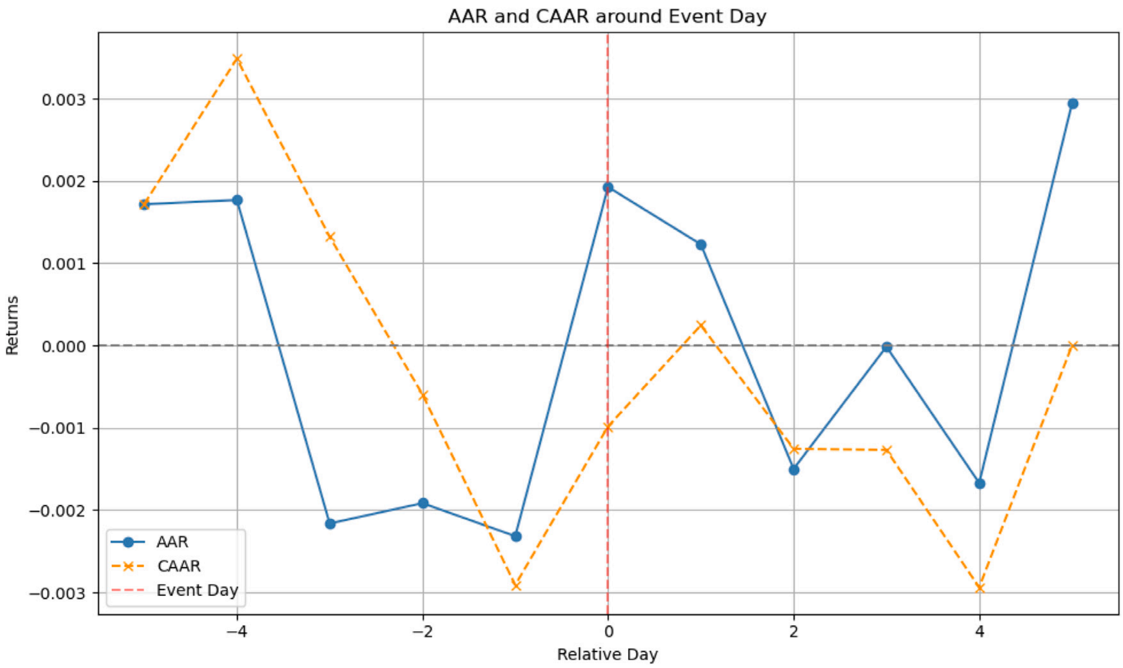


Fig. 9. 5-day event window.

Table 6
Event study results with ±5-day window.

Relative day	AAR	AAR p-value	AAR Sig.	CAAR	CAAR p-value
−5	0.001716	0.258690		0.001716	0.258690
−4	0.001768	0.372885		0.003484	0.210532
−3	−0.002162	0.242228		0.001322	0.657704
−2	−0.001915	0.376802		−0.000594	0.885933
−1	−0.002316	0.327498		−0.002910	0.547972
0	0.001926	0.392775		−0.009836	0.867212
1	0.001229	0.464258		0.000245	0.970184
2	−0.001499	0.527784		−0.001254	0.863486
3	−0.000015	0.994500		−0.001269	0.860552
4	−0.001670	0.362827		−0.002938	0.686278
5	0.002938	0.136855		−0.004716	1.000000

- $\text{CAR}_{i,t}$ represents the cumulative abnormal return for event i up to relative day t;
- N is the total number of events.

$\boldsymbol{AR_{it}}$: AR in event window.

$$AR_{it} = \sum_{k \neq -10} \beta_k \cdot \mathbb{1}[\text{relative\_day} = k] + \epsilon_{it} \tag{9}$$

We transform relative_day into dummy variables, using day −10 as the reference category. AR_{it} represents the abnormal return for firm i on day t.

Appendix C. Event window

When we use a ±5-day window around the event, the results are shown in Fig. 9 and Table 6.

Data availability

Data will be made available on request.

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