Who Responds to ECB Green Speeches?
Green–Brown Stock Repricing across Institutional Ownership Groups

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ABSTRACT

Recent research suggests that climate-focused central bank communication can affect asset prices. Different investor types may, however, respond differently to these communications. We study whether ECB green communication is associated with short-horizon repricing between greener and browner stocks in major European equity markets, and whether responses vary across institutional ownership (IO) and over time. In 2010–2020, when ECB green speeches were relatively rare and novel, economically meaningful positive green–brown return differentials are concentrated on high-intensity speech days, and we find no evidence of IO heterogeneity across groups, suggesting broad market incorporation. In 2021–2024, we see that ECB climate communication becomes more frequent. In addition, event-day effects attenuate, consistent with communication operating more as a persistent signal that may reinforce existing beliefs and be incorporated more gradually. Any remaining sensitivity in some specifications is more detectable among high-IO stocks.

Keywords: Green finance; central bank communication; European Central Bank (ECB); stock returns; institutional ownership.

JEL: E58; G11; G23

1. Introduction

Climate change can generate wide-ranging, hard-to-quantify, and unevenly distributed economic risks. Such risks are amplified by non-linearities and tail risks, and can propagate into systemic financial spillovers. Consequently, central banks and financial supervisors are motivated to engage increasingly with climate-related financial risk (Dietz et al. 2016; Battiston et al. 2017; Diaz and Moore 2017; Trust et al. 2025). While markets are starting to price in climate risks, many believe they remain systematically underpriced due to dispersed benefits, collective costs, structural barriers, and behavioural biases (Bolton et al. 2020; Eren et al. 2022; Bauer et al. 2024). In Europe, the European Central Bank (ECB) has taken a proactive role in integrating climate considerations into policy, risk management, and supervision (Neszveda and Siket 2025; European Central Bank 2022a, 2022b, 2025). Within this broader agenda, ECB green communication is a key component of the policy toolkit because it can shape expectations and

[1] *The views expressed in this paper are those of the author(s) and do not necessarily reflect the views of the Magyar Nemzeti Bank*

move markets, thereby potentially supporting climate-related policy efforts aligned with those objectives (Blinder et al. 2008; Eliet-Doillet and Maino 2022; Neszveda and Siket 2025; Campiglio et al. 2025).

In financial markets, prices emerge from the interactions of market participants and are assumed to reflect their beliefs and preferences. Investors' beliefs shape their expectations about an asset's future prospects, including their perceptions of expected returns and risks, as well as synchronisation risk, and thus play a central role in pricing (Egan et al. 2014; Bauer et al. 2024; Ceccarelli and Ramelli 2024). Consequently, Central Bank green speeches may not merely be general remarks, but public signals that may help coordinate expectations about the green transition path and thereby generate real market effects (Abreu and Brunnermeier 2002). Therefore, studying the green central bank communication impact on asset prices is important because market prices provide a revealed-preference measure of whether investors treat central bank green communication as valuation-relevant.

Existing evidence on "green" central bank communication largely documents average market effects but has not directly tested whether these effects vary with investor composition, particularly between more institutionally dominated and more retail-dominated market segments. This question is relevant given well-documented differences in how institutional and retail investors process climate and Environmental, Social, and Governance (ESG) information. Compared with institutional investors, retail investors may be less responsive when signals are complex or text-heavy (Bazrafshan 2023; Moss et al. 2024). By contrast, the evidence for institutional investors is more consistent with climate risk being reflected in portfolio decisions, as shown by survey-reported concern about financially material climate risks and lower exposure to high-emissions firms (Krueger et al. 2020; Bolton and Kacperczyk 2021; Enders et al. 2025). Taken together, these differences imply that investor composition may shape how ECB green communication is incorporated into prices, motivating our tests of whether market reactions differ between institutionally dominated and retail-dominated segments. More broadly, this analysis speaks to the potential reach of public green communication by shedding light on how widely such messaging can coordinate expectations and be reflected in market pricing.

Building on Neszveda and Siket (2025), we construct a speech-level measure of ECB "green tone" from ECB speeches using a dictionary-based approach and form green and brown portfolios based on firms' emissions performance to examine the relationship between ECB green speeches and green–brown returns in major European equity markets (Germany, France, and Italy). Consistent with prior work, and across a range of methods, we find that in 2010–2020, economically meaningful positive green–brown return differentials are concentrated on rare, high-intensity speech days, suggesting that such episodes may have carried novel information, consistent with markets treating these communications as relatively novel signals about the ECB's climate stance and adjusting prices accordingly.

We then extend Neszveda and Siket's (2025) approach and examine whether the response varies across institutional-ownership (IO) groups (high IO: more institutionally dominated; mid IO: mixed institutional–retail; low IO: more retail dominated). In 2010-2020, we find no evidence of IO heterogeneity across groups. The absence of robust cross-group differences suggests that when ECB green communication is salient enough to trigger repricing, the response is not confined to a narrow investor clientele and is reflected more broadly in prices, which is consistent with attention/sentiment channels alongside standard risk-premium channels, though we cannot cleanly identify the underlying mechanism. Such episodes may reinforce the valuation relevance of climate information for institutions with discretion to rebalance, while also drawing attention from more attention-driven investors, thereby potentially amplifying the overall market response.

We further test whether the relationship between ECB green speeches and a differential return between Green and Brown portfolios persists post-2020 (2021–2024), when climate-related ECB communication becomes markedly more frequent (Figure 1) and may therefore convey less incremental information to markets. In 2021–2024, this relationship attenuates. As ECB climate messaging becomes more frequent and anticipated, repeated communication may increasingly confirm an established policy stance rather than trigger large belief updates on the event day, so pricing effects may be smaller and/or more gradual. The ownership pattern also shifts: in the later period, the panel omnibus tests indicate IO-related differences across groups, with some evidence for modestly greater sensitivity among high-IO stocks. This is consistent with institutional investors being more fundamentals-oriented and more likely to incorporate recurring policy signals into pricing (Lai et al. 2013; Chen et al. 2022; Cui et al. 2025). Caution in the IO conclusion for the post-2020 period is merited, however, as the effect is not consistently observed across all methods employed.

This study contributes to the discussion of the role of green central-bank communication by providing market-based evidence on whether green central-bank communication is reflected in prices and how the relationship varies by ownership structure and over time, which helps assess whether the response is broad or concentrated across investor clienteles. Our findings suggest that sufficiently intense ECB green communication is associated with short-horizon return differences between greener and browner firms. This pattern is consistent with the view that climate-related communication is linked to shifts in investor attention and beliefs, as well as with the relative pricing of climate-transition risk exposure.

As ECB climate communication becomes more frequent and less surprising, the marginal event-day market impact of individual speeches may decline. This pattern is consistent with a shift from “event news”, toward a more persistent policy signal. If repeated communication primarily reinforces an already anticipated longer-run stance, repricing may occur more gradually rather than as sharp jumps on speech days, with effects more detectable in institutionally dominated stocks whose investors may track and incorporate policy signals continuously. In that setting, the consistency and credibility of the signal may matter more, with weaker event-day effects potentially reflecting communication that increasingly confirms existing beliefs about the financial relevance of climate risk and contributes to more gradual adjustment in the pricing of transition risk.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the data and empirical methodology, including the construction of the ECB green sentiment index. Section 4 presents the empirical results. Section 5 discusses the main findings and their implications.

2. Literature Review

A growing policy and academic debate concerns the appropriate role of central banks in addressing climate-related financial risks. Climate change and natural disasters are increasingly viewed as potential sources of systemic risk to financial stability, strengthening the case for incorporating climate considerations into central banking, and for prudential oversight (Dikau and Volz 2018). Some scholars argue that central banks should take a more active role in supporting the transition to a low-carbon economy, including through adjustments to operational frameworks and financial-stability tools (Monnin 2018; Dikau and Volz 2021). More recently, the literature emphasises that this role is evolving, with banks gradually taking a more proactive stance as climate risks become more clearly material to central-bank mandates (Thiemann et al. 2023).

As climate considerations are increasingly discussed in relation to central banks' existing objectives, central bank communication plays an increasingly important role because it can influence beliefs (including expectations of others' behaviour) and market responses, and may therefore help advance climate-oriented actions (Blinder et al. 2008). Egan et al. (2014) showed that investors' beliefs about others' return expectations predicted stock portfolio allocations, even after accounting for their own expectations. Participants reported allocating more of their portfolios to stocks when they perceived others as more optimistic about the stock market. Specifically in the context of green investing, Ceccarelli and Ramelli (2024) provided causal evidence that transition beliefs, including beliefs about public support, played an important role in shaping green return expectations and investment decisions. Similarly, Bauer et al. (2024) found that shifting investors' second-order beliefs about climate risks and the pricing of those risks through information provision affected return expectations. Respondents who received a message stating that most other participants believed climate risks were important for pricing and currently underpriced were more likely to report higher expected excess returns for the MSCI World Climate Action Index relative to its parent index. More broadly, Mildenberger and Tingley (2019) found that support for pro-climate policies increased after respondents updated their second-order beliefs, following information that the true share of the population believing climate change was occurring was higher than they had previously thought.

The findings above connect directly to the notion of synchronisation risk in Abreu and Brunnermeier (2002), who formalise the central role of second-order beliefs. Their framework highlights that when correcting mispricing requires coordinated action by a critical mass of sophisticated investors, arbitrage becomes risky because traders are uncertain whether a sufficient number of others share their assessment and will also trade against the mispricing. Because dispersion in beliefs is central to synchronisation risk, Abreu and Brunnermeier (2002) discuss two mechanisms that can reduce it: announcements and information revealed through trading. While announcements can accelerate correction by making mispricing more widely known, private "guru" statements may be non-credible due to incentives to manipulate prices (Bénabou and Laroque 1992). Compared with self-interested trader announcements, central bank communication may be viewed as a more credible public signal, which can compress belief dispersion and accelerate repricing.

Viewed through this lens, climate-related central bank communication may act as a focal signal that coordinates beliefs about the pricing relevance of climate risks. Emerging evidence suggests that "green" central-bank communication can influence asset prices and sustainable financial behaviour, potentially supporting central banks' climate-related objectives. For example, ECB green communication coincides with significantly positive green–brown equity return spreads, lower green bond yields, and higher euro-area green bond issuance (Eliet-Doillet and

Maino 2022; Neszveda and Siket 2025). Campiglio et al. (2025), using firm-level data from 41 countries, find that greener firms' stock returns benefit when central-bank speeches feature more frequent and salient climate focus. Dikau and Volz (2023) document that green window guidance in China promoted sustainable lending and investment, while Lupu and Criste (2023) find that central banks' climate-related discourse in Europe is associated with improved financial stability indicators.

Although emerging evidence suggests that "green" central-bank communication may influence asset prices and sustainable financial behaviour, the extent to which these effects are concentrated in particular investor clienteles, or distributed more broadly, remains unclear. In particular, responses may vary between more institutionally dominated segments and more retail-dominated segments. There are well-documented differences in how institutional and retail investors process climate and ESG information. Compared with institutional investors, retail investors may be less responsive when signals are complex or text-heavy: studies find little retail reallocation around ESG press releases and limited attention/trading responses to detailed ESG text, whereas simplified, salient signals (e.g., prominent ESG rankings) do attract retail attention and trading (Bazrafshan 2023; Moss et al. 2024). By contrast, the literature provides clearer evidence that institutional investors incorporate climate risk into portfolio decisions. Krueger et al (2020) show that institutional investors perceived climate risks as financially relevant and as already materialising, particularly through regulatory channels. These concerns reflect a combination of reputational, moral or legal, and risk/return motives. Consistent with this, Bolton and Kacperczyk (2021) and Enders et al. (2025) find evidence that institutional investors are less willing to hold shares in firms with higher carbon exposure, relative to firms with lower carbon exposure.

The above differences in how retail and institutional investors process and act on climate/ESG information align with a broader literature on investor sophistication. In particular, institutional investors are, on average, more fundamentals-oriented than retail investors, even though they still exhibit behavioural biases. Institutional investor behaviour tends to be more closely tied to valuation-relevant information and is often associated with more efficient price discovery and stronger long-run return patterns (Lai et al. 2013; Chen et al. 2022; Cui et al. 2025). By contrast, retail investors are more attention-driven, trading disproportionately in attention-grabbing stocks and in stocks with elevated search intensity, which could generate temporary price pressure, post-announcement drift, and subsequent reversals (Barber and Odean 2008; Da et al. 2011; Hervé et al. 2019; Chen et al. 2022).

Taken together, the evidence discussed thus far suggests that institutional investors tend to face lower ESG information-processing costs than retail investors and are therefore more likely to treat climate-related information as valuation-relevant for risk management and fundamentals. Retail investors, by contrast, are more likely to react to green signals when they are salient, simple, and easy to interpret. As a result, investor composition may shape how climate-related narratives—including central bank climate communication—are incorporated into prices: institutional investors may respond when communication reinforces a credible longer-run policy stance, whereas retail investors may respond more to signal simplicity and salience. More generally, the market impact of climate communication may depend not only on investor composition but also on the communication's characteristics (e.g., intensity, framing, and frequency).

In particular, differences in investor attention and processing may lead market reactions to vary with the salience and frequency of climate communication. Novel and rare communications, which are likely to be more salient, may be more likely to generate visible responses on the speech day, especially if attention-driven trading plays a large role. In contrast, more frequent and routine communication may be less surprising, less salient and incorporated more gradually. This motivates our ownership-based tests of whether market reactions to ECB green communication differ across investor segments and vary with the salience and frequency of communication. More broadly, evidence on how widely such signals are reflected in market prices helps gauge the potential reach of ECB green messaging.

3. Data and Methodology

This study leverages transparent, reproducible datasets, enabling us to link time-stamped ECB speeches to daily equity pricing. We construct a speech-based measure of ECB climate communication and merge it with LSEG Workspace (Refinitiv) returns, firms' emissions scores, institutional ownership data, and standard risk factors from the Kenneth R. French Data Library. This combination allows us to quantify short-horizon pricing around climate-related communication, examine heterogeneity across investor bases, and assess whether patterns remain stable in the post-2020 period, when climate communication became more frequent.

To facilitate comparability with prior evidence, our baseline empirical design follows a closely related approach to Neszveda and Siket (2025), including the construction of the ECB green-sentiment measure, sample construction and data-cleaning procedures, and the core specification linking green communication intensity to the green–brown equity return spread. We complement the baseline analysis with additional robustness and validation checks. We then extend the framework in two directions: first, we test whether market responses vary across institutional-ownership groups (high, mid, and low IO); second, we re-estimate the same design in an extended sample from January 2021 to December 2024 to assess whether the association remains stable in the post-2020 period.

3.1. Data and sample construction

Our empirical analysis spans two periods: a primary sample from January 2010 to December 2020, matching Nesveda and Siket's (2025) original study period, and a post-period extension from January 2021 to December 2024. This structure preserves comparability with the benchmark period while extending the analysis in two directions: heterogeneity across institutional ownership groups and an extension of the sample to 2021–2024 to assess whether the documented patterns persist in the later period. We use LSEG Workspace (Refinitiv) to retrieve our financial market data, including daily total-return indices, trading volume, common shares outstanding, and closing prices for both active and delisted Ordinary Shares with primary listings on exchanges in Germany, France, and Italy. We also obtain firm-level emission-reduction scores and institutional ownership data and merge them with market data. We then preprocess the data to mitigate the influence of extreme observations and ambiguously coded emission-score observations (e.g., whether zero values represent the lowest possible score or missing data; see **Appendix S1** for details).

Institutional ownership (IO) is a practical, observable proxy for a firm's investor base, classifying stocks as high IO (more institutionally dominated), mid IO (mixed), or low IO (more retail dominated). Laarits et al. (2022) show that high retail-trading-intensity stocks tend to have lower institutional ownership. In the climate-finance and ESG literature, IO also reflects systematic institutional positioning: institutional ownership is lower for firms with higher carbon intensity, consistent with reduced institutional exposure to more carbon-intensive ("brown") stocks (Bolton and Kacperczyk 2021; Enders et al. 2025). Collectively, this supports IO as a transparent, empirically grounded way to distinguish relatively institutional- versus retail-dominated stocks in our IO-based heterogeneity analysis of reactions to ECB green communication.

To construct the portfolios, we sort firms into ten emissions-score deciles. We then form IO groups within each emissions-score decile by splitting firms into IO-score tertiles (low, mid, high), so that IO comparisons are made among firms with similar emissions-reduction scores. Institutional ownership (IO) is observed at quarter-end. Therefore, to avoid look-ahead bias and mitigate reverse causality, where events occurring within a quarter t could influence quarter-end IO for that same quarter, we form IO tertiles using lagged IO from the quarter $t-1$ and keep these group assignments fixed throughout the quarter t.

3.2. ECB green sentiment measure and event definition

The core explanatory variable is the ECB Green Sentiment Index, constructed using dictionary-based textual analysis of speeches and Q&A transcripts from ECB websites. The index is defined as the daily total count of the following ten pre-specified climate-related keywords: *green, climate change, climate risk, climate-related, emission, global warming, environmental, carbon, ecological,* and *ESG*. Formally, the index is:

$$\text{SENTIMENT}_t = \sum_{k \in \mathcal{K}} \text{count}_t\,(k) \tag{1}$$

where $\mathcal{K}$ denotes the keyword set and $\text{count}_t(k)$ is the frequency of the keyword k on day t.

A calendar day is classified as a green speech day if $\text{SENTIMENT}_t \geq 1$. We identify the five greenest speeches by ranking all green speech days by SENTIMENT_t (highest to lowest) and then verifying that the corresponding speech title contains at least one climate-related keyword. In the primary sample (January 2010–December 2020), this procedure yields the following five greenest dates: 8 November 2018, 27 November 2018, 17 April 2019, 5 February 2020, and 28 September 2020. In the post-period extension (January 2021–December 2024), the five greenest dates are: 29 April 2021, 3 June 2021, 16 November 2022, 1 October 2023, and 26 May 2024. We also find that green speech days become much more frequent after November 2018, increasing from 76 in the primary sample (2010–2020) to 192 in the extended sample (2021–2024) **(Figure 1).**

3.3. Empirical Methodology

Building on the empirical approach in Neszveda and Siket (2025), we begin with the aggregate analysis for 2010–2020, using an event-study approach to estimate the average market response of the green–brown return spread (formed based on emissions scores) around the five speech days with the highest green-sentiment intensity. We then estimate complementary cross-sectional regressions to assess whether the intensity of ECB green sentiment predicts returns on the green–brown portfolio. Together, these two steps constitute our baseline design. We then complement the baseline design with additional robustness and validation analyses. First, to account for the possibility that effects may be concentrated among high-intensity events, we use cross-validation to select a sentiment-intensity threshold that best captures where the spread reaction is strongest (Varian 2014). Second, conditional on this threshold, we conduct a permutation-based placebo test that reassigns event dates within a restricted pre-event window and compares the observed statistic to the resulting randomisation distribution. This helps mitigate concerns that our high-intensity estimates are confounded by other news occurring near ECB communication dates (e.g., climate policy announcements or major climate news; Ernst 2004; Corrado 2011; Winkler et al. 2014).

Extending the baseline design to test for heterogeneity by IO, in the IO-based analysis for 2010–2020, we estimate firm-level panel regressions with firm and day fixed effects to test whether responses vary by emissions performance and IO (Gormley and Matsa 2014). For cross-group heterogeneity, we place primary weight on omnibus (joint) tests and across-group contrasts; within-group results are treated as complementary diagnostics. As a complementary diagnostic, we implement a within-group permutation-based placebo test as a robustness check, analogous to the procedure used in the aggregate analysis. We additionally assess whether market frictions are more prevalent among groups exhibiting stronger responses by comparing, across groups, the shares of stocks with high values of two friction proxies: residual institutional ownership (Weber 2017) and idiosyncratic volatility (Pontiff 2006; Ali et al. 2003).

Finally, we extend the sample to 2021–2024 and re-estimate the same set of tests for the aggregate and IO-based analysis in this later period. We complement these results with a pooled portfolio-level regression that allows the sentiment–greenness relationship to vary between the 2010–2020 (pre-2021) and 2021–2024 (post-2020) periods and differ across IO groups.

3.3.1. The event study

We conduct an event study (Fama et al. 1969) on the five highest-intensity (“greenest”) ECB speech days in each sample period. We form equal-weighted decile portfolios based on firms’ Refinitiv Emission Scores (Decile 10 = greenest; Decile 1 = brownest) and analyse the green–brown long–short return spread. Abnormal returns for the spread are computed relative to standard expected-return benchmarks (market model, Fama–French three-factor, and Carhart four-factor), using European Fama–French factors and the European momentum (WML) factor. We evaluate cumulative average abnormal returns for the spread over short event windows around each speech; **Appendix S2** reports portfolio construction, model specifications, and inference details. This design is closely aligned with Neszveda and Siket (2025).

3.3.2. Cross-sectional and pooled regression

To complement the event-study evidence, we estimate regressions on green-speech days relating the green–brown return spread to ECB green sentiment. Our baseline controls include VIX, Euro STOXX 50 returns, and European SMB (small-minus-big), HML (high-minus-low), and WML (winners-minus-losers) factors, consistent with Neszveda & Siket (2025). We assess robustness using alternative speech-day definitions (SENTIMENT ≥ 1 vs ≥ 2) and by excluding the five highest-sentiment speeches. To examine post-2020 stability, we estimate pooled specifications on the combined sample with a sentiment × post-2020 interaction. For IO-based analysis, we estimate analogous pooled regressions on IO-group spread returns, allowing the sentiment effect to differ across periods and IO groups via interaction terms (details and full specifications in **Appendix S3**).

3.3.3. Cross-validation threshold

To identify the sentiment intensity at which return responses become measurable, we select a "high-intensity" threshold using the 2010–2020 green-speech-day sample ($SENTIMENT_t \geq 1$; 76 days). Drawing on the cross-validation approach discussed in Varian (2014), we use 3-fold cross-validation to choose among pre-specified candidate thresholds (70th–85th percentiles) in a hinge-regression framework, selecting the threshold that minimises out-of-sample RMSE. In this setting, cross-validation provides an out-of-sample validation criterion for selecting the threshold that defines "high-intensity" sentiment, reducing reliance on in-sample fit and helping to mitigate overfitting (Varian 2014). Full implementation details are provided in **Appendix S4.**

3.3.4. Permutation-based placebo test

To mitigate concerns that our estimates may be confounded by other news occurring near ECB communication dates, we implement a restricted permutation-based placebo test (Ernst 2004; Winkler et al. 2014). Permutation inference compares the observed statistic to an empirical null generated by reassigning event dates, which can help mitigate false rejections (Type I error) provided the reassignment scheme yields valid placebo comparisons. This nonparametric approach is also useful because abnormal returns may deviate from normality, in which case standard t-tests can be poorly specified (Corrado 2011). We apply the test in both the 2010–2020 and 2021–2024 samples, for the aggregate and within IO-based analyses. Full implementation details are reported in **Appendix S5.**

3.3.5. Panel regression

To assess whether return responses vary by institutional ownership (IO), we estimate two-way fixed-effects panel regressions with firm and day fixed effects, relating stock returns to interactions between ECB green sentiment, emissions-score rank, and institutional-ownership group. Consistent with Gormley and Matsa (2014), day fixed effects absorb common time-varying shocks, and firm fixed effects control for time-invariant unobserved firm characteristics. With day fixed effects, the level effect of sentiment is absorbed, so identification comes from the interaction terms capturing differential responses across emissions and ownership segments. We also include standard time-varying firm-level controls (Beta [Carhart 4-factor], Size, Book-to-market [B/M], and Momentum) and report two-way clustered standard errors by firm and day (Petersen 2009). **Appendix S6** reports the full specification, variable definitions, and alternative heterogeneity tests (linear trends and tail contrasts).

3.3.6. Descriptive: Market Friction Analysis

Finally, we provide a descriptive market-frictions diagnostic to assess whether speech-day return responses are stronger among stocks with tighter trading frictions, proxied by RIOR (short-selling constraints) and IVOL (idiosyncratic risk). Details on the construction of residual institutional ownership (RIOR) as a proxy for short-selling constraints (Weber 2017) and idiosyncratic volatility as a proxy for idiosyncratic risk and limits to arbitrage (Pontiff 2006; Ali et al. 2003) are reported in **Appendix S7.**

4. Results

4.1. Overview

Overall, the evidence suggests that return response to ECB green communication is concentrated in sufficiently high-intensity speeches, and that its strength varies across periods and inference approaches. In 2010–2020, the event study around the five “greenest” speeches shows economically large and statistically significant green–brown differentials (brown underperforms green by at least 0.5% per day). Cross-sectional regressions on green-speech days show that higher ECB green sentiment is associated with a larger Green–Brown return spread, but it becomes close to zero once the five highest-sentiment speeches are excluded, indicating that the relationship is driven by rare, extreme events. Using cross-validation, we select a high-intensity threshold at roughly the 85th percentile (sentiment > 12.5; 12 days), and permutation-based placebo tests indicate a positive and statistically significant effect above this cutoff. In the IO-based analyses, omnibus (joint Wald) tests in the panel do not provide statistically significant evidence that the sentiment–greenness relationship differs across IO tertiles. Within-group permutation tests provide a complementary, non-parametric check and are consistent with the high-intensity signal being directionally most evident in the mid-IO group. This pattern also does not appear to be primarily driven by market frictions. However, these within-group patterns do not translate into statistically significant cross-group differences and should be interpreted cautiously. Overall, we find no strong evidence of systematic heterogeneity across IO groups.

In 2021–2024, the event-study evidence no longer shows green outperformance on the five greenest days, and pooled regressions imply attenuation after 2020. Permutation-based tests on later-period days that exceed the pre-2020 high-intensity cutoff (sentiment >12,5; 50 days) indicate that there may still be a positive abnormal-return signal on comparably intense speech days. In the IO-based analyses for 2021–2024, panel omnibus (joint Wald) tests indicate statistically significant IO-related differences in the sentiment–greenness relationship. Simple-slope (Wald) tests of the implied within-group slopes and the corresponding across-group contrasts suggest relatively greater sensitivity among high-IO firms, although the magnitude is modest. In pooled regressions, an omnibus (joint Wald) test of the sentiment × post-2020 term indicates overall attenuation, but the non-significant three-way interaction (sentiment × post-2020 × IO group) provides no robust evidence that the degree of attenuation differs across IO groups. Within-group permutation tests are non-significant for all tertiles. These IO differences, particularly the relatively stronger high-IO response, are unlikely to be driven by market frictions. Overall, while the panel evidence points to IO-related differences, the identification of high-IO as the most sensitive group is not uniformly supported across complementary tests and should be interpreted cautiously.

4.2 ECB Green Speeches and the Green–Brown Return Spread (2010-2020)

Event Study

For 2010–2020, our baseline event-study results are consistent with Neszveda and Siket (2025); detailed replication results are reported in **Appendix S8**. The event-day response of the green–brown spread is positive and statistically significant across expected-return models, with little evidence of pre-speech drift or persistence beyond the immediate window.

Cross-sectional regression

Baseline cross-sectional regressions also yield positive and statistically significant sentiment coefficients, consistent with Neszveda and Siket (2025); detailed comparisons are reported in **Appendix S9**. However, when the five highest-sentiment speeches are excluded, the coefficient falls close to zero and is no longer statistically significant, suggesting that the association is concentrated in a small number of high-intensity speeches.

Cross-validation

Motivated by the cross-sectional results suggesting that the sentiment–return relationship is concentrated in very high-intensity speeches, we use 3-fold cross-validation on 2010–2020 green-speech days ($SENTIMENT \geq 1$) to select a high-sentiment threshold (70th–85th percentiles; see **Appendix S3**). Candidate thresholds were pre-defined to balance distinctiveness and sample size in the high-sentiment range. Because high-sentiment days were limited, thresholds above the 85th percentile could not be evaluated in cross-validation, as this would have produced folds with too few event days. **Figure 2** reports the mean out-of-sample RMSE by candidate threshold; RMSE declines as the cut-off increases and is minimised at the ≈85th percentile. We therefore adopt the ≈85th-percentile threshold as our preferred definition of high intensity (sentiment score $>$ 12,5; 12 days). We then use this threshold to define the high-intensity event set and assess whether the associated abnormal returns are unusual relative to chance using a permutation-based placebo test.

Permutation-based placebo test

Using the randomisation-based inference described in **Appendix S4**, we test whether factor-adjusted abnormal returns on high-intensity green-speech days (defined using the cross-validated threshold) differ from what would be expected under a null of no effect. We compare the observed mean residual on the true event dates to a placebo distribution generated from 1,000 restricted reassignments of event dates within the pre-event window. In each iteration, each event date is reassigned to a random trading day in its seven-day pre-event window $[d-7, d-1]$, with placebo dates drawn without replacement within that iteration. This provides complementary inference by benchmarking the observed statistic against a permutation-based placebo distribution, relative to parametric event-study and regression tests that rely on standard-error estimates and *t*-based inference**. Figure 3** shows that the observed mean residual lies above the 95th percentile of the placebo distribution (one-sided p = 0.036), suggesting that abnormal returns on high-intensity speech days are unusually large relative to the placebo benchmark.

4.3 Ownership Structure: Institutional Ownership and the Green–Brown Return Spread (2010-2020)

Panel regression

We use two-way fixed-effects panel regression to test whether the return response to green sentiment varies jointly with emissions performance and IO tertiles (low/mid/high). We report linear trends across emissions deciles and tail contrasts between the greenest and brownest firms; methodological details are described in **Appendix S5**.

Omnibus (joint Wald) tests provide no statistically significant evidence that the sentiment–greenness relationship differs across IO tertiles in 2010–2020. Across the linear-trend and tail-contrast specifications, the three-way interaction terms of sentiment x greenness (emissions-score rank) x IO group are not statistically significant (p = 0.144 for the linear decile trend; p = 0.405, 0.211, 0.177, and 0.107 for the top–bottom contrasts with k = 10, 20, 30, and 40, respectively; where k is the percentage cut-off used for the tail contrast, comparing firms in the top k% and bottom k% of the emissions-decile distribution - for example, k=10 compares firms in Decile 10 [greenest firms] with those in Decile 1 [brownest firms], while k=20 compares firms in Deciles 9–10 with those in Deciles 1–2). Accordingly, we treat any cross-group or within-group patterns, including a permutation-based placebo test and market friction diagnostic, with caution; these results are reported for completeness in **Appendix S10.** This pattern is consistent with the possibility that, when high-intensity green communication is relatively rare, the market response may be broadly incorporated rather than concentrated in particular investor segments, thereby reducing detectable differences across IO groups.

4.4 ECB Green Speeches and the Green–Brown Return Spread: Evidence from 2021–2024

4.4.1. ECB Green Speeches and the Green–Brown Return Spread (2021–2024)

Event Study

In contrast to 2010–2020, there is no positive event-day reaction: the [0,0] CAAR is small, negative, and not statistically significant across models (−0.14% to −0.35%; $t = -1.03$ to -1.51). Overall, the five greenest speech days in 2021–2024 do not show green outperformance, and any negative response is model-dependent and should not be over-interpreted. One possible explanation is that the impact of green ECB communication has diminished as such messages become more frequent and anticipated. Even the most strongly green speeches may add little new information. As a result, any price response is less likely to appear as a concentrated jump on the event day (detailed results are reported in **Appendix S11)**.

Pooled regression

We complement the event study with pooled regressions on green-speech days, relating the green–brown spread to ECB green sentiment, as described in **Appendix S2**. **Table 1** indicates attenuation after 2020: the interaction between sentiment and the post-2020 indicator is negative and statistically significant ($\beta_{\text{sentiment}\times\text{Post-2020}} = -0.013,\ p < 0.01$), implying that the association between ECB green sentiment and the green–brown return spread on the event day is weaker in 2021–2024 than in 2010–2020. The implied post-2020 sentiment slope is close to zero ($\beta_{\text{sentiment}} + \beta_{\text{sentiment}\times\text{Post-2020}} = -0.002$) and is not statistically distinguishable from zero (Wald test with HC1 robust standard errors: $F(1{,}259) = 1.11,\ p = 0.294$). This pattern is consistent with more frequent and anticipated climate communication conveying less incremental information, thereby reducing the event-day return response.

Permutation-based placebo test

Following the primary-sample randomisation framework described in **Appendix S4**, we apply the same permutation-based placebo test to 2021–2024. **Figure 4** shows that the observed mean factor-adjusted abnormal return on high-intensity speech days (sentiment $>$ 12,5; 50 days) lies above the placebo benchmark ($p = 0.047$). Overall, the results suggest that high-intensity speeches may still be associated with abnormal returns in the later period, but the signal is less pronounced. This is consistent with more frequent communication conveying less incremental information.

4.4.2. Ownership Structure: Institutional Ownership and the Green–Brown Return Spread (2021-2024)

Panel regression

Following the two-way fixed-effects panel framework described in **Appendix S5**, we assess whether the return response to green sentiment varies jointly with emissions performance and the IO group.

In contrast to 2010–2020, omnibus (joint Wald) tests in 2021-2024 provide statistically significant evidence that the sentiment–greenness relationship differs across IO tertiles. Across specifications, the three-way interaction terms of sentiment x greenness (emissions-score rank) x IO group are significant for the linear decile-trend model ($p = 0.010$) and for the tail-contrast models with $k = 20$, 30, and 40 ($p = 0.046$, 0.006, and 0.036, respectively), with marginal significance for $k = 10$ ($p = 0.098$). These results suggest that, in the later period, the sensitivity of the green–brown return spread to ECB green sentiment varies across IO tertiles.

Figure 5 reports the 2021–2024 panel estimates by IO tertile (full estimates in **Appendix S12**). In the linear-trend specification, the estimated sentiment × greenness effect is largest for the high-IO group and is statistically significant within the group ($p = 0.038$). The high-IO effect is also significantly larger than the mid-IO effect ($p = 0.004$). This implies that as ECB green sentiment rises, greener stocks tend to outperform browner stocks most strongly among institutionally dominated firms.

Figure 6 presents the tail-contrast results (full estimates in **Appendix S13**). The top-minus-bottom effect in high-IO is consistently positive across tail definitions ($k = 10, 20, 30, 40$), with relatively stable statistical significance, both within and across groups, particularly compared with the mid-IO group. This pattern again indicates greater sensitivity among high-IO firms in the later period.

As a robustness check, we repeat the analysis using an IO median split (full estimates in **Appendices S14 and S15**). The estimated effects are positive and statistically significant in the high-IO group, consistent with the tertile results. Overall, the high-IO group exhibits the largest estimated effects, suggesting greater sensitivity to green sentiment. However, the magnitude is economically modest. The within-group sentiment × greenness effect for high-IO ranges from 0.003 to 0.006 (**Appendix S13**), implying that a 50-point increase in sentiment corresponds to at least a 0.15% higher daily green–brown return spread.

Pooled regression

We complement the panel analysis with pooled regressions on green-speech days to test whether the sentiment–green–brown association changes after 2020 and differs by IO group as described in **Appendix S2**.

Omnibus (joint Wald) tests from the pooled IO-based regression indicate attenuation after 2020: the sentiment × post-2020 interaction term is statistically significant ($p = 0.0077$), implying that, overall, the association between ECB green sentiment and the green–brown return spread differs between 2010–2020 and 2021–2024. By contrast, the three-way interaction (sentiment × post-2020 × IO tertile) is not statistically significant ($p = 0.2355$), providing no evidence that the degree of attenuation varies across IO groups. For completeness, we report the implied within-IO-group pre/post slopes and the corresponding across-IO-group comparisons in **Appendix S16**; these decompositions suggest that the post-2020 weakening is most pronounced in the mid-IO group, but the across-group differences are not statistically significant. This is consistent with the non-significant omnibus three-way test, so the pattern should be interpreted cautiously.

Permutation-based placebo test

Following the aggregate procedure described in **Appendix S4**, we apply permutation-based placebo tests to 2021–2024 to provide complementary non-parametric inference in each IO group. **Figure 7** shows that for all three IO groups, the observed mean factor-adjusted abnormal return does not exceed the 95% cutoff of the placebo distribution. Taken together with the pooled parametric results, this suggests that in the later period, high-intensity green speeches do not generate statistically detectable concentrated abnormal returns within narrow event windows in any IO subgroup.

Although the panel results point to relatively greater sensitivity among high-IO firms post-2020, the corresponding permutation statistic is not extreme relative to the placebo distribution (one-sided $p = 0.215$). This is consistent with the possibility that more frequent and anticipated climate communication may be incorporated more gradually in institutionally dominated stocks (high-IO), leaving less to be reflected in narrow event windows.

Market Friction Analysis

To complement the IO-based results, we present a descriptive market-frictions diagnostic based on short-selling constraints and idiosyncratic risk. The share of constrained stocks across IO groups does not align with the strongest response occurring in high-IO, suggesting frictions are unlikely to be the primary driver; details and figures are reported in **Appendix S17**.

5. Discussion

Our results suggest that ECB green communication is associated with short-horizon repricing between greener and browner stocks when the communication is sufficiently intense. In the 2010–2020 sample, high-intensity green speeches coincide with economically meaningful and statistically significant positive green–brown return differentials, suggesting that green central bank signals may be reflected in how investors price transition-related information. Building on this baseline evidence, we conduct additional robustness checks and provide two novel contributions. First, in 2010–2020, we find no evidence that the impact differs across IO groups, consistent with broad market incorporation rather than concentration in a particular investor segment. Second, we demonstrate that the average event-day response was greatly attenuated (and inconsistently observed across measures) when looking at the influence of green speeches between 2021 and 2024. Additionally, we observe suggestive evidence that relative sensitivity shifted towards the high-IO (institutionally dominated) group post-2020.

The broad incorporation of ECB green communication across markets between 2010 and 2020 may plausibly be related to the rarity and novelty of these communications in this period.

Consequently, high-intensity speech signalled a potential shift in direction and was therefore viewed as more informative, generating belief updates and price adjustments. As a result, these speeches attracted broad market attention and prompted repricing across a wide investor base. Such episodes may heighten the perceived valuation relevance of climate information for institutions with discretion to rebalance, while also coordinating the attention among less sophisticated, retail investors, thereby potentially magnifying the aggregate market response. While mechanisms cannot be cleanly identified, the evidence is consistent with attention/sentiment channels shaping investors' expectations through heightened salience of climate information and coordinated attention, alongside standard risk-premium channels.

In addition to observing an attenuated influence of green speeches post 2020, perhaps the clearest result we observed was the increase in speeches expressing green sentiment (from 76 to 192). Such a result is heartening from a sustainability perspective, potentially reflecting the increasing level of importance assigned to sustainability concerns by the ECB. This increased frequency of green speeches offers a plausible explanation for the lesser impact of each speech on stock pricing. Specifically, as green communication becomes more frequent and anticipated, even speeches conveying a strong message of sustainability may convey less incremental information, weakening the abnormal-return signal on high-intensity days. One possible explanation is that, as green speeches occur closer together (although they still provide some additional information), price adjustment may spill over across adjacent communications and surrounding days, making it harder to isolate a distinct event-day jump for any single speech within a narrow window. At the same time, repeated communication may function as a persistent signal of the ECB's longer-run climate policy stance, more often confirming existing expectations than conveying new information, which may be particularly relevant for institutionally dominated stocks whose investors monitor policy signals continuously and incorporate them into valuations more gradually. Our finding that post-2020 sensitivity appears somewhat stronger among High IO stocks is consistent with this interpretation. Institutional investors tend to be more fundamentals-oriented (Lai et al. 2013; Chen et al. 2022; Cui et al. 2025). In this sense, climate-related central-bank communication may be reflected less in discrete event-day repricing and more in gradual, valuation-relevant updating about longer-run policy stance and transition risk. The consistency and credibility of the signal may therefore help anchor expectations, with communication reinforcing existing beliefs about the financial relevance of climate risk and supporting more gradual adjustment in the pricing of transition risk. Consequently, the attenuated influence of green speeches post-2020 in our short-term market-based analysis does not necessarily imply that communication is irrelevant, but may instead reflect a smaller surprise component and more gradual adjustment over time.

Future research should aim to explore the longer-term influence of sustained climate-related communications from central banks. Furthermore, the current market-based design cannot directly identify the underlying psychological mechanisms, including how different investors interpret the ECB messages, how beliefs update, or which message features increase salience and persuasion. This motivates complementary experimental evidence potentially employing experimental methods to estimate the causal effects of climate communication on beliefs, attention, and portfolio choices, and to test which characteristics of messages (e.g., framing, concreteness, emphasis on risks versus opportunities), as well as contextual factors such as public trust in the communicator, are most effective in shaping responses. Such designs would complement the market evidence by identifying mechanisms and clarifying how communication influences preferences even when empirical identification is difficult under high-frequency green communication regimes. For now, however, the current findings suggest that ECB green communication matters for the pricing of climate-related risks, with its effects emerging most sharply when communication is novel, rare, and intense, and potentially more gradually when communication becomes frequent.

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CRediT author statement

Ajeng Ratna Kartina: Conceptualisation, Methodology, Software, Validation, Formal Analysis, Investigation, Data Curation, Writing-Original Draft, Writing-Review & Editing, Visualisation. **Gabor Neszveda:** Methodology, Validation, Writing-Review & Editing. **Henrik Singmann:** Methodology, Validation, Writing-Review & Editing, Supervision. **Adam J. L Harris:** Conceptualisation, Writing-Review & Editing, Supervision, Project Administration.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Table 1. Summary of regression estimates of the Green–Brown emissions-score portfolio return on the ECB green sentiment index, controlling for several additional variables (2021-2024)

Term	Model: sentiment ≥ 1
Sentiment	0.011**
	(0.01)
Post-2020 dummy	0.209**
	(0.11)
VIX	0.003
	-0.005
Stoxx 50	0.180***
	(0.06)
SMB	-0.534***
	(0.11)
HML	0.132**
	(0.06)
WML	-0.113**
	(0.05)
Sentiment × Post-2020	-0.013***
	(0.01)
Num.Obs.	268

Table 1 reports coefficient estimates while controlling for standard financial and asset-pricing variables (VIX, STOXX 50, SMB, HML, and WML). Robust (HC1) standard errors are reported in parentheses. Statistical significance is denoted by stars: *p < .10, **p < .05, and ***p < .01.

Figure 1. ECB green speech days and green sentiment score

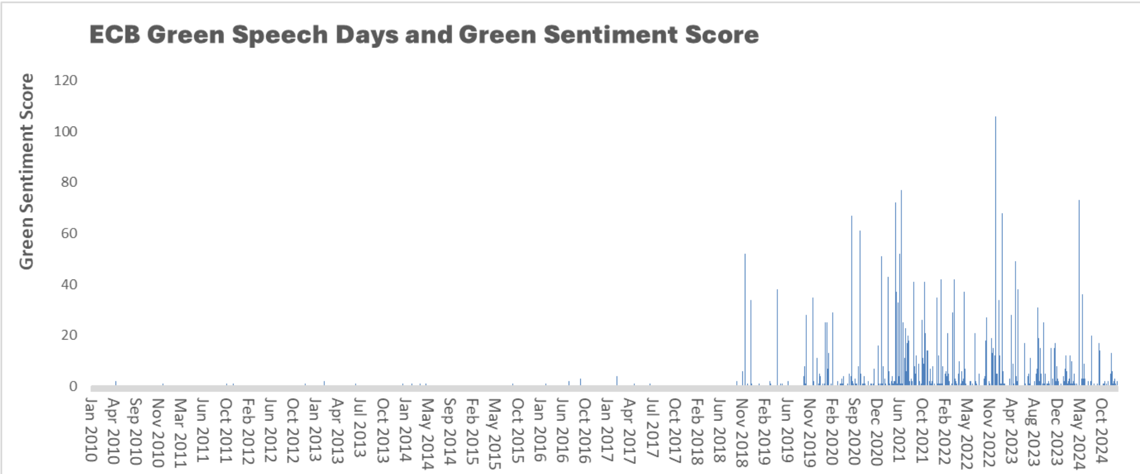


Figure 2. Cross-validation selection of the green-sentiment threshold

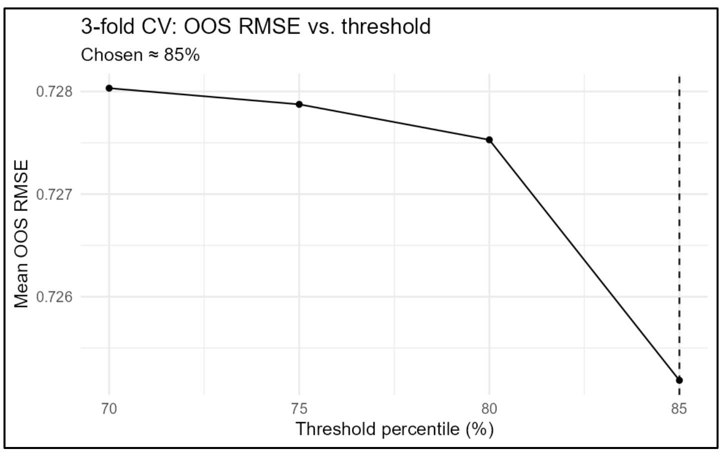


Figure 3. Permutation-based placebo test for factor-adjusted Green–Brown abnormal returns (2010-2020)

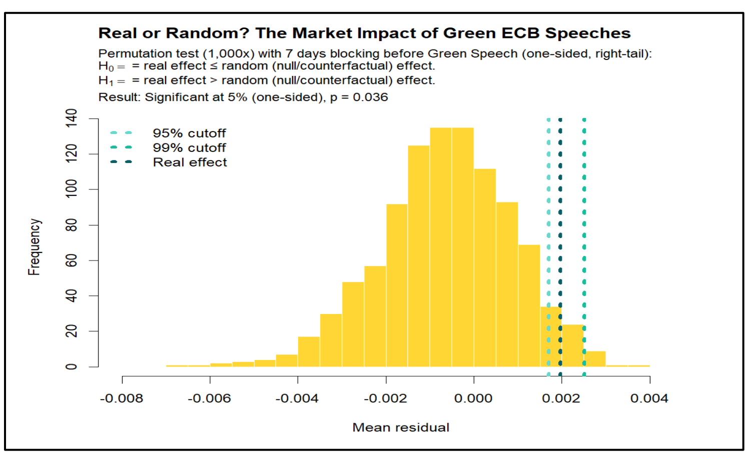


Figure 4. Permutation-based placebo test for factor-adjusted Green–Brown abnormal returns (2021-2024)

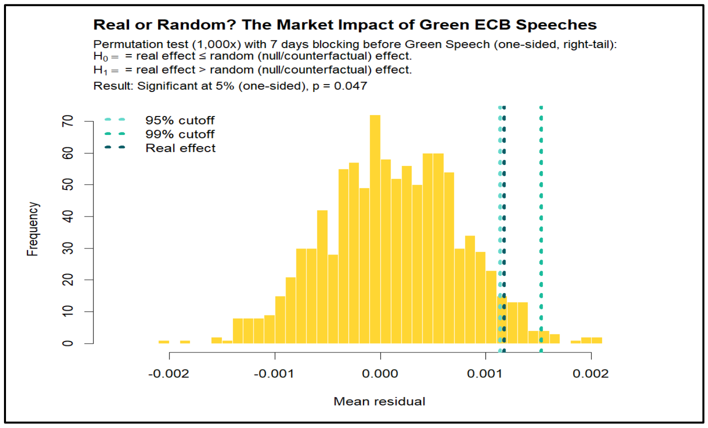


Figure 5. Heterogeneous sentiment response by institutional ownership tertiles (linear trend) (2021-2024)

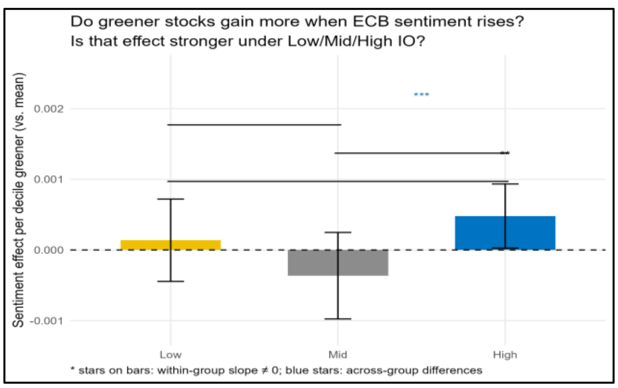


Figure 6. Heterogeneous sentiment response by institutional ownership tertiles (tail contrast) (2021-2024)

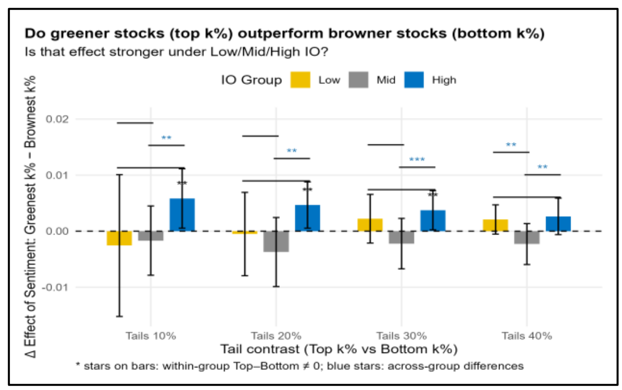


Figure 7. Permutation-based placebo test by IO tertile (2021-2024)

Low IO (more retail-dominated)

Mid IO (mixed)

High IO (more institutionally dominated)

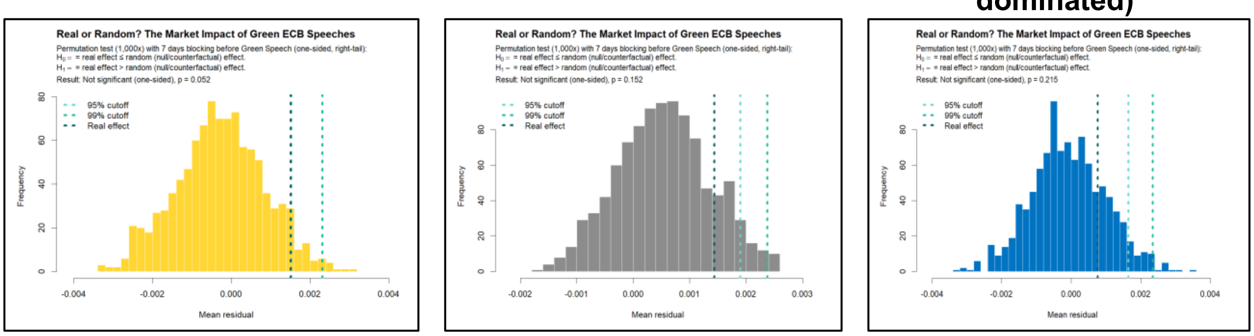


Figure captions

Figure 1. Daily ECB Green Sentiment Index, defined as the total daily count of ten climate-related keywords in ECB speeches and Q&A transcripts. Days with SENTIMENT_t ≥ 1 are classified as green speech days. Sample: January 2010–December 2024.

Figure 2. The mean out-of-sample RMSE for candidate cut-offs defined by the 70th, 75th, 80th, and 85th percentiles of the sentiment distribution.

Figure 3. The placebo distribution of the mean factor-adjusted Green–Brown abnormal return (Carhart+VIX residual), based on 1,000 restricted reassignments within [d − 7, d − 1], with placebo dates drawn without replacement within each iteration. Vertical lines mark the observed effect and the 95% and 99% placebo-distribution cutoffs.

Figure 4. The placebo distribution of the mean factor-adjusted Green–Brown abnormal return (Carhart+VIX residual), based on 1,000 restricted reassignments within [d − 7, d − 1], with placebo dates drawn without replacement within each iteration. Vertical lines mark the observed effect and the 95% and 99% placebo-distribution cutoffs.

Figures 5 and 6. Figure 5 reports the linear-decile specification, where emissions performance is measured from 1 (brownest) to 10 (greenest). Figure 6 reports the tail-contrast specification, comparing the top *k*% greenest stocks with the bottom *k*% brownest stocks. Estimates are from two-way fixed-effects panel regressions of daily stock returns on interactions between the green sentiment index, emissions performance, and IO-tertile indicators, including all implied lower-order terms, firm and day fixed effects, and standard time-varying firm controls. Standard errors are two-way clustered by firm and day. Stars on bars indicate within-group simple-slope Wald tests of whether the sentiment × greenness effect differs from zero; for low-IO and high-IO groups, the effect is the mid-IO baseline plus the relevant interaction. Stars on horizontal comparison lines report between-group Wald tests: Mid vs Low and Mid vs High test the corresponding three-way interaction terms, while Low vs High tests the difference between those interactions. * $p < .10$, ** $p < .05$, *** $p < .01$.

Figure 7. The figure shows the placebo distribution of the mean factor-adjusted Green–Brown abnormal return (Carhart+VIX residual), based on 1,000 restricted reassignments within [d − 7, d − 1]. Vertical lines mark the observed effect and the 95% and 99% placebo-distribution cutoffs.

Supplementary Information

Appendix S1. Data Preprocessing

We preprocess the data by excluding all observations with missing or zero emission scores, deleting all stocks that yield a 200% return in a day and excluding the 10% most illiquid stocks for each day based on the Amihud (2002) ILLIQ measure. Daily stock returns are computed from total return indices (TRI) as:

$$R_{it} = \frac{TRI_{it}}{TRI_{it-1}} - 1, \tag{S.1}$$

where R_{it} is the daily return of firm *i* on day *t*, and TRI_{it} is the daily closing total return index for firm *i* on day *t*.

The Amihud (2002) illiquidity measure is calculated as:

$$ILLIQ_{it} = \frac{|\ R_{i,t}\ |}{V_{i,t} * P_{i,t}}, \tag{S.2}$$

where $|\ R_{i,t}\ |$ is the absolute value of the daily return of the stock i on day t, $V_{i,t}$is the corresponding daily trading volume, and $P_{i,t}$ is the stock price on day t.

These filters are applied to mitigate the influence of extreme observations and ambiguously coded emission-score observations (e.g., whether zero values represent the lowest possible score or missing data). Overall, the research includes 504,399 observations in the primary sample from January 2010 to December 2020, and 467,543 observations in the post-period extension from January 2021 to December 2024.

Appendix S2. The Event Study Methodology

Following Neszveda and Siket (2025), we conduct an event study using the classic Fama et al. (1969) framework to measure the market reaction to ECB green communication. Because we focus on the speeches with the highest green sentiment, our event set consists of the five greenest ECB speeches in each sample period, identified as described in Section 3.2.

Portfolio formation and return definition

We sort stocks with available emissions scores greater than zero into ten equal-weighted decile portfolios based on the Refinitiv Emission Score, where higher scores indicate greener firms. Decile 10, therefore, contains the greenest firms and Decile 1 the brownest. For each decile, the daily portfolio return is the equal-weighted (simple average) return of its constituent stocks. We then construct the green–brown (high-minus-low) long–short portfolio by taking a long position in Decile 10 and a short position in Decile 1, and compute its natural logarithm return as:

$$\mathrm{R}_{(Green-Brown)escore,t} = \ln\left(1 + (R_{Green} - R_{Brown})\right), \tag{S.3}$$

where $R_{Green,t}$ and $R_{Brown,t}$ denote the daily simple returns of the green and brown portfolios, respectively (computed from TRI as defined in Section 3.1).

The market's natural logarithm return is

$$R_{m,t} = \ln \frac{P_t}{P_{t-1}}, \tag{S.4}$$

where $R_{m,t}$ is the daily market log return and P_t is the closing price of the Stoxx 50 index on day *t*.

Estimation window and event windows

To avoid overlap between the estimation and event windows, the expected return is estimated using a fixed pre-event estimation window from $t = -250$ to $t = -30$ trading days relative to the first green-communication event in each sample period, providing 220 daily observations for model calibration. Specifically, the estimation window is anchored to 8 November 2018 for the primary sample (January 2010–December 2020) and to 29 April 2021 for the post-period extension (January 2021–December 2024). The resulting parameter estimates are used to compute expected returns for all events within the corresponding period. Six event windows are examined: [-1, -1], [-1,0], [0,0], [0,1], [1,1], and [0,2].

Expected return models

We estimate the expected return of the Green–Brown portfolio using time-series regressions on common risk factors over the pre-event estimation window. Expected returns are generated using three benchmarks to assess robustness to alternative risk adjustments and to reduce sensitivity to expected-return model misspecification: a market model (Binder 1998), a Fama–French three-factor model (Fama and French 1992), and a Carhart four-factor model (Carhart 1997). Factor returns are taken from the Fama–French European factor datasets. The model specifications are as follows:

Market model:

$$ER_{(Green-Brown)\,escore,t} = a + b_m R_{m,t} + \varepsilon_t, \tag{S.5}$$

Fama–French three-factor model:

$$ER_{(Green-Brown)\ escore,t} = a + b_m R_{m,t} + b_s R_{SMB,t} + b_h R_{HML,t} + \varepsilon_t \tag{S.6}$$

Carhart four-factor model:

$$ER_{(Green-Brown)\ escore,t} = a + b_m R_{m,t} + b_s R_{SMB,t} + b_h R_{HML,t} + b_{mo} R_{MOM,t} + \varepsilon_t, \tag{S.7}$$

Here, $SMB_t$is the size factor (small minus big), $HML_t$is the value factor (high minus low), and $MOM_t$is the momentum factor (winners minus losers).

Abnormal returns, CAR, and CAAR

Abnormal returns are computed as the difference between the observed and model-implied expected return:

$$AR_{(Green-Brown)escore,t} = R_{(Green-Brown)\ escore,t} - ER_{(Green-Brown)\ escore,t} \tag{S.8}$$

To capture the impact of each event over a longer horizon, we compute cumulative abnormal returns (CAR) by summing abnormal returns within the event window $[T_1, T_2]$:

$$CAR_{(Green-Brown)\ escore,r} = \sum_{t=T_1}^{T_2} AR_{(Green-Brown)\ escore,r,t}, \tag{S.9}$$

where r indexes events and $T_1$and T_2 denote the start and end of the event window. We then obtain the average effect across events by calculating the cumulative average abnormal return (CAAR) as the mean of event-specific CARs:

$$CAAR_{(Green-Brown)\ escore} = \frac{1}{n} \sum_{r=1}^{n} CAR_{(Green-Brown)\ escore,r} \tag{S.10}$$

Statistical significance is assessed using the Binder (1998) test statistic, which standardises the CAAR by its estimated standard deviation:

$$t_{CAAR} = \sqrt{N}\ \frac{CAAR_\tau}{s_{CAAR_\tau}}, \tag{S.11}$$

where $N$is the number of events and s_{CAAR_τ} is the estimated standard deviation of $CAAR_\tau$.

Appendix S3. Cross-sectional and pooled regression methodology

To complement the event-study results in our aggregate analysis for the primary sample from January 2010 to December 2020, following the methodology of Neszveda and Siket (2025), we also estimate cross-sectional regressions on days when green ECB speeches are delivered. Our specification includes a range of control variables, such as the VIX to proxy global uncertainty, STOXX50 returns to capture aggregate market movements, and European size, value, and momentum factors: SMB (small minus big), HML (high book-to-market minus low), and WML (past winners minus past losers), which are standard predictors of expected returns.:

$$R_{(Green-Brown)\ escore,t} = \alpha + \beta_1 \text{SENTIMENT}_t + \beta_2 \text{VIX}_t + \beta_3 \text{STOXX50}_t + \beta_4 \text{SMB}_t + \beta_5 \text{HML}_t + \beta_6 \text{WML}_t + \varepsilon_t \quad \text{(S.12)}$$

Where $R_{(Green-Brown)\ escore,t}$ denotes the realised return on the Green-Brown emissions score portfolio for day t.

We estimate three variants to check robustness: (1) the baseline model using all green speech days with $\text{SENTIMENT}_t \geq 1$; (2) a stricter specification using only days with $\text{SENTIMENT}_t \geq 2$; and (3) a specification excluding the five highest-sentiment speeches to assess sensitivity to extreme-sentiment events.

To test whether the association between sentiment and the green–brown return spread differs between the pre-2020 and post-2021 periods, in our aggregate analysis using the full sample (primary and post-period extension), we augment the baseline aggregate specification with an interaction term and estimate a pooled regression on the full sample (primary period plus the post-period extension). Specifically, we include $Sentiment_t \times Post2020_t$, where $Post2020_t = 1$ for January 2021–December 2024 and 0 otherwise.

For the IO-based analysis, we estimate the model on a stacked dataset of daily green–brown return spreads by IO group, treating it as a pooled regression with standard errors clustered by day. Using the full sample, we extend the baseline specification by including the triple interaction $Sentiment_t \times Post2020_t \times IO_g$, where $Post2020_t = 1$ for January 2021–December 2024 and 0 otherwise, and IO_g denotes indicator variables for IO tertiles (high, mid, low), with low-IO as the omitted reference group. This allows us to test whether the association between sentiment and the green–brown return spread differs between the pre- and post-periods and across IO groups.

Appendix S4. Cross-validation threshold methodology

To determine the minimum sentiment intensity required to influence the green–brown spread, we use the January 2010–December 2020 sample restricted to ECB green-speech days with $Sentiment_t \geq 1$; (76 event days). We select a sentiment threshold via 3-fold cross-validation (Varian 2014).

First, we divide the event-day sample into three stratified folds, where observations are randomly assigned to folds stratified by sentiment rank to ensure each fold contains a comparable mix of low-, mid-, and high-sentiment events. We then consider candidate thresholds corresponding to the 70th, 75th, 80th, and 85th percentiles of the sentiment distribution in the January 2010–December 2020 event-day sample. Candidate thresholds were pre-defined to balance distinctiveness with adequate sample size in the high-sentiment range, and for each candidate threshold γ we construct a hinge variable:

$$H_t(\gamma) = \max\{0, Sentiment_t - \gamma\} \tag{S.13}$$

For each fold, we estimate the following regression on the two training folds and evaluate performance on the held-out fold using the root mean squared error (RMSE):

$$R_{(Green-Brown)\,escore,t} = \alpha + \beta H_t(\gamma) + \delta' X_t + \varepsilon_t, \tag{S.14}$$

where $R_{(Green-Brown)\,escore,t}$ is the daily green–brown return spread and X_t contains the control variables (VIX, STOXX50 returns, SMB, HML and WML). We select the threshold that minimises the average out-of-sample RMSE across the three held-out folds, implementing Varian's train–test validation framework by choosing the model based on validation performance rather than in-sample fit.

Appendix S5. Permutation-based placebo test

To mitigate concerns that our estimates may be confounded by other news occurring near ECB communication dates (e.g., climate policy announcements or major climate news), we implement a restricted permutation-based placebo test. Permutation inference compares the observed test statistic with an empirical null distribution generated by repeatedly reassigning event dates, which helps reduce false rejections (Type I error), provided that the reassignment scheme yields valid placebo comparisons (Ernst 2004; Winkler et al. 2014). This nonparametric approach is useful as a robustness check because abnormal returns (market-model prediction errors) may deviate from normality; in such cases, parametric t-tests that rely on a normal/t reference distribution can be poorly specified and less reliable (Corrado 2011).

The procedure is applied to the primary 2010–2020 sample and to the extended post-period sample (2021–2024) for both the aggregate and within IO-based analyses. We define “high-sentiment” event dates as ECB green-speech days for which the sentiment score exceeds the cross-validation–selected threshold described in **Appendix 3**; the resulting event dates are recorded and supplied to the randomisation procedure.

We obtain factor-adjusted green–brown return spreads by estimating a Carhart factor regression augmented with VIX_t and retaining the regression residuals as abnormal returns. Our test statistic is the mean abnormal return (residual) across the high-sentiment event dates. To construct the null distribution, we repeatedly reassign each event date to a randomly selected trading day in the seven-day pre-event window $[d-7, d-1]$, excluding all true event dates and enforcing that placebo dates are unique within each draw. Following Winkler et al. (2014)’s restricted reassignment principle, we restrict reassignment to this pre-event window rather than drawing placebo dates from the full sample, making exchangeability under the null more plausible by keeping market conditions locally comparable. Restricting placebo dates to the seven-day pre-event window helps control for contemporaneous shocks, so real and placebo dates are expected to share similar market conditions by construction.

Because the set of admissible reassignments can be very large, we approximate the permutation reference distribution via Monte Carlo sampling of valid reassignments (Ernst 2004). Specifically, we draw 1,000 valid placebo assignments and, for each draw, compute the mean residual across the placebo dates to form the placebo distribution. We compute the one-sided (right-tail) p-value as the proportion of placebo statistics at least as large as the observed statistic; equivalently, we reject at the 5% level if the observed mean residual lies in the upper 5% of the placebo distribution.

Appendix S6. Panel Regression

To examine the heterogeneity of reactions across firms' emissions-reduction performance and ownership structure, we estimate a two-way fixed effects panel model:

$$R_{i,t} = \alpha + \beta_1(\text{SENTIMENT}_t \times \text{DECILE}_{i,t} \times \text{IO}_{i,t}) + \beta_2' Z_{i,t} + \delta_t + \gamma_i + \varepsilon_{i,t}, \quad \text{(S.15)}$$

and include the full set of lower-order terms implied by this interaction (i.e., all constituent main effects and lower-order interactions). We interpret the interaction coefficients as capturing heterogeneity in the response to ECB green sentiment.

Here $R_{i,t}$is the daily return of the stock i on day t; $\text{DECILE}_{i,t}$is the emission-score decile rank (1 = brownest, 10 = greenest); and $\text{SENTIMENT}_t$is the ECB green sentiment index. $\text{IO}_{i,t}$is a dummy variable for the tertile split into Bottom, Mid, and Top (33%), denoted as low IO (more retail-dominated), mid IO (mixed), and high IO (more institutionally dominated).

To rigorously control for unobserved heterogeneity, a fundamental challenge in empirical finance research, and consistent with the recommendations of Gormley and Matsa (2014), our model includes day fixed effects δ_t to absorb common time-varying shocks and firm fixed effects γ_i to absorb unobservable time-invariant firm characteristics. With day fixed effects, SENTIMENT_t is absorbed; we therefore interpret only its interactions to assess heterogeneous responses by firms' emissions performance and ownership structure. We also include firm-level controls $Z_{i,t}$: Carhart beta, book-to-market, size (log market capitalisation), and past 12-month momentum to further control for firm-specific time-varying factors not absorbed by the fixed effects (Table A1).

Following Petersen (2009) and given a sufficiently large number of clusters in each dimension, we use two-way clustered standard errors by firm and day to account for within-firm serial correlation and within-day cross-sectional dependence in the regression residuals, reducing the risk of downward-biased standard errors and overstated statistical significance.

As an additional robustness check, we also implement a median split of institutional ownership to form two groups. This provides a more balanced comparison between retail-heavy and institution-heavy stocks and allows us to assess whether the results are sensitive to the definition of ownership groups.

The panel regressions test both linear trends across emissions deciles and tail contrasts to assess whether effects strengthen gradually as firms become greener, concentrate in the extreme tails, remain flat across the distribution, or fade outside the tails. In the linear-trend specification, the emissions decile is entered as a continuous variable (1 to 10). In the tail contrast specification, we compare the top $k\%$ and bottom $k\%$ of firms based on their emissions score for $k \in \{10,20,30,40\}$ by focusing on firms in these two tails, coding the top tail as 1 and the bottom tail as 0, and interpreting the estimated coefficient as the top minus bottom effect.

Table A1 Control Variables in the Panel Regression Analysis: Definitions and Construction

Variable	Description and Calculation
Beta (Carhart 4-factor)	▪ A dynamic daily beta is used to better capture time-varying risk exposure. This approach empirically validates the CAPM more effectively than traditional static beta estimates, particularly when analysing daily returns (Hollstein 2020). ▪ Daily conditional betas for each of the Carhart four factors are estimated for each stock using rolling 250-day regressions of excess returns on factor returns, based solely on data available prior to day $t + 1$.
Size	▪ Market Equity (ME) is obtained from LSEG Workspace (Refinitiv), measured at the end of June in year t, transformed using the natural logarithm (*In (ME)*), and included as a control variable to account for firm size. The value is held constant from July of year t to June of year $t + 1$ to avoid look-ahead bias.
Book-to-Market (B/M)	▪ Book-to-Market (B/M) is obtained from LSEG Workspace (Refinitiv), at each firm's fiscal year-end. To avoid look-ahead bias, a six-month reporting lag is assumed — the ratio becomes available six months after the fiscal year-end (e.g., data from 31 Dec 2008 is available by 30 Jun 2009). Each B/M value is then matched to stock returns from July of the following year to June of the next (e.g., July 2009–June 2010). ▪ Book-to-Market (B/M) is reported in per cent and therefore divided by 100 to obtain the ratio. The variable is winsorised at the 1st and 99th percentiles to limit the influence of extreme values.
Momentum (12–2)	▪ Momentum is measured following the standard approach of Jegadeesh and Titman (1993), as incorporated in the Carhart (1997) four-factor model. For each stock at the end of month $t-1$, momentum is calculated as the cumulative gross return over the prior 11 months ($t-12$ to $t-2$). ▪ This captures medium-term price persistence, while excluding the most recent month ($t-1$) mitigates short-term reversal effects. ▪ The resulting momentum value is then matched to stock returns in month t to ensure that only information available at the time is used, thereby avoiding look-ahead bias.

Appendix S7. Market Frictions and Limits to Arbitrage (Descriptive Analysis)

Market frictions in market structure can enable abnormal returns for a given group of IOs, such as limited institutional participation and high idiosyncratic risk, which make it harder and riskier to trade against mispricing (Pontiff 2006; Weber 2017). To examine whether abnormal returns around ECB green speeches are shaped by limits to arbitrage, we conduct a descriptive analysis of market frictions by building a matrix to evaluate the share of highly constrained stocks in each IO group, particularly with respect to short-selling and idiosyncratic risk. The core idea is that sentiment-driven price pressure can persist when it is difficult or risky for sophisticated investors to trade against mispricing. If limits to arbitrage matter in this setting, the speech-day return responses should be larger for stocks that are more constrained.

For the short-selling constraint proxy, we construct residual institutional ownership (RIOR) following the size adjustment approach in Nagel (2005), as implemented in Weber (2017). For each calendar year, we estimate a cross-sectional regression of the logit-transformed institutional ownership on firm size, with institutional ownership first capped to the interval [0.0001, 0.999] to avoid logit values becoming undefined. The regression specification is:

$$log\,\frac{IOR_{it}}{1-IOR_{it}} = \alpha + \beta_1 \log(ME) + \beta_2 (\log(ME))^2 + \; RIOR_{it}, \tag{S.16}$$

where IOR_{it} denotes the share of institutional ownership, ME denotes firm size measured by market equity and $RIOR_{it}$ denotes the residual from this regression, which we use as residual institutional ownership.

To avoid look-ahead bias, we compute residuals using the December $(t-1)$ snapshot and apply them to the subsequent measurement window from July of the year t to June of the year $t+1$. For example, residuals estimated from the December 2008 snapshot are assigned to observations from July 2009 through June 2010. We then form high-, mid-, and low-constraint groups using a tertile split of this proxy, implemented within emissions deciles, mirroring the grouping strategy used for raw institutional ownership.

Idiosyncratic volatility (IVOL) is measured as the rolling standard deviation of residuals from a market model estimated on daily data. For each firm, we estimate over a rolling window of $L \in \{20,60\}$ trading days:

$$R_{it=}\alpha + \beta_1 R_{m,t} + \varepsilon_{i,t} \tag{S.17}$$

where $R_{i,t}$ and $R_{m,t}$ are firm and market excess returns. The market return $r_{m,t}$ is computed from the STOXX 50 index, and we form excess returns as $R_{i,t} = r_{i,t} - r_{f,t}$and $R_{m,t} = r_{m,t} - r_{f,t}$, where $r_{f,t}$is the daily risk-free rate obtained from the Kenneth R. French Data Library (Europe Fama–French dataset). We define $IVOL_{i,t}$ as the standard deviation of $\varepsilon_{i,\tau}$ within the rolling window ending at $t-1$ (i.e., $IVOL_{i,t}$is lagged by one trading day to avoid look-ahead bias). Higher IVOL increases the risk of trading against mispricing and, therefore, may be associated with tighter arbitrage limits (Pontiff 2006; Weber 2017).

Appendix S8. Event Study (2010-2020)

We obtain qualitatively identical (in terms of patterns of significance) event-study results to those of Neszveda and Siket (2025) for 2010–2020. Table 1 reports cumulative average abnormal returns (CAARs) for the green–brown spread under the market, Fama–French three-factor (FF3), and Carhart benchmarks. The event-day response is positive and statistically significant at 1% across models: the CAAR ranges from 0.68% to 0.77% (t = 2.59–2.71) at day [0,0]. There is no evidence of positive pre-speech drift (day [-1,-1] CAARs are negative, and [-1,0] CAARs are positive but not significant), and the effect does not persist beyond the immediate window ($[0,1]$ is positive but weak at best; $[1,1]$ turns negative and is not significant). Overall, the pattern is similar across benchmarks, suggesting limited sensitivity to the expected-return specification. The results indicate that markets pay attention to green speeches by ECB decision-makers. These speeches underscore the importance of climate change and environmental issues, and the information appears to be incorporated into prices immediately. The Green–Brown spread reacts on the event day, with little evidence of persistence beyond the immediate window.

Table A2. Event Study Findings for the Green-Brown Portfolio Using Various Expected Return Models Following the Top 5 ECB Green Speeches (2010-2020)

Window	[-1;-1]	[-1;0]	[0;0]	[0;1]	[0;2]	[1;1]
CAAR (Market model)	**-0.31%**	**0.46%**	**0.77%**	**0.45%**	**0.13%**	**-0.32%**
Standard deviation (Market model)	0.37%	0.87%	0.64%	0.69%	0.81%	0.77%
t-statistic (Market model)	-1.88*	1.17	2.71***	1.44	0.37	-0.94
CAAR (F-F three-factor model)	**-0.35%**	**0.33%**	**0.68%**	**0.42%**	**0.11%**	**-0.26%**
Standard deviation (F-F three-factor model)	0.31%	0.82%	0.58%	0.60%	0.72%	0.66%
t-statistic (F-F three-factor model)	-2.56**	0.90	2.63***	1.56	0.36	-0.90
CAAR (F-F three-factor + momentum model)	**-0.32%**	**0.39%**	**0.72%**	**0.43%**	**0.13%**	**-0.28%**
Standard deviation (F-F three-factor + momentum model)	0.31%	0.84%	0.62%	0.58%	0.72%	0.68%
t-statistic (F-F three-factor + momentum model)	-2.3**	1.04	2.59***	1.68*	0.42	-0.94

Table A2 reports estimates of the green–brown return spread using several expected-return models. The first sub-table shows results using the commonly applied market model, followed by the Fama-French three-factor model and its extension that includes the momentum factor. Each model is assessed across six event windows: [−1;1], [−1;0], [0;0], [0;1], [1;1], and [0;2]. Event windows are reported as $[a, b]$, where 0 denotes the event day, a and b are the number of trading days before or after the event. For example, $-1, +1$ covers the day before, the event day, and the day after. Rows present the event windows, CAARs, standard deviations, and t-statistics. Returns are calculated as the natural logarithm of raw returns. Statistical significance is indicated as follows: *p < .1; **p < .05; ***p < .01.

Appendix S9. Cross-sectional regression (2010-2020)

In line with Neszveda and Siket (2025), the cross-sectional sentiment coefficients, shown in Table 2, are positive, statistically significant, and closely aligned in magnitude (0.012 and 0.013 in our sample versus 0.013 and 0.014 in Neszveda and Siket for $SENTIMENT \geq 1$ and $SENTIMENT \geq 2$, respectively). The estimated coefficients are stable across specifications (0.012–0.013), implying an economically meaningful association. For example, a 50-point increase in green sentiment is associated with roughly a 0.60% higher daily green–brown return spread.

When we go beyond Neszveda and Siket's (2025) analysis and exclude the five highest-sentiment speeches (Model 3), the sentiment coefficient is reduced to 0.001 (SE = 0.004; cap N equals 71) and is not statistically significant. This suggests that the association is concentrated in a small number of very high-intensity speeches: days with only mild climate references show little measurable effect, whereas more intense communication is associated with a larger green–brown repricing response.

Table A3. Summary of regression estimates of the Green–Brown emissions-score portfolio return on the ECB green sentiment index, controlling for several additional variables (2010-2020)

Term	Model 1: Sentiment ≥1	Model 2: Sentiment ≥2	Model 3: Exclude 5 Greenest Sentiment
Sentiment	0.012**	0.013**	0.001
	(0.005)	(0.006)	(0.004)
VIX	0.008	0.016	0.006
	(0.012)	(0.016)	(0.011)
Stoxx 50	0.091	0.208	0.046
	(0.129)	(0.193)	(0.124)
SMB	-0.395*	-0.475	-0.360
	(0.232)	(0.297)	(0.238)
HML	-0.165	-0.451	-0.275
	(0.268)	(0.286)	(0.273)
WML	-0.233	-0.404**	-0.262
	(0.176)	(0.191)	(0.189)
Num.Obs.	76	37	71

We estimate regressions of the Green–Brown return spread on the ECB green sentiment measure, using only days on which green speeches occur. Table A3 reports coefficient estimates for green sentiment while controlling for standard financial and asset-pricing variables (VIX, Euro STOXX 50, SMB, HML, and WML). For each specification, estimated coefficients are reported with robust (HC1) standard errors in parentheses. Statistical significance is denoted by *p < .10, **p < .05, and ***p < .01.

Appendix S10. Two-Way Fixed-Effects Panel Estimates by IO Tertile (2010–2020), Permutation-Based Placebo Test by IO Tertile (2010-2020) and Market Frictions Diagnostic: Short-Sale and Arbitrage Constraints (2010-2020)

Figure A1. Heterogeneous sentiment response by institutional ownership tertiles (linear trend) (2010-2020)

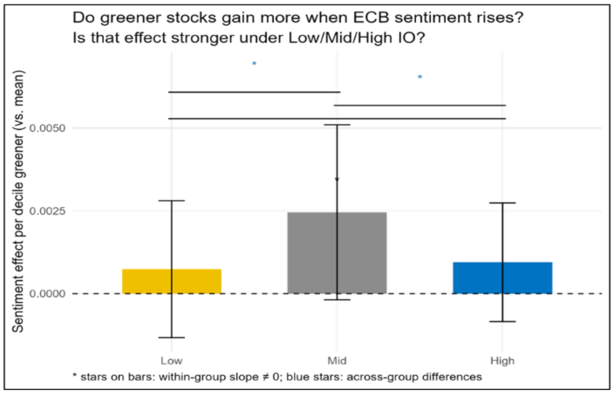
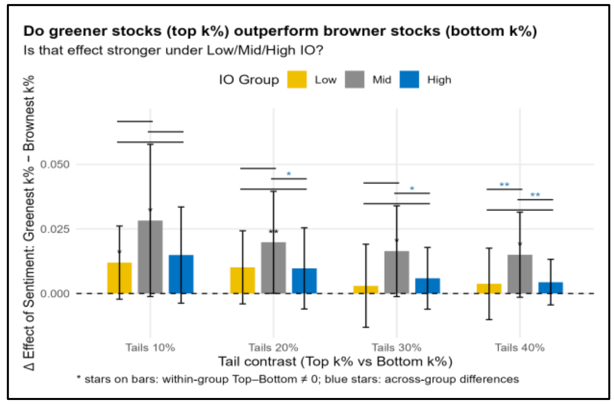


Figure A2. Heterogeneous sentiment response by institutional ownership tertiles (tail contrast) (2010-2020)



The figure reports estimates from a two-way fixed-effects panel regression testing whether the return response to ECB green sentiment varies jointly with emissions performance and institutional ownership (IO). Daily stock returns are regressed on interactions between the green sentiment index, emissions rank, and IO-tertile indicators (low/mid/high), including all implied lower-order terms, with firm and day fixed effects. Emissions performance is measured either as a linear decile rank (1–10) or via tail contrasts comparing the top $k\%$(greenest) to the bottom $k\%$(brownest). Controls include standard time-varying firm characteristics, and standard errors are two-way clustered by firm and day.

Note: * $p < .10$, ** $p < .05$, *** $p < .01$. Stars on bars indicate whether the within-group sentiment × greenness effect differs from zero (simple-slope (Wald) tests; for low-IO and high-IO, the effect is the mid-IO baseline plus the relevant interaction). Blue stars on the horizontal lines report simple-slope (Wald) between-group tests: Mid vs Low and Mid vs High test the corresponding three-way interaction terms, and Low vs High tests the difference between those interactions.

Figure A1 reports the 2010–2020 panel estimates by IO tertiles (full estimates in **Table A4**). In the linear-trend specification, the estimated sentiment effect is largest for the mid-IO group, with smaller responses for low-IO and high-IO firms. This implies that as ECB green sentiment rises, greener stocks tend to outperform browner stocks most strongly among mid-IO firms. However, the evidence is weak (significant only at the 10% level), so the differences should be interpreted as suggestive.

Table A4 Full Regression Tables for Figure 4: IO Tertiles with Linear Trend (2010–2020)

test	estimate	se	t-stat	p
[WITHIN] per-decile slope (Mid)	0.002	0.001	1.822	0.068
[WITHIN] per-decile slope (High)	0.001	0.001	1.038	0.299
[WITHIN] per-decile slope (Low)	0.001	0.001	0.701	0.483
[ACROSS] per-decile (High−Mid)	-0.002	0.001	-1.897	0.058
[ACROSS] per-decile (Low−Mid)	-0.002	0.001	-1.737	0.082
[ACROSS] per-decile (High−Low)	0.000	0.001	0.305	0.761

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log{(ME)}$. **Within-group** rows report the estimated **Sentiment** × **greenness (emissions-decile slope)** within each IO tertile. Because Mid-IO is the reference group, the within-group slopes for Low-IO and High-IO are tested using Wald tests that combine the Mid-IO baseline coefficient with the corresponding interaction term. **Across-group** rows report Wald tests of whether the **Sentiment** ×**greenness** slope differs between IO tertiles. Specifically, the High–Mid and Low–Mid tests correspond to the three-way interaction terms $Sentiment \times Decile \times High\text{-}IO$and $Sentiment \times Decile \times Low\text{-}IO$, respectively, and the High–Low test evaluates the difference between these two interaction coefficients.

Figure A2 presents the tail-contrast results (full estimates in **Table A5**). The top-minus-bottom effect is generally positive across IO groups, but magnitudes and significance vary across tail definitions ($k = 10,20,30,40$). The mid-IO group again tends to show the largest effects. The magnitude is also economically large. The within-group sentiment × greenness effect for mid-IO ranges from 0.015 to 0.028 (**Table A5**), implying that a 50-point increase in sentiment corresponds to at least a 0.75% higher daily green–brown return spread. However, the omnibus (joint Wald) test for the three-way interaction (sentiment × tail contrast × IO tertile) is not statistically significant, and within-group significance varies across k, so the patterns should be interpreted as suggestive rather than conclusive.

Table A5 Full Regression Tables for Figure 5: IO Tertiles with Tail Contrast (2010–2020)

model	test	estimate	se	t-stat	p
Tails 10%	[WITHIN] Top−Bottom (Mid) — Tails 10%	0.028	0.015	1.882	0.060
Tails 10%	[WITHIN] Top−Bottom (High) — Tails 10%	0.015	0.010	1.565	0.118
Tails 10%	[WITHIN] Top−Bottom (Low) — Tails 10%	0.012	0.007	1.655	0.098
Tails 10%	[ACROSS] (High−Mid) of Top−Bottom — Tails 10%	-0.013	0.011	-1.213	0.225
Tails 10%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 10%	-0.016	0.014	-1.193	0.233
Tails 10%	[ACROSS] (High−Low) of Top−Bottom — Tails 10%	0.003	0.011	0.258	0.797
Tails 20%	[WITHIN] Top−Bottom (Mid) — Tails 20%	0.020	0.010	1.966	0.049
Tails 20%	[WITHIN] Top−Bottom (High) — Tails 20%	0.010	0.008	1.213	0.225
Tails 20%	[WITHIN] Top−Bottom (Low) — Tails 20%	0.010	0.007	1.402	0.161
Tails 20%	[ACROSS] (High−Mid) of Top−Bottom — Tails 20%	-0.010	0.006	-1.762	0.078
Tails 20%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 20%	-0.010	0.008	-1.254	0.210
Tails 20%	[ACROSS] (High−Low) of Top−Bottom — Tails 20%	0.000	0.006	-0.070	0.944
Tails 30%	[WITHIN] Top−Bottom (Mid) — Tails 30%	0.016	0.009	1.828	0.068
Tails 30%	[WITHIN] Top−Bottom (High) — Tails 30%	0.006	0.006	0.967	0.334
Tails 30%	[WITHIN] Top−Bottom (Low) — Tails 30%	0.003	0.008	0.365	0.715
Tails 30%	[ACROSS] (High−Mid) of Top−Bottom — Tails 30%	-0.010	0.006	-1.819	0.069
Tails 30%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 30%	-0.013	0.008	-1.611	0.107
Tails 30%	[ACROSS] (High−Low) of Top−Bottom — Tails 30%	0.003	0.006	0.519	0.603
Tails 40%	[WITHIN] Top−Bottom (Mid) — Tails 40%	0.015	0.008	1.788	0.074
Tails 40%	[WITHIN] Top−Bottom (High) — Tails 40%	0.004	0.005	0.979	0.327
Tails 40%	[WITHIN] Top−Bottom (Low) — Tails 40%	0.004	0.007	0.529	0.597
Tails 40%	[ACROSS] (High−Mid) of Top−Bottom — Tails 40%	-0.011	0.005	-2.007	0.045
Tails 40%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 40%	-0.011	0.006	-2.004	0.045
Tails 40%	[ACROSS] (High−Low) of Top−Bottom — Tails 40%	0.001	0.003	0.198	0.843

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment** ×**tails contrast (Top–Bottom effect)** within each IO tertile, where the tails contrast is defined as the difference between the top-k% (greenest) and bottom-k% (brownest) emissions portfolios for $q \in \{10,20,30,40\}$. Because Mid-IO is the reference group, the within-group effects for Low-IO and High-IO are tested using Wald tests that combine the Mid-IO baseline coefficient with the corresponding interaction term. **Across-group** rows report Wald tests of whether the **Sentiment** ×**tails contrast** differs between IO tertiles. Specifically, the High–Mid and Low–Mid tests correspond to the three-way interaction terms $Sentiment \times TailContrast_k \times High\text{-}IO$ and $Sentiment \times TailContrast_k \times Low\text{-}IO$, respectively, and the High–Low test evaluates the difference between these two interaction coefficients.

As a robustness check, we repeat the analysis using an IO median split (full estimates in **Tables A6 and A7**). The estimated effects are positive but statistically insignificant in both groups, consistent with the median split being too coarse and with the tertile results suggesting concentration in the mid-IO group.

Table A6 Full Regression: IO Median Split with Linear Trend (2010–2020)

test	estimate	se	t-stat	p
[WITHIN] per-decile slope (High)	0.0015	0.0010	1.4646	0.1430
[WITHIN] per-decile slope (Low)	0.0012	0.0010	1.1643	0.2443
[ACROSS] per-decile (Low−High)	-0.0003	0.0004	-0.7481	0.4544

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment** × **greenness (emissions-decile slope)** within each IO group, where High-IO and Low-IO are defined using a median split of institutional ownership. With **High-IO as the omitted reference group**, the **High-IO** within-group slope equals the baseline coefficient on $Sentiment \times Decile$. The **Low-IO** within-group slope is obtained by combining this baseline coefficient with the interaction term $Sentiment \times Decile \times LowIO$ (Wald test). **Across-group** rows test whether the sentiment × greenness slope differs between Low-IO and High-IO. With High-IO as the omitted reference group, this difference (Low − High) is given by the coefficient on $Sentiment \times Decile \times LowIO$, and we test whether this coefficient differs from zero.

Table A7 Full Regression: IO Median Split with Tail Contrast (2010–2020)

model	test	estimate	se	t-stat	p
Tails 10%	[WITHIN] Top−Bottom (High) — Tails 10%	0.020	0.011	1.771	0.076
Tails 10%	[WITHIN] Top−Bottom (Low) — Tails 10%	0.016	0.009	1.908	0.056
Tails 10%	[ACROSS] (Low−High) of Top−Bottom — Tails 10%	-0.003	0.010	-0.320	0.749
Tails 20%	[WITHIN] Top−Bottom (High) — Tails 20%	0.013	0.008	1.579	0.114
Tails 20%	[WITHIN] Top−Bottom (Low) — Tails 20%	0.013	0.007	1.774	0.076
Tails 20%	[ACROSS] (Low−High) of Top−Bottom — Tails 20%	0.000	0.004	-0.087	0.931
Tails 30%	[WITHIN] Top−Bottom (High) — Tails 30%	0.010	0.006	1.489	0.137
Tails 30%	[WITHIN] Top−Bottom (Low) — Tails 30%	0.007	0.007	0.949	0.343
Tails 30%	[ACROSS] (Low−High) of Top−Bottom — Tails 30%	-0.003	0.003	-0.869	0.385
Tails 40%	[WITHIN] Top−Bottom (High) — Tails 40%	0.008	0.005	1.561	0.119
Tails 40%	[WITHIN] Top−Bottom (Low) — Tails 40%	0.007	0.007	0.966	0.334
Tails 40%	[ACROSS] (Low−High) of Top−Bottom — Tails 40%	-0.002	0.002	-1.016	0.310

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment** ×**tails contrast (Top–Bottom effect)** within each IO group, where High-IO and Low-IO are defined using a median split of institutional ownership. The tails contrast is defined as the difference between the top-k% (greenest) and bottom-k% (brownest) emissions portfolios for $k \in \{10,20,30,40\}$. With **High-IO as the omitted reference group**, the High-IO within-group effect equals the baseline coefficient on $Sentiment \times TailContrast_k$. The Low-IO within-group effect is obtained by combining this baseline coefficient with the interaction term $Sentiment \times TailContrast_k \times LowIO$. **Across-group** rows test whether the Sentiment ×tails contrast differs between Low-IO and High-IO; this difference (Low − High) is given by the coefficient on $Sentiment \times TailContrast_k \times LowIO$.

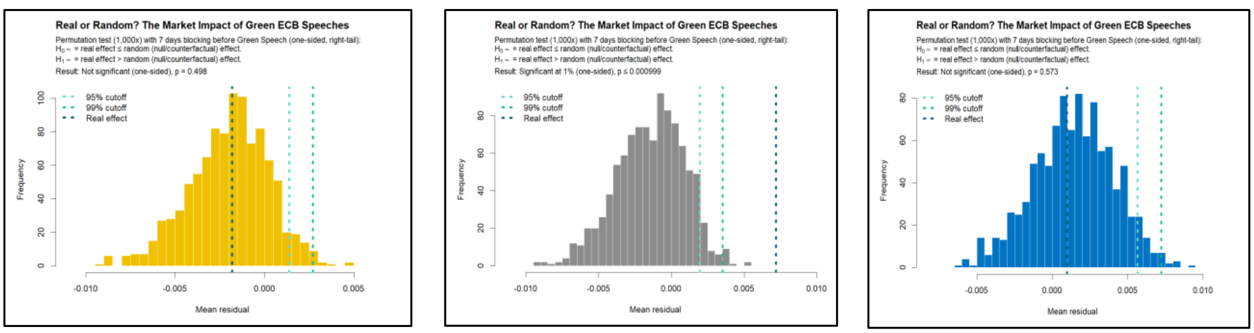
Permutation-based placebo test by IO tertile (2010-2020)

Following the aggregate procedure described in **Appendix S4**, we run permutation-based placebo tests within each IO group on high-intensity green-speech days (85th-percentile threshold). While the omnibus tests do not detect IO-related differences, the permutation-based results indicate that the high-intensity signal is most evident in the mid-IO group.

In Figure A3, the observed mean residual for mid-IO lies above the 99th percentile of its placebo distribution (one-sided p ≈ 0.001), while the low-IO and high-IO tests are not significant ($p = 0.498$ and $p = 0.573$). Taken together, these within-group results suggest that the high-intensity abnormal-return signal is not uniformly detectable across IO groups, with the strongest evidence in the mid-IO segment. However, because these are within-group tests, differences across IO groups should be interpreted as suggestive.

Figure A3. Permutation-based placebo test by IO tertile (2010-2020)

Low IO (more retail-dominated)	Mid IO (mixed)	High IO (more institutionally dominated)



The figure shows the placebo distribution of the mean factor-adjusted Green–Brown abnormal return (Carhart+VIX residual) from 1,000 restricted reassignments within $[d-7, d-1]$; vertical lines mark the 95% and 99% cutoffs and the observed effect.

Market Frictions Diagnostic: Short-Sale and Arbitrage Constraints (2010-2020)

To complement the IO-based analysis results, we present descriptive evidence on two market-friction proxies that may restrict investors from trading against mispricing: short-selling and arbitrage constraints. We use a matrix approach to show how “high-constraint” and “low-constraint” stocks are distributed across each IO group as described in Appendix 2.

Short-selling constraints (RIOR)

Following Nagel (2005), as implemented by Weber (2017) and described in Section **Appendix S2**, we construct residual institutional ownership (RIOR) as a size-adjusted proxy for short-selling constraints.

Figure A4 Raw IO vs Residual IO (RIOR) by IO Group (2010-2020)

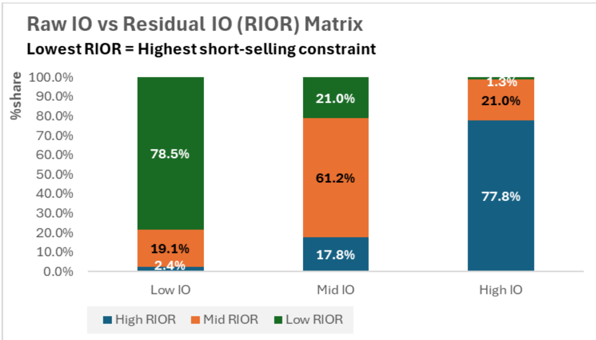
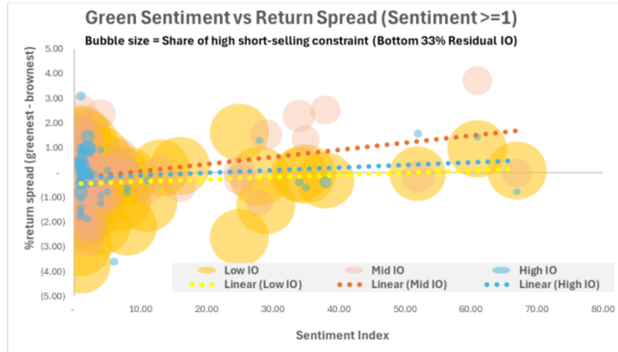


Figure A5 Sentiment Index and Raw IO vs Residual IO (RIOR) by IO Group (2010-2020)



RIOR is computed as the residual from an annual cross-sectional regression of logit (IO) on log (ME) and [log (ME)]² (IO capped to [0.0001, 0.999]). Stocks are then classified into low-, mid-, and high-constraint groups by RIOR tertiles within emissions deciles; bar heights and bubble sizes show group shares.

Lower RIOR indicates tighter short-sale constraints. Low-IO stocks are disproportionately in the most-constrained (low-RIOR) tertile, whereas high-IO stocks are disproportionately in the least-constrained (high-RIOR) tertile (Figure A4). Although the sentiment–spread relationship is steepest for mid-IO, the concentration of highly constrained stocks is greatest for low-IO, suggesting that the mid-IO response is unlikely to be primarily explained by short-sale constraints (Figure A5).

Arbitrage constraints (IVOL)

Figure A6 Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (20-day rolling window) (2010-2020)

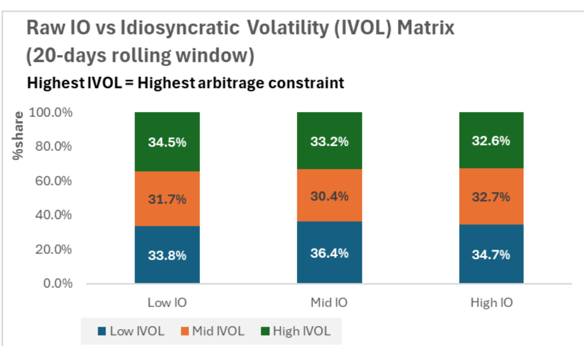
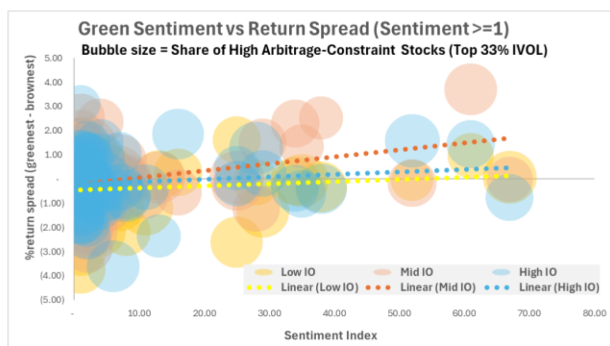


Figure A7 Sentiment Index and Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (20-day rolling window) (2010-2020)



IVOL is the 20-day rolling standard deviation of CAPM residuals (market return = STOXX 50 excess return), lagged one trading day, so that $IVOL_t$ uses information up to $t-1$. Stocks are then classified into low-, mid-, and high-constraint groups by IVOL tertiles within emissions deciles; bar heights and bubble sizes show group shares.

Higher IVOL indicates tighter arbitrage constraints. In contrast to the RIOR results, the IVOL distribution appears broadly balanced across IO groups, with only small differences in the shares of high-IVOL stocks (Figure A6). However, because high-IVOL (high-constraint) stocks are not disproportionately concentrated in the mid-IO group, the stronger mid-IO sentiment response is unlikely to be primarily explained by arbitrage constraints (Figure A7). The same qualitative pattern holds when using a longer rolling window IVOL (60) (Figure A8 and A9).

Figure A8 Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (60-day rolling window) (2010-2020)

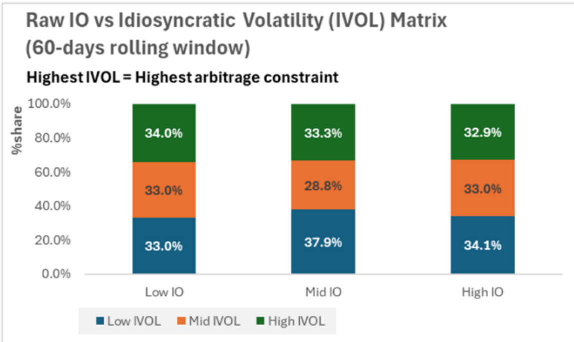
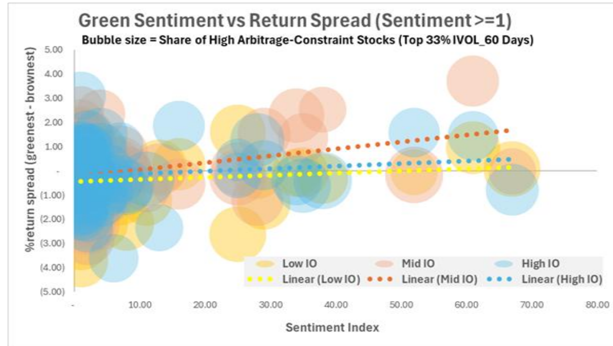


Figure A9 Sentiment Index and Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (60-day rolling window) (2010-2020)



Overall, the distribution of RIOR- and IVOL-based constraints across IO groups is not aligned with the strongest within-group evidence appearing in mid-IO, suggesting that market frictions are unlikely to be the primary driver.

Appendix S11. Event Study (2021-2024)

Table A8. Event Study Findings for the Green-Brown Portfolio Using Various Expected Return Models Following the Top 5 Climate Change-Related Speeches (2021-2024)

Window	[-1;-1]	[-1;0]	[0;0]	[0;1]	[0;2]	[1;1]
CAAR (Market model)	**-0.14%**	**-0.29%**	**-0.15%**	**-0.15%**	**-0.13%**	**0.00%**
Standard deviation (Market model)	0.25%	0.42%	0.32%	0.45%	0.53%	0.37%
t-statistic (Market model)	-1.24	-1.51	-1.03	-0.75	-0.54	-0.03
CAAR (F-F three-factor model)	**-0.15%**	**-0.50%**	**-0.35%**	**-0.47%**	**-0.47%**	**-0.12%**
Standard deviation (F-F three-factor model)	0.43%	0.84%	0.52%	0.68%	0.78%	0.35%
t-statistic (F-F three-factor model)	-0.78	-1.34	-1.51	-1.54	-1.34	-0.75
CAAR (F-F three-factor + momentum model)	**-0.13%**	**-0.28%**	**-0.14%**	**-0.36%**	**-0.44%**	**-0.21%**
Standard deviation (F-F three-factor + momentum model)	0.18%	0.19%	0.32%	0.41%	0.47%	0.43%
t-statistic (F-F three-factor + momentum model)	-1.69*	-3.32***	-1.01	-1.92*	-2.11**	-1.12

Table A8 reports estimates of the green–brown return spread using several expected-return models. The first sub-table shows results using the commonly applied market model, followed by the Fama-French three-factor model and its extension that includes the momentum factor. Each model is assessed across six event windows: [−1;1], [−1;0], [0;0], [0;1], [1;1], and [0;2]. Event windows are reported as a, b, where 0 denotes the event day, a and b are the number of trading days before or after the event. For example, $-1, +1$ covers the day before, the event day, and the day after. Rows present the event windows, CAARs, standard deviations, and t-statistics. Returns are calculated as the natural logarithm of raw returns. Statistical significance is indicated as follows: *p < .1; **p < .05; ***p < .01.

Appendix S12. Two-Way Fixed-Effects Panel Estimates by IO Tertile (2021–2024)

Table A9 Full Regression Tables: IO Tertiles with Linear Trend (2021–2024)

test	estimate	se	t-stat	p
[WITHIN] per-decile slope (Mid)	-0.0004	0.0003	-1.1641	0.2444
[WITHIN] per-decile slope (High)	0.0005	0.0002	2.0733	0.0381
[WITHIN] per-decile slope (Low)	0.0001	0.0003	0.4644	0.6424
[ACROSS] per-decile (High−Mid)	0.0008	0.0003	2.8582	0.0043
[ACROSS] per-decile (Low−Mid)	0.0005	0.0004	1.2416	0.2144
[ACROSS] per-decile (High−Low)	0.0003	0.0003	1.2240	0.2209

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log{(ME)}$. **Within-group** rows report the estimated **Sentiment** ×**greenness (emissions-decile slope)** within each IO tertile. Because Mid-IO is the reference group, the within-group slopes for Low-IO and High-IO are tested using Wald tests that combine the Mid-IO baseline coefficient with the corresponding interaction term. **Across-group** rows report Wald tests of whether the **Sentiment** ×**greenness** slope differs between IO tertiles. Specifically, the High–Mid and Low–Mid tests correspond to the three-way interaction terms $Sentiment \times Decile \times High\text{-}IO$ and $Sentiment \times Decile \times Low\text{-}IO$, respectively, and the High–Low test evaluates the difference between these two interaction coefficients.

Appendix S13. Two-Way Fixed-Effects Panel Estimates by IO Tertile (2021–2024)

Table A10 Full Regression Tables: IO Tertiles with Tail Contrast (2021–2024)

model	test	estimate	se	t-stat	p
Tails 10%	[WITHIN] Top−Bottom (Mid) — Tails 10%	-0.002	0.003	-0.534	0.593
Tails 10%	[WITHIN] Top−Bottom (High) — Tails 10%	0.006	0.003	2.158	0.031
Tails 10%	[WITHIN] Top−Bottom (Low) — Tails 10%	-0.003	0.006	-0.397	0.691
Tails 10%	[ACROSS] (High−Mid) of Top−Bottom — Tails 10%	0.008	0.004	2.128	0.033
Tails 10%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 10%	-0.001	0.007	-0.129	0.897
Tails 10%	[ACROSS] (High−Low) of Top−Bottom — Tails 10%	0.008	0.007	1.138	0.255
Tails 20%	[WITHIN] Top−Bottom (Mid) — Tails 20%	-0.004	0.003	-1.184	0.236
Tails 20%	[WITHIN] Top−Bottom (High) — Tails 20%	0.005	0.002	2.213	0.027
Tails 20%	[WITHIN] Top−Bottom (Low) — Tails 20%	-0.001	0.004	-0.134	0.894
Tails 20%	[ACROSS] (High−Mid) of Top−Bottom — Tails 20%	0.008	0.003	2.463	0.014
Tails 20%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 20%	0.003	0.004	0.766	0.443
Tails 20%	[ACROSS] (High−Low) of Top−Bottom — Tails 20%	0.005	0.004	1.246	0.213
Tails 30%	[WITHIN] Top−Bottom (Mid) — Tails 30%	-0.002	0.002	-0.967	0.334
Tails 30%	[WITHIN] Top−Bottom (High) — Tails 30%	0.004	0.002	2.092	0.036
Tails 30%	[WITHIN] Top−Bottom (Low) — Tails 30%	0.002	0.002	1.004	0.315
Tails 30%	[ACROSS] (High−Mid) of Top−Bottom — Tails 30%	0.006	0.002	2.920	0.003
Tails 30%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 30%	0.004	0.003	1.455	0.146
Tails 30%	[ACROSS] (High−Low) of Top−Bottom — Tails 30%	0.002	0.002	0.769	0.442
Tails 40%	[WITHIN] Top−Bottom (Mid) — Tails 40%	-0.002	0.002	-1.232	0.218
Tails 40%	[WITHIN] Top−Bottom (High) — Tails 40%	0.003	0.002	1.593	0.111
Tails 40%	[WITHIN] Top−Bottom (Low) — Tails 40%	0.002	0.001	1.569	0.117
Tails 40%	[ACROSS] (High−Mid) of Top−Bottom — Tails 40%	0.005	0.002	2.499	0.012
Tails 40%	[ACROSS] (Low−Mid) of Top−Bottom — Tails 40%	0.004	0.002	2.318	0.020
Tails 40%	[ACROSS] (High−Low) of Top−Bottom — Tails 40%	0.001	0.001	0.410	0.682

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment ×tails contrast (Top–Bottom effect)** within each IO tertile, where the tails contrast is defined as the difference between the top-k% (greenest) and bottom-k% (brownest) emissions portfolios for $q \in \{10,20,30,40\}$. Because Mid-IO is the reference group, the within-group effects for Low-IO and High-IO are tested using Wald tests that combine the Mid-IO baseline coefficient with the corresponding interaction term. **Across-group** rows report Wald tests of whether the **Sentiment ×tails contrast** differs between IO tertiles. Specifically, the High–Mid and Low–Mid tests correspond to the three-way interaction terms $Sentiment \times TailContrast_k \times High\text{-}IO$ and $Sentiment \times TailContrast_k \times Low\text{-}IO$, respectively, and the High–Low test evaluates the difference between these two interaction coefficients.

Appendix S14. Two-Way Fixed-Effects Panel Estimates by Median Split with Linear Trend (2021–2024)

Table A11 Full Regression: IO Median Split with Linear Trend (2021–2024)

test	estimate	se	t-stat	p
[WITHIN] per-decile slope (High)	0.0004	0.0002	2.0571	0.0397
[WITHIN] per-decile slope (Low)	-0.0003	0.0002	-1.1195	0.2629
[ACROSS] per-decile (Low−High)	-0.0007	0.0002	-4.0336	0.0001

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment** × **greenness (emissions-decile slope)** within each IO group, where High-IO and Low-IO are defined using a median split of institutional ownership. With **High-IO as the omitted reference group**, the **High-IO** within-group slope equals the baseline coefficient on $Sentiment \times Decile$. The **Low-IO** within-group slope is obtained by combining this baseline coefficient with the interaction term $Sentiment \times Decile \times LowIO$ (Wald test). **Across-group** rows test whether the Sentiment × greenness slope differs between Low-IO and High-IO. With High-IO as the omitted reference group, this difference (Low − High) is given by the coefficient on $Sentiment \times Decile \times LowIO$, and we test whether this coefficient differs from zero.

Appendix S15. Two-Way Fixed-Effects Panel Estimates by Median Split with Tail Contrast (2021–2024)

Table A12 Full Regression: IO Median Split with Tail Contrast (2021–2024)

model	test	estimate	se	stat	p
Tails 10%	[WITHIN] Top−Bottom (High) — Tails 10%	0.006	0.003	2.344	0.019
Tails 10%	[WITHIN] Top−Bottom (Low) — Tails 10%	-0.005	0.005	-1.020	0.307
Tails 10%	[ACROSS] (Low−High) of Top−Bottom — Tails 10%	-0.011	0.006	-1.874	0.061
Tails 20%	[WITHIN] Top−Bottom (High) — Tails 20%	0.003	0.002	1.589	0.112
Tails 20%	[WITHIN] Top−Bottom (Low) — Tails 20%	-0.003	0.003	-1.066	0.287
Tails 20%	[ACROSS] (Low−High) of Top−Bottom — Tails 20%	-0.006	0.003	-2.381	0.017
Tails 30%	[WITHIN] Top−Bottom (High) — Tails 30%	0.003	0.002	2.015	0.044
Tails 30%	[WITHIN] Top−Bottom (Low) — Tails 30%	-0.001	0.002	-0.512	0.608
Tails 30%	[ACROSS] (Low−High) of Top−Bottom — Tails 30%	-0.004	0.001	-3.082	0.002
Tails 40%	[WITHIN] Top−Bottom (High) — Tails 40%	0.002	0.001	1.627	0.104
Tails 40%	[WITHIN] Top−Bottom (Low) — Tails 40%	-0.001	0.001	-0.526	0.599
Tails 40%	[ACROSS] (Low−High) of Top−Bottom — Tails 40%	-0.003	0.001	-2.527	0.011

Note: Panel regressions include firm and day fixed effects, with standard errors two-way clustered by firm and day. All specifications include the additive controls: $\beta_{mkt}, \beta_{smb}, \beta_{hml}, \beta_{wml}$, Momentum, B/M, and $\log(ME)$. **Within-group** rows report the estimated **Sentiment ×tails contrast (Top–Bottom effect)** within each IO group, where High-IO and Low-IO are defined using a median split of institutional ownership. The tails contrast is defined as the difference between the top-k% (greenest) and bottom-k% (brownest) emissions portfolios for $k \in \{10,20,30,40\}$. With **High-IO as the omitted reference group**, the High-IO within-group effect equals the baseline coefficient on $Sentiment \times TailContrast_k$. The Low-IO within-group effect is obtained by combining this baseline coefficient with the interaction term $Sentiment \times TailContrast_k \times LowIO$. **Across-group** rows test whether the Sentiment ×tails contrast differs between Low-IO and High-IO; this difference (Low − High) is given by the coefficient on $Sentiment \times TailContrast_k \times LowIO$.

Appendix S16. Pooled Regressions by Period and IO Tertile: Implied Slopes and Full Results

Table A13: Pre-2021–Post-2020 comparison of the Green–Brown response to ECB green sentiment by IO tertile

Test (Within Group)	Estimate	Standard Error
Low IO (Pre-2021): within-group sentiment effect	0.003	0.005
Mid IO (Pre-2021): within-group sentiment effect	0.024**	0.011
High IO (Pre-2021): within-group sentiment effect	0.006	0.007
Low IO (Post-2020): within-group sentiment effect	-0.005	0.006
Mid IO (Post-2020): within-group sentiment effect	-0.003	0.003
High IO (Post-2020): within-group sentiment effect	0.002	0.003
Low IO: change in effect (Post-2020 − Pre-2021)	-0.008	0.008
Mid IO: change in effect (Post-2020 − Pre-2021)	-0.027**	0.012
High IO: change in effect (Post-2020 − Pre-2021)	-0.004	0.008

We regress the Green–Brown return spread on ECB green sentiment using green-speech days only. To test whether the sentiment–spread association changes after 2020 and differs by ownership structure, we include a Post-2020 indicator (Jan 2021–Dec 2024) and interact it with sentiment and IO-tertile indicators (low/mid/high). The "Test (Within Group)" column reports Wald tests for (i) the within-group sentiment slope in each period and (ii) the within-group pre–post change (Post − Pre). Low IO is the reference group; mid/high-IO effects are obtained by adding the relevant interaction terms. Stars denote Wald-test significance using day-clustered HC1 robust standard errors. Controls include VIX, STOXX 50, SMB, HML, and WML. Significance: * $p < .10$, ** $p < .05$, *** $p < .01$.

Within-group effects (post-2020 vs pre-2021). Table A13 reports implied within-group sentiment slopes pre-2021 and post-2020, and the corresponding pre–post changes, computed as Wald-tested linear combinations. Pre-2021, the slope is positive and significant only for mid-IO (0.024, $p < 0.05$); low-IO (0.003) and high-IO (0.006) are small and not significant. Post-2020, slopes are close to zero for all groups (low: −0.005; mid: −0.003; high: 0.002) and not significant. The pre–post decline is largest for mid-IO (−0.027, $p < 0.05$), with smaller, insignificant changes for low-IO (−0.008) and high-IO (−0.004). Overall, the pooled results indicate attenuation after 2020, most clearly for mid-IO.

Table A14: Differences across IO groups in the change of sentiment effect (post-2020 vs pre-2021)

Test (Across Group)	Estimate	Standard Error
Mid IO - Low IO	-0.019	0.015
High IO - Low IO	0.004	0.013
High IO - Mid IO	0.023*	0.014

The "Test (Across Group)" column reports Wald tests comparing the *pre–post* change in the sentiment effect across IO tertiles. Low IO is the reference group: Mid − Low tests Sentiment × Post2020 × Tertile2, High − Low tests Sentiment × Post2020 × Tertile3, and High − Mid tests the difference between these two triple interactions. Stars denote Wald-test significance using day-clustered HC1 robust standard errors.

Across-group differences (post-2020 vs pre-2021). Table A14 tests whether the post-2020 change differs across IO groups. The mid-IO change is lower than low-IO (−0.019; not significant), and the high-IO change does not differ from low-IO (0.004; not significant). The high-IO shift differs from the mid-IO shift (0.023, $p < 0.10$), providing weak evidence that attenuation is less pronounced for high-IO than for mid-IO.

These pooled regressions indicate a weaker sentiment–spread relationship after 2020. In the later period, the pooled estimates are directionally most positive for high-IO, but magnitudes are modest and statistically insignificant, so the pattern should be interpreted cautiously.

Table A15 Full Results: Pooled Green-Speech-Day Regressions by Period and IO Group

Term	Estimate
Intercept	-0.255**
	(0.102)
Sentiment_c (centered)	0.003
	(0.005)
Post-2020	0.245**
	(0.123)
Tertile 2	0.392**
	(0.175)
Tertile 3	0.227
	(0.160)
VIX	0.004
	(0.005)
Stoxx 50	0.199***
	(0.052)
SMB	-0.520***
	(0.099)
HML	0.121**
	(0.056)
WML	-0.131***
	(0.044)
Sentiment_c × Post-2020	-0.008
	(0.008)
Sentiment_c × Mid IO	0.021*
	(0.012)
Sentiment_c × High IO	0.003
	(0.009)
Post-2020 × Mid IO	-0.324*
	(0.195)
Post-2020 × High IO	-0.213
	(0.183)
Sentiment_c × Post-2020 × Mid IO	-0.019
	(0.014)
Sentiment_c × Post-2020 × High IO	0.004
	(0.011)
Num.Obs.	802

We regress the Green–Brown return spread on ECB green sentiment using green-speech days only. Controls include VIX, STOXX 50 returns, SMB, HML, and WML. Standard errors are day-clustered (HC1) and reported in parentheses. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Appendix S17. Market Frictions Diagnostic: Short-Sale and Arbitrage Constraints (2021-2024)

To complement the IO-based analysis results, we present descriptive evidence on two market-friction proxies that may restrict investors from trading against mispricing: short-selling and arbitrage constraints. The construction of both proxies and the matrix-style presentation follows the same procedure as in the primary (pre-2021), as described in **Appendix 2**.

Short-selling constraints (RIOR)

Lower RIOR indicates tighter short-sale constraints. Low-IO stocks are disproportionately in the most-constrained (low-RIOR) tertile, whereas high-IO stocks are disproportionately in the least-constrained (high-RIOR) tertile (Figure A10). Although the sentiment–spread relationship appears to have a somewhat steeper slope in the high-IO group, the concentration of highly constrained stocks is greatest in the low-IO group. This mismatch suggests that the stronger high-IO response is unlikely to be driven primarily by short-sale constraints (Figure A11).

Figure A10 Raw IO vs Residual IO (RIOR) by IO Group (2021-2024)

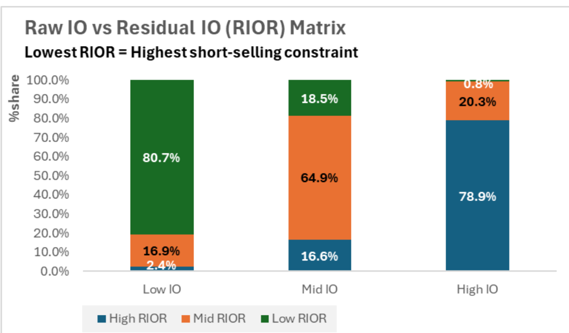
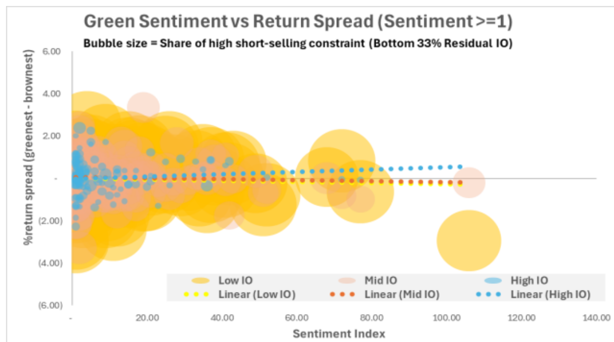


Figure A11 Sentiment Index and Raw IO vs Residual IO (RIOR) by IO Group (2021-2024)



RIOR is computed as the residual from an annual cross-sectional regression of logit (IO) on log (ME) and [log (ME)]² (IO capped to [0.0001, 0.999]). Stocks are then classified into low-, mid-, and high-constraint groups by RIOR tertiles within emissions deciles; bar heights and bubble sizes show group shares.

Arbitrage constraints (IVOL)

Figure A12 Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (20-day rolling window) (2021-2024)

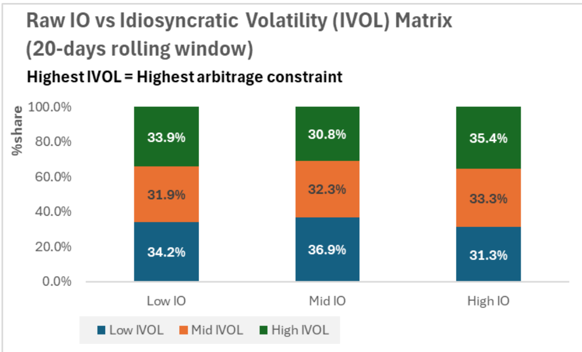
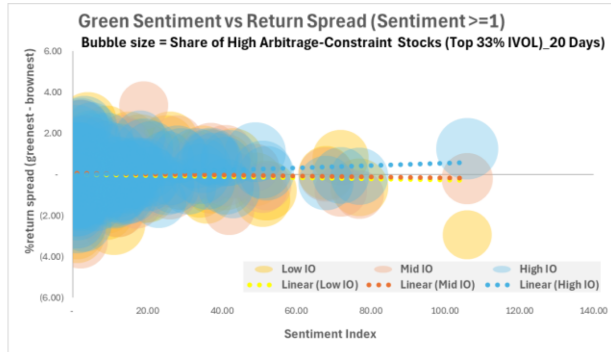


Figure A13 Sentiment Index and Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (20-day rolling window) (2021-2024)



IVOL is the 20-day rolling standard deviation of CAPM residuals (market return = STOXX 50 excess return), lagged one trading day, so that $IVOL_t$ uses information up to $t-1$. Stocks are then classified into low-, mid-, and high-constraint groups by IVOL tertiles within emissions deciles; bar heights and bubble sizes show group shares.

Higher IVOL indicates tighter arbitrage constraints. In contrast to the RIOR results, the IVOL distribution appears broadly balanced across IO groups, with only small differences in the shares of high-IVOL stocks (Figure A12). However, because high-IVOL (high-constraint) stocks are not disproportionately concentrated in the high-IO group, the stronger high-IO sentiment response is unlikely to be primarily explained by arbitrage constraints (Figure A13). The same qualitative pattern holds when using a longer rolling window IVOL (60) (Figure A14 and A15).

Figure A14 Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group (60-day rolling window) (2021-2024)

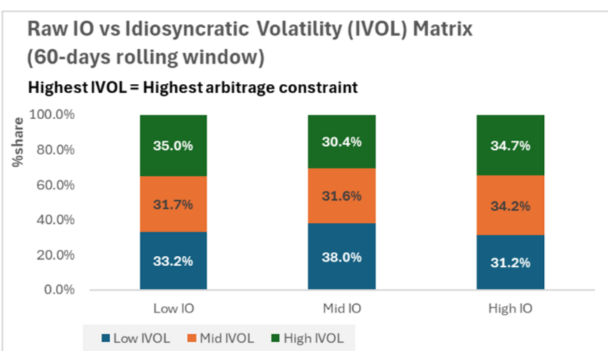
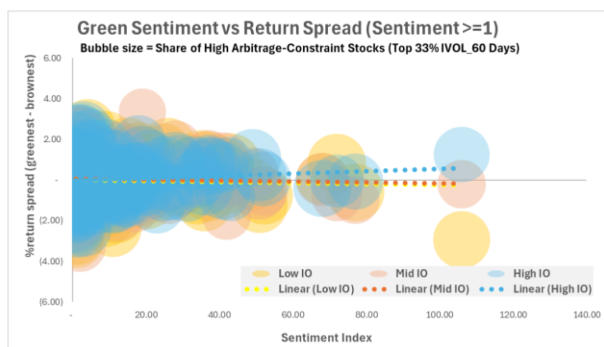


Figure A15 Sentiment Index and Raw IO vs Idiosyncratic Volatility (IVOL) by IO Group

(60-day rolling window) (2021-2024)



Overall, the distribution of RIOR- and IVOL-based constraints across IO groups is not aligned with the strongest response occurring in high-IO, suggesting that market frictions are unlikely to be the primary driver.