In Search of the Causal Greenium

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April 30, 2025

We propose a regression discontinuity design to determine whether there is a difference in the expected returns of green versus brown securities (greenium). We analyze daily changes in option-implied expected returns following the outcome of close vote ecology-related shareholder proposals to estimate the causal impact of a small change in investors' aggregate greenness perception on expected returns. Upon proposals' passage, expected returns with a forecast horizon of 365 (730) days drop by approximately 9.3% (6.9%) relative to proposals' failure, indicating the existence of a negative greenium in US equity markets. Our results are robust to the introduction of a battery of fixed effects and when accounting for multiple periods around shareholder proposal voting dates.

JEL-Classification: G11, G12, G14, Q5
Keywords: Greenium, option-implied expected returns, regression discontinuity, shareholder proposals

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1 Introduction

A key question in the field of sustainable finance is related to the performance of green-versus-brown investment strategies, i.e., whether there is a difference in expected returns denoted as the 'greenium'. The theoretical literature (e.g., Heinkel et al., 2001; Pedersen et al., 2021; Pástor et al., 2021; Baker et al., 2022) generally agrees on the fact that green securities should have lower expected returns than their brown counterparts, i.e., they argue for the existence of a negative greenium. This wedge arises because investors prefer green over brown securities, from which they derive non-pecuniary benefits (demand channel), and because green securities serve as a hedge against climate (transition) risk (risk premium channel). The real implications of a negative greenium are expected to be significant. Green firms would enjoy lower cost of capital relative to their browner counterparts and hence would end up with relatively more positive net present value investment projects. This, in turn, shifts the allocation of capital in equilibrium towards projects of green firms that are potentially more climate-friendly than those of brown firms. In this context, a negative greenium might act as an efficient tool to mitigate climate change through corporate investment and, thus, it potentially contributes to social welfare gains over the next decades.

We propose a regression discontinuity design (RDD) to determine whether there is a difference in the expected returns of green versus brown securities. We do so by exploiting information inherent in close-vote shareholder proposals related to ecological concerns. Assuming that passing ecology-related shareholder proposals (E-proposal) increases investors' aggregate perception of a firm's greenness score, vote-dependent changes in option-implied expected returns capture the greenium's existence. Guided by prior literature (e.g., Cuñat et al., 2012; Flammer, 2015), we claim that the passage of close-vote shareholder proposals can be seen as an 'as-good-as-random' (quasi-)natural experiment since proposals that pass/fail close to the majority threshold are similar in nature. The only difference lies in that some of the proposals pass and some of them fail by chance. It follows that we can interpret the impact of close-vote proposal voting outcomes on changes in option-implied expected returns as causal.

Why do we need another (empirical) paper on the greenium? Despite the clear the-

oretical prediction in favor of a negative premium for green versus brown securities, empirical evidence of its existence and sign remains ambiguous. Prior studies yield conflicting results and report either negative, positive, or even insignificant premia related to a firm's greenness.[1] In the following, we explicitly mention three concerns apparent in the existing literature that we believe to overcome within our setup.

First, we do not infer expected returns from realized returns but use forward-looking expected return proxies similar to Eskildsen et al. (2024). Using realized returns as proxies for expected returns is problematic in the sense that cashflow and discount rate news contaminate realized returns. If these news components do not cancel out on average, realized returns cannot be interpreted as unbiased proxies for expected returns as they must reflect cashflow/discount rate innovations to some degree (e.g., Elton, 1999). In this regard, Pástor et al. (2022) make a strong case by suggesting that high realized returns of green stocks in the 2010s were mainly driven by climate change concern rather than ex-ante high expected returns, which underpins the importance of a careful interpretation of realized returns, especially when short sample periods are studied.

Second, theoretical models, as in Pástor et al. (2021), require an aggregate greenness perception of investors as input when testing for the existence of a greenium, and we think it is arguable whether provider-specific greenness measures fulfill this requirement.[2] Eskildsen et al. (2024) take a first step to address the issue and use a 'robust green score' which they obtain by averaging over provider-specific metrics and which, according to the authors, reflects a proxy that "[..] most investors consider in practice [..]". We, on the other hand, do not rely on explicit greenness measures from data providers such as MSCI, Sustainalytics, Trucost or the Environmental Protection Agency (EPA) at all. Instead, we assume that the passage of ecology-related shareholder proposals leads to an implicit increase in the aggregate greenness perception of investors.

[1] See, e.g., Bolton and Kacperczyk (2021, 2023); Hsu et al. (2023); Pástor et al. (2022); Eskildsen et al. (2024) for evidence on a negative greenium. Opposed to that, Zhang (2025) finds a positive greenium when correctly accounting for time lags in data availability and Aswani et al. (2023) show that any return differential disappears when controlling for a firm's productivity or when using only actually disclosed emissions data rather than vendor estimates.

[2] Berg et al. (2022) show that greenness measures diverge substantially across providers, raising the question which or if any provider-specific measure can represent aggregate greenness perception among investors in the market.

Finally, we believe that all existing studies share a common caveat: Their results might suffer from endogeneity. When conducting portfolio sorts or panel analyses, one cannot rule out that (unobservable) confounding factors introduce bias to the estimates. E-scores, pollution data, and returns (expected or realized) might be jointly correlated with another factor the econometrician either cannot control for or is not aware of. It follows that this factor is potentially driving return premia instead of a firm's greenness if it remains uncontrolled.

In our baseline setup, we find a *negative* discontinuous jump around the majority threshold of passing E-proposals, which corresponds to 9.3 (6.9) percentage points when considering option-implied expected returns with a forecast horizon of 730 (365) days. Our estimate is statistically significant at conventional levels, and we use polynomials in the vote share of order three. Intuitively, option-implied expected returns on the next 730 (365) days drop by roughly 9.3% (6.9%) when passing relative to failing an E-proposal around the majority threshold.

We plot our RDD estimates and visualize the discontinuous jump to address concerns related to overfitting the data and account for a potential effect of proposal passage/failure on option-implied expected returns over multiple periods by introducing a panel data structure. This setup then additionally allows us to run a battery of fixed effects (firm-meeting, distance to vote date, year) on our data. Results with a forecast horizon of 730 days hold up in these specifications.

Further, we find an inverse relationship between realized returns and changes in option-implied expected returns, consistent with the interpretation that the latter reflect discount rate adjustments. Depending on forecast horizon, we estimate a slope that amounts to roughly 0.2 to 0.25 with R^2 values ranging between 23% and 33% in univariate regressions of realized abnormal returns on changes in option-implied expected returns on the day of the vote.

Under the assumption that a firm becomes greener by a small magnitude when passing E-proposals and given the negative reaction of option-implied expected returns upon passage on average, we provide evidence for the existence of a negative (causal) greenium in the US equity market. Note that our finding is driven by the limited number of firms with close-vote shareholder proposals, so caution is warranted when drawing conclusions about the broader population of firms.

The rest of the paper is organized as follows. In Section 2, we review related literature on the greenium and expected return proxies derived from options. We describe data sources and data handling in Section 3. Section 4 provides further details on our methodology. We present our results in Section 5 while Section 6 concludes.

2 Literature

In what follows, we review relevant literature on the greenium from both a theoretical as well as an empirical angle and summarize the evolution of option-implied expected return proxies.

2.1 Theory and empirical evidence on the greenium

Our study contributes to the asset pricing literature dealing with the implications of sustainable investing, particularly with regards to expected return differentials between green and brown securities (greenium). The theoretical asset pricing literature started to incorporate non-financial preferences (e.g., by gaining non-pecuniary benefits from investing in environmental-friendly or socially responsible assets) into investors' utility functions to address this question.

Foundational models as in Heinkel et al. (2001) demonstrate that given that there is a considerable fraction of investors that derives additional utility from holding sustainable assets, excess demand raises prices of green securities and, in turn, compresses expected returns. More recently, Pástor et al. (2021) expanded on Heinkel et al. (2001) with a richer general equilibrium model that allows for dynamic shifts in investor sentiment. The authors highlight how changes in investor or consumer preferences can affect realized returns. Their model suggests that even if green assets have lower expected returns than brown assets ex ante, they may outperform brown assets when preferences for green assets grow stronger over time.

Another important channel emphasized by Pástor et al. (2021) is related to green assets' hedging properties. The authors argue that green assets might be relatively better positioned against long-term risks posed by climate change and the transition

towards net-zero economies. Hsu et al. (2023) add to this argument by developing a model that focuses on transition risk and find that firms with high toxic emissions yield higher expected returns.

Overall, the theoretical asset pricing literature suggests that the greenium should be smaller or equal to zero. To the best of our knowledge, there is no theoretical work that claims for the existence of a positive greenium at the time of writing this manuscript.

Numerous studies aim to empirically test the relationship between greenness and expected returns in equity markets. These studies are usually motivated by theoretical work that relates aggregate greenness perception of investors to the "market price of greenness" suggesting that ecological performance could be priced in financial markets (e.g., Pástor et al., 2021). Investors' perception of a firm's greenness is commonly proxied with proprietary E-scores and pollution data from data providers such as MSCI, Sustainalytics, Trucost, or the Environmental Protection Agency (EPA) and expected returns are inferred from realized returns or forward-looking expected return proxies. In the following, we summarize the current state of empirical research without claiming to be exhaustive.

Bolton and Kacperczyk (2021) test whether realized returns are associated with the total amount of carbon emissions in the US equity market and find a negative relationship. In a subsequent study, the authors extend the initial framework while covering a sample of global firms and conclude that their initial findings also hold for stock returns around the globe (Bolton and Kacperczyk, 2023). The authors' work is corroborated by Hsu et al. (2023), who find that realized returns can be explained by the total amount of released toxic emissions and develop a model that fits their empirical results well.

One outcome of the above-mentioned studies deserves particular attention: realized returns are not related to carbon emission intensity - an equally important measure of a firm's greenness as argued by Aswani et al. (2023). When scaling emissions by a proxy of productivity (firm size in this case), the negative relationship between realized returns and greenness seems to disappear. Additionally, when considering only actually disclosed emissions by firms rather than emissions estimated by data vendors, the negative relation does not hold up. Zhang (2025) also questions the

existence of a (negative) greenium and stresses that one should correctly account for the time lag in which emissions data become available to the public as these are likely to proxy for information on firm fundamentals which in turn might be driving stock returns. When accurately controlling for the time lag, she finds that the greenium switches its sign in the US sample and becomes insignificant on a global scale.

Eskildsen et al. (2024) are the first to use forward-looking expected return proxies derived from analysts' forecasts and options as dependent variables and a 'robust green score' as their main independent variable in panel data analyses. The authors detect a small but significant negative greenium across different asset classes and countries.

In this paper, we contribute to the ongoing debate on the empirical greenium by addressing several limitations present in earlier studies that examine the link between greenness and expected returns. First, we do not rely on third-party E-scores or pollutions data which are likely not representing aggregate greenness perception of investors required by theoretical models as in Pástor et al. (2021). Instead, we interpret close vote E-proposal passage as a small increase in investors aggregate perception of a firm's greenness. Second, we use forward-looking expected return proxies instead of realized returns as dependent variables. If cashflow and discount rate news do not cancel out on average, realized returns do not provide a clean representation of expected returns. Third, we mitigate general endogeneity concerns by employing an RDD which allows us to estimate the causal effect of close vote E-proposal passage/failure on option-implied expected returns. Finally, we would like to emphasize that evidence in Eskildsen et al. (2024) on the existence of a negative greenium is convincing. Nevertheless, we believe that it is worthwhile to study the issue further, especially from a causal angle and with a clear focus on expected (not realized) returns.

2.2 Expected return proxies derived from options

Expected return proxies derived from options rely on a key finding in Breeden and Litzenberger (1978): risk-neutral densities can be extracted from observable option prices and hence we can understand risk-neutral return expectations through

derivatives.

Armed with this insight and based on the assumption that a log investor puts all her wealth in the stock market, Martin (2017) derives a lower bound for the expected excess return of the market ($SVIX^2$). The author's concept boils down to measuring risk-neutral variance of out-of-the-money put and call options using an integral representation and to control for an additional covariance term between the stochastic discount factor (SDF) and the market return under the physical (real-world) probability measure. Under the assumption that the negative correlation condition (NCC) holds, risk-neutral variance of the market can be interpreted as a lower bound on the expected excess return of the market.[3] Martin and Wagner (2019) extend the initial framework and develop a methodology to estimate the expected excess return of individual stocks within the S&P 500 index. The authors combine the expected return of the market ($SVIX^2$) with stock-level risk-neutral variance ($SVIX_i^2$) and a value-weighted average of stock-level risk-neutral variance across S&P 500 index constituents ($\overline{SVIX}^2$) at a given point in time.

Kadan and Tang (2019) ask whether stock i's risk-neutral variance alone can be interpreted as its lower bound on the expected excess return, i.e., they apply Martin (2017) to individual stocks. In order to justify their approach, the authors derive a sufficient condition that requires stock i's variance divided by its covariance with the market to be smaller or equal to the coefficient of relative risk aversion in order for the NCC in Martin (2017) to hold. They conclude that the sufficient condition is likely met for a large fraction of their observations and demonstrate that individual risk-neutral variance forecasts returns reasonably well.

In addition to a lower bound, Chabi-Yo and Loudis (2020) derive an upper bound for the expected excess return of the market. Their methodology differs from Martin (2017) in the sense that besides risk-neutral variance, their bounds also reflect third-order (risk-neutral skewness) and fourth-order (risk-neutral kurtosis) moments. Through a decomposition exercise, the authors show that these additional

[3] Martin (2017) argues that the NCC likely holds at the aggregated market level and emphasizes that this is a standard assumption in all leading asset pricing models. Intuitively, the NCC states that the covariance between the product of marginal utility and market returns and market returns themselves should be negative. This assumption is plausible if the market portfolio is a proper proxy for the growth-optimal portfolio and the coefficient of relative risk aversion is greater or equal to 1.

moments are important drivers of expected excess returns, especially in turbulent times. Chabi-Yo et al. (2023) apply the general concept of upper and lower bounds in the spirit of Chabi-Yo and Loudis (2020) to the cross-section of stocks covered by OptionMetrics and obtain estimates that outperform all existing expected return proxies. According to the authors, the main advantage is due to the exploitation of the entire risk-neural distribution of returns.

3 Data

We combine multiple data sources to identify the effect of passing ecologically related shareholder proposals around the majority threshold on option-implied expected return proxies.

3.1 Institutional Shareholder Services (ISS)

We use shareholder proposals from the Institutional Shareholder Services (ISS) Company Vote Results US database from 2003 to 2024. The data covers proposals sponsored by management and shareholders that were on the ballot at annual general meetings (AGM) of Russell 3000 index constituents and some additional widely held firms covered by the data provider. We have information on company names and identifiers, meeting dates, vote shares, and short descriptions of proposal contents. To be included in our sample, we require proposals to be sponsored by shareholders with non-missing information on the vote outcome. ISS groups proposals into two resolution types, i.e., governance (GOV) and socially responsible investing (SRI), but also provides a more detailed categorization within GOV and SRI (see item *ISSAgendaItemIDs*). We refer to this more granular categorization and additionally rely on He et al. (2023), who check and classify proposals manually to ensure we correctly capture proposals that are related to ecological issues.

Figure 1 present the number of E-proposals by vote share. Note that we compute vote share by referring to voting rules defined in corporate charters. Unlike the so-called "simple majority rule", these rules might also include withheld votes. It is easy to see that most proposals fail and that they usually do so by large

margins. Since the potential effect of passing close vote E-proposals on option-implied expected returns lays at the heart at our empirical analysis, it follows naturally that our investigations will be based on a relative small number of relevant observations.

Table 1 presents summary statistics on E-proposals by year. While the total number of proposals generally increased over time, a notable surge occurred around the time of the Paris Agreement in 2015 and 2016, followed by a return to previous levels. In more recent years, another significant spike in shareholder proposals is observed. The overall pattern aligns well with broader societal awareness of environmental issues that likely spills over to the investor base of firms receiving proposals. As the total number of E-proposals increases over time, so does the total number of close votes which are the main ingredients to our analyses. It follows that our findings will be mainly driven by some specific periods within the sample, e.g., by years following the Paris Agreement. Furthermore, Table 1 confirms that the average support for E-proposals is small. Nevertheless, it tends to correlate with the total number of proposals being recorded by ISS.

Table A-1 reports summary statistics by proposal type. The most common themes addressed by shareholders include 'GHG Emissions', 'Report on Climate Change', and 'Report on Sustainability'. These findings suggest that shareholders primarily seek greater transparency regarding environmental issues through better reporting and likely expect firms to take action on GHG emission reduction.

In order to merge proposals with information from other data sources, we match ISS CUSIPs with 8- and 6-digit CUSIPs from CRSP in the first step. In case there is no appropriate match using CUSIPs, we continue the matching procedure based on standardized company names and tickers. Finally, we check for potential backward-filling in the ISS data by using a forward-looking name/CUSIP/ticker combination. Finally, we manually check proposals that remain unmatched and assign identifying information if available. Overall, we are able to match most shareholder proposals from ISS with CRSP identifying information following our procedure.

Figure 1: Number of E-proposals by vote share.
This figure shows the total number of E-proposals by vote share. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering a period from 2003 to 2024. Proposals are being classified as ecology-related based on He et al. (2023) who check and classify proposals manually. We use voting rules defined in corporate charters to determine the vote share received by a proposal.

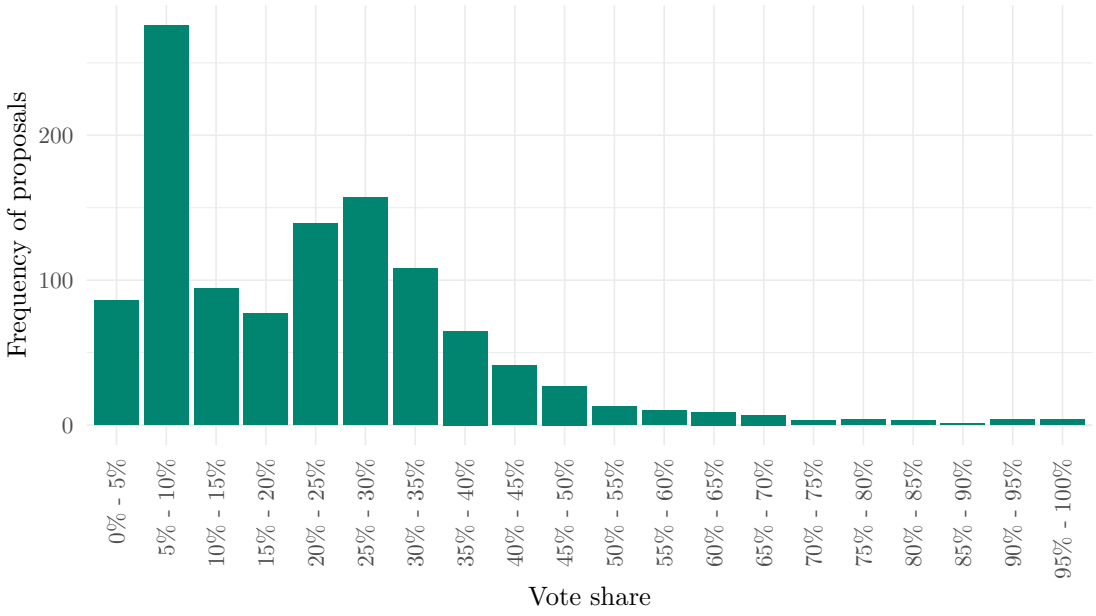


Table 1: E-Proposals over Time

This table provides summary statistics on E-proposals by year. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering a period from 2003 to 2024. Proposals are being classified as ecology-related based on He et al. (2023) who check and classify proposals manually. We use voting rules defined in corporate charters to determine the vote share received by a proposal. We report the total amount of (passed) proposals, those that are decided close to the majority threshold (close votes) and the relative fraction of passed proposals along with averages and standard deviations of vote shares. Vote share metrics and the fraction of passed proposals are expressed in percentages.

	Proposals			Vote share		Close votes	
Year	Total	Passed	Passed (Rel.)	Mean	SD	5%	10%
2003	25	0	0.00	13.54	8.49	0	0
2004	21	0	0.00	11.02	8.07	0	0
2005	26	0	0.00	13.55	8.94	0	0
2006	38	0	0.00	13.63	10.84	0	1
2007	43	0	0.00	17.11	12.48	0	2
2008	43	0	0.00	17.11	10.57	0	0
2009	38	1	2.63	17.67	11.83	1	1
2010	60	2	3.33	20.06	13.09	0	3
2011	48	1	2.08	20.98	16.46	2	4
2012	43	0	0.00	20.36	12.31	2	3
2013	53	1	1.89	18.40	13.45	1	3
2014	64	0	0.00	19.87	10.21	0	0
2015	84	1	1.19	20.39	10.47	0	1
2016	90	1	1.11	21.75	13.13	2	9
2017	78	4	5.13	26.46	15.06	4	13
2018	57	7	12.28	27.20	18.55	9	13
2019	32	0	0.00	23.21	12.32	1	4
2020	32	7	21.88	29.77	19.87	6	8
2021	33	16	48.48	50.81	26.41	5	8
2022	70	16	22.86	35.09	25.53	4	10
2023	72	1	1.39	21.91	12.63	1	3
2024	78	2	2.56	20.49	12.33	2	5
Total	1128	60	5.32	22.35	16.24	40	91

3.2 OptionMetrics

IvyDB US by OptionMetrics provides daily options data on all listed US companies and indexes from 1996 to 2023. We primarily focus on volatility surface data, which gives standardized pricing data on put and call options for different maturities and strikes by using a kernel smoothing technique. Using these data, we can construct option-implied expected returns on the market and individual stocks (see Martin and Wagner, 2019). The computation of option-implied expected returns also requires a measure of the risk-less rate as input. We use the zero curve file by OptionMetrics and interpolate to obtain risk-free rates for pre-specified target maturities.[4] More information on using OptionMetrics data is provided in Section 4.

To match OptionMetrics with ISS, we first rely on a linking table that matches the primary identifier in OptionMetrics (SECID) with PERMNOs from CRSP available through the Wharton Research Data Service (WRDS).[5] Then, we define appropriate matches between CRSP and ISS by exploiting our matching procedure outlined in Section 3.1.

3.3 Compustat & CRSP

We extract standard accounting data from Compustat on an annual basis (*comp.funda*) and follow typical conventions when downloading the data. A comprehensive list of balance sheet item we use is provided in the appendix. We follow Davis et al. (2000) in constructing book equity and ensure to keep only the latest observation if there are multiple reporting dates in a given year. We match company identifiers from Compustat (GVKEY) with PERMNOs from CRSP.[6]

We rely on daily market data from CRSP (*crsp_a_stock.dsf_v2*) and collect data for all firms that have at least one shareholder proposal voting outcome in ISS.

[4] We define our target maturities to be in line with the forecast horizon of the option-implied expected returns governed by the structure of the volatility surface data. Following Martin and Wagner (2019), we use maturities of 30, 91, 182, 365, and 730 days, respectively.

[5] The linking table is called 'Option Metrics CRSP History Link (opcrsphist)' and is accessible via WRDS. We keep links with matching scores ranging from one to five while dropping data points with a score equal to six. According to WRDS, a score of six refers to the category 'no matching'.

[6] We use the linking table 'crsp.ccmxpf_lnkhist' accessible via WRDS.

We keep daily total returns, shares outstanding and SIC industry codes. Then, we construct market equity by multiplying shares outstanding with closing prices and link SIC codes to 49 industries based on the Fama-French industry classification.[7] We also gather daily factor return data from Kenneth French's website to compute abnormal returns.

4 Methodology

In the first part of this section we show how to construct stock-level option-implied expected return proxies in the spirit of Martin (2017) and Martin and Wagner (2019).[8] Explaining changes in these variables on shareholder proposal voting days as a function of vote share lays at the heart of our empirical analysis. We continue with a brief summary on our identification strategy in the second part of this section.

4.1 Option-implied expected return proxies

In the following, we focus on the empirical construction of option-implied expected returns while referring to theoretical concepts derived in Martin (2017) and Martin and Wagner (2019) whenever necessary. To begin, we fetch volatility surface and security price data for the whole universe of stocks covered by OptionMetrics from 1996 to 2023 on a daily basis as well as their zero yield curve file via WRDS.

For each stock and the S&P 500 index, we then compute risk-neutral variance from out-of-the-money (OTM) put and call option using a version of the so called "spanning formula" based on standardized option maturities governed by the structure of the volatility surface file as follows[9]

[7] The industry definitions are accessible via Kenneth French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html.

[8] Code to construct option-implied expected returns will be made publicly available soon via https://www.tidy-finance.org/.

[9] As mentioned in Section 3, OptionMetrics uses a kernel smoothing technique to construct standardized option maturities of 10, 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 days. Following Martin and Wagner (2019), we use maturities of 30, 91, 182, 365, and 730 days.

$$SVIX_t^2 = \frac{2}{R_{f,t}S_t^2}\left\{\int_0^{F_{t,T}} put_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} call_{t,T}(K)dK\right\}, \tag{1}$$

where $R_{f,t}$ is the risk-free rate from t to T, S_t and $F_{t,T}$ are the security's spot price and forward price from t to T, respectively, and $put_{t,T}$ and $call_{t,T}$ are prices of OTM put and call options with strike price K written on the security under consideration expiring at time T.

Note that the integrals in equation (1) require continuous strikes but since these are not observable in practice, we use a discretized version of equation (1) based on strikes that are available in the data. In this context, we require at least two out-of-the money put and call options for the spanning formula to be estimated. In order to define the "cutoff" for OTM put and call options, equation (1) additionally requires forward prices which we compute as $F_t = S_t e^{rT}$.

One comment on our definition of forward prices is in order. OptionMetrics itself provides "off-the-shelf" forward prices for standardized maturities that also include dividend projections and borrow rates.[10] However, since options are written on capital gain returns only, we believe that it is reasonable to neglect dividends and borrowing costs in the construction of forward prices. We further justify our approach by noting that OptionMetrics' computations are not easily comprehensible/replicable in many cases so we stick to our "simplified" methodology which is also in line with the procedure in the original studies (Martin, 2017; Martin and Wagner, 2019).

We use the zero yield curve file to construct (gross) risk-free rates. The file provides us with zero-coupon yields for different (irregular) maturities based on IBA LIBOR on a daily basis. We linearly interpolate these yields to match the standardized maturities in the volatility surface file. If interpolated yields are unavailable for a given date, we backfill using the most recent prior date with available data.

Martin and Wagner (2019) define the expected excess return of a stock by extending

[10] Field description can be found in IvyDB US file and data reference manual as of 02/26/2024. "Off-the shelf" forwards prices are available within the "standardized options" file of OptionMetrics.

the initial framework in Martin (2017). Specifically, stock-level expected excess returns consist of three components:

1. risk-neutral variance of the market ($SVIX_t^2$),
2. risk-neutral variance of the individual stock ($SVIX_{i,t}^2$),
3. average of stock-level risk-neutral variance of S&P 500 index constituents weighted by market capitalization ($\overline{SVIX}_t^2$).

After some tedious but straight-forward computations, the authors derive the following expression for the expected return on a stock

$$\frac{\mathbb{E}\left[R_{i,t+1} - R_{f,t+1}\right]}{R_{f,t+1}} = SVIX_t^2 + \frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX_t^2}\right). \tag{2}$$

We construct expected returns for the whole universe of stocks covered by OptionMetrics with sufficient data quality by computing the three components and plugging them into equation (2) for each day within our sample period. Note that one can easily construct an event study analog of abnormal realized returns from the market model by subtracting $SVIX_t^2$ from both sides of equation (2) to obtain the expected return of a stock in excess of the market

$$\frac{\mathbb{E}\left[R_{i,t+1} - R_{m,t+1}\right]}{R_{f,t+1}} = \frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX_t^2}\right). \tag{3}$$

In later parts of this study, we will use option-implied expected returns in excess of the market to check the robustness of our baseline results.

Before we close this section, we introduce some notation that will prove useful in investigating daily changes in option-implied expected returns. Let $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \frac{\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]}{\mathbb{E}_{i,t-1}\left[R_{i,t+\tau} - R_{f,t+\tau}\right]} - 1$ denote the relative change in option-implied expected excess return for firm i and forecast horizon τ from the day before the voting $t-1$ to the day of the voting t based on options' closing

prices. At time 0, investors form expectations about the excess return over the 30-day period from day 1 to day 30. At time 1, these expectations are updated, now referring to the period from day 2 to day 31. Our notation hence describes the change in expectations from time 0 to time 1. Note that to arrive at our notation, one first needs to multiply both sides of equation (2) by $R_{f,t+1}$ to get rid of the discounting term.

Martin (2017) and Martin and Wagner (2019) demonstrates why forward-looking expected return proxies are a crucial innovation: expected returns are more time-varying, more volatile and more right skewed than previously acknowledged.

Notice that conventional expected return proxies derived from valuation ratios or asset pricing models such as the CAPM or factor models do not produce the observed pattern. Moreover, these approaches are no proper choice if the econometrician wishes to analyze daily changes in expected returns. Imagine, for example, an arbitrary factor model to estimate expected returns. The procedure prescribes that one needs to compute factor risk premia as well as factor exposures from historical data with sufficiently long look-back periods. If the econometrician now moves from one day to the next, risk premia and factor exposures and hence expected returns will barely change. Put differently, the change in expected returns is an extremely slow-moving process within these frameworks.

The advantages of option-implied methods, on the other hand, is that only combinations of option prices and strikes matter. Since these reflect risk-neutral expectations of investors observable in real-time, one can derive a lower bound on expected returns under the physical (real-world) probability measure on a daily basis and get around some of the limitations of conventional methods.

4.2 Regression Discontinuity in Shareholder Votes

Our empirical setup is guided by Cuñat et al. (2012) who analyze abnormal returns around close-vote governance shareholder proposal and Flammer (2015) who extend the initial framework to CSR proposals. However, instead of using abnormal stock returns as main dependent variable, we refer to daily changes in option-implied expected returns and analyze proposal related to ecological issues in isolation. We

argue that option-implied expected returns are an ideal choice to analyze properties of the greenium in equity markets because they reflect information on forward-looking return expectations for individual securities implementable on a daily basis.

Given that abnormal returns reflect cashflow news, discount rate news or a combination of both (Campbell and Shiller, 1988a,b) and assuming that a greenium exists, stock price movements around close-vote E-proposals are informative about changes in expected returns. The challenge is about how to isolate the component in realized stock returns one seeks to identify. In this regard, the beauty of our approach is that we do not need to run complex estimation procedures such as vector autoregressions (VAR) to tease out discount rate news (early implementations of this approach are provided in Campbell, 1991; Campbell and Vuolteenaho, 2004). Instead, we directly identify discount rate news from changes in observable option prices.[11]

The identifying assumption of our design is that near the majority threshold (usually, but not necessarily, at a cutoff value of 50%), proposal passage is an "as-good-as-random" assignment. We claim that firms just above and below the threshold are ex ante similar in observable and unobservable characteristics. Hence, differences in market reactions can be causally attributed to proposal passage. Technically, as Cuñat et al. (2012) put it: "[..] treatment probability changes *discretely* around the majority threshold. However, the distribution of other observable and unobservable firm characteristics is *continuous* around the threshold." Note that we expect changes in option-implied expected returns to be most pronounced around the majority threshold because ex ante investors assign similar probabilities to passage versus failure in the case of close-vote proposals. It follows that upon voting, uncertainty is resolved and expected returns adjust accordingly.

We begin with a simple cross-sectional exercise, estimating the impact of proposal passage on changes in option-implied expected returns on (or around) shareholder proposal voting dates. Following the notation in Flammer (2015), we define $pass_{i,t} := \mathbf{1}(v_{i,t} \geq v^*)$ as an indicator variable, where $v_{i,t}$ denotes the vote share and v^* is the majority threshold. That is, $pass_{i,t}$ equals one if a proposal passes and

[11] Our logic closely follows Knox and Vissing-Jorgensen (2022), who develop an index return decomposition based on observable inputs such as analysts' estimates, option-implied expected returns, and risk-free rates.

zero otherwise. We then run regressions of the following form using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \beta \times pass_{i,t} + \alpha_y + \epsilon_{i,t}, \tag{4}$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected return from the day before the voting to the day of the voting based on options' closing prices (see Section 4.1), α_y denotes year fixed effects and $pass_{i,t}$ is defined as described above. Our variable of interest is β, which captures the effect of proposal passage relative to failure on option-implied expected returns. This setup is applied to increasingly narrow bandwidths around the majority threshold (i.e., $\pm 15\%$, $\pm 10\%$, $\pm 7.5\%$, $\pm 5\%$, and $\pm 2.5\%$), and in each specification, we cluster standard errors at the year level.

Focusing on these "close-call" proposals allows us to get a consistent and unbiased estimate of the causal effect of passing an E-proposal on the change in option-implied expected returns. However, following prior literature, we next include all shareholder proposals, i.e., also non-close votes, to improve estimation efficiency. We apply a parametric RDD with local polynomials of order three to incorporate the full range of vote shares while maintaining our identifying assumption. Put differently, the RDD estimates a continuous relationship between $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ and $v_{i,t}$ while allowing for a discontinuous jump at the majority threshold. Note that this approach generalizes the simple dummy specification from equation (4). We introduce polynomials in the vote share on the left-hand side $P_l\left(v_{i,t}, \gamma^l\right)$ and on the right-hand side $P_r\left(v_{i,t}, \gamma^r\right)$ of the majority threshold where γ^l and γ^r are defined as the coefficients of the polynomials. The full RDD setup reads as follows

$$\begin{aligned}\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \beta \times pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) \\ + \alpha_y + \epsilon_{i,t}.\end{aligned} \tag{5}$$

Again, β is our variable of interest and captures the discontinuous jump in daily option-implied expected returns changes. It hence provides us with an estimate on the causal effect of passing relative to failing close-vote E-proposals on expected

returns. We cluster standard errors at the year level as before.

4.3 Multiple Proposals and Multiple Periods

As pointed out in Cuñat et al. (2012) and Flammer (2015), we face two issues when running raw ISS shareholder proposal data on Equations (4) and (5). First, we need to consider that a voting outcome on meeting date t can, in principle, affect expected returns over multiple periods (i.e., $t+1$, $t+2$ etc.). This might be due to initial under- or overreaction which would cause revisions in expected returns on subsequent days or insider knowledge about the vote outcome which would affect preceding days. Second, firms may face multiple E-proposals within a single shareholder meeting. To address both issues, we adopt an approach to aggregate multiple proposals in a given meeting and incorporate multiple periods of changes in option-implied expected returns following Cuñat et al. (2012).

We allow for a multi-period impact of voting outcomes by implementing a panel structure that tracks changes in expected returns for some time before and after each shareholder meeting. More formally, for each firm-meeting combination, we follow Cuñat et al. (2012) and Flammer (2015) and collect observations at time $t+h$ with h taking values in a range from -2 to $+7$.

In this dynamic setup, the effect of proposal passage on option-implied expected returns is allowed to vary with the event horizon h. Thus, the pass coefficient β_h now depends on h, but we add the restriction that it equals zero for all periods prior to the vote, i.e., $h < 0$. The same applies to the polynomial coefficients γ_h^l and γ_h^r. They are allowed to vary with h but are restricted to zero prior to the vote date. Note that pooling pre- and post-event observations into a panel data structure in this fashion enables us to include firm-meeting fixed effects $\alpha_{i,t}$ and distance to vote date fixed effects α_h in our regressions. These will account for all time-invariant characteristics of a firm's shareholder meeting and time-invariant characteristics of particular distances to the vote date in days, respectively. We also continue to include year fixed effects α_y.

To accommodate multiple E-proposals that are voted on in a single meeting, we aggregate proposal outcomes into a single treatment variable. Instead of using an

indicator variable that takes the value of one (pass) or zero (fail) for each individual proposal as in Equation (5), we replace it with a count variable reflecting the number of E-proposals passed out of all N E-proposals voted on in the meeting. Accordingly, we also aggregate the vote share by summing over all E-proposals.

Our procedure results in a multi-period and multi-proposal version of Equation (5) with additional fixed effects and is summarized as follows

$$\begin{aligned}\Delta_{\%}\mathbb{E}_{i,t+h}\left[R_{i,t+h+1+\tau} - R_{f,t+h+1+\tau}\right] =& \beta_h \sum_{n=1}^{N} pass_{i,t}^{n} + \\ & P_l\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma_h^{n,l}\right) + P_r\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma^{n,r}\right) + \\ & \alpha_{i,t} + \alpha_h + \alpha_y + \epsilon_{i,t},\end{aligned} \tag{6}$$

where $\Delta_{\%}\mathbb{E}_{i,t+h}\left[R_{i,t+h+1+\tau} - R_{f,t+h+1+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$. As before, we cluster standard errors at the year level.

5 Results

In this section we present our findings on dynamics in option-implied expected return proxies around shareholder proposal voting dates with a particular focus on *close-vote* proposal related to ecological issues. We classify proposal as "ecology-related" by relying on a scheme in He et al. (2023) who check and classify proposals manually as ISS classifications have been proven unreliable in some cases (see Section 3 for details). Unlike earlier studies such as Cuñat et al. (2012) and Flammer (2015) that use the so-called "simple majority rule", we rely on voting rules declared in corporate charters to define a pass or a fail. The difference is that firm-specific voting rules may include abstentions while simple majority are computed as Votes

For / Votes Against.[12]

Recall that we expect changes in option-implied expected returns to be most pronounced at small margins around the majority threshold because ex ante investors assign similar probabilities to passage versus failure in the case of close-vote proposals. It follows that upon voting, uncertainty is resolved and expected returns adjust accordingly. We approximately capture this adjustment through β in Equations (4), (5) and (6). Under the assumption that a firm becomes greener by a small magnitude upon E-proposal passage and given that a negative (positive) greenium exists in financial markets, option-implied expected returns should decrease (increase) following the vote and hence we predict a negative (positive) sign on β.

5.1 Changes in option-implied expected returns around the majority threshold

Table 2 reports our results on estimating Equation (4). We do not find a significant effect of proposal passage when incorporating either all or only non-close voting outcomes in in the first two columns over all forecast horizons. Our estimates on β are small in magnitude and indistinguishable from zero. These findings are not surprising given the assumption that the market is able to accurately price the consequences of proposal passage/failure if voting outcomes are, on average, far away from the majority threshold. Put differently, investors are able to anticipate the vote outcome of non close-vote proposals.

As we move to smaller margins around the majority threshold, coefficients increase in magnitude and are statistically different from zero at the 5% level. In specifications that include proposal with a distance to the majority threshold of up to 5%, option-implied expected returns with forecast horizons of 365 and 730 days drop by roughly 5% to 6% when E-proposals are passed relative to being failed. Note that our results indicate that the effect of passing close-vote E-proposals on option-implied expected return is present for intermediate- and longer-term forecast horizons, that is, periods of 182, 365, and 730 days, respectively. We report esti-

[12]There are convincing arguments for using either of the two voting rules. However, we decide to use voting rules from corporate charters as baseline because we think that management is more likely to follow a proposal if vote share exceeds the threshold it actually defined.

mates for shorter forecast horizon of 30 and 91 days in Table A-2 in the appendix and do not find a significant effect of proposal passage/failure on option-implied expected returns in this set of specifications.

We view the observed pattern as being plausible given that it usually takes time for passed proposals to be addressed by management (Bach and Metzger, 2018). This, in turn, implies that firms do not become greener right away after proposal passage and hence we do not expect to observe immediate effects on short-term expected returns. Another comment on forecast horizons is in order. It is well-known that daily changes in option-implied expected returns are highly volatile, especially for short forecast horizons of 30 or 90 days. Even if there is an effect of proposal passage on short-term expected returns, we have little hope to capture it due to the presence of considerable noise in daily changes of short-term option-implied expected returns.

5.2 Full RDD setup

Our earlier findings are based on estimating equation (4) for a battery of specifications while each of them separately accounts for a small subsample of the data. To overcome this limitation, we now turn our attention to the full RDD setup incorporating all voting outcomes while controlling for the vote share by fitting polynomials of order 3 to the left and right sides of the threshold, respectively. Table 3 shows that our findings from the full RDD setup closely mirror those from estimating Equation (4). We identify a negative discontinuous jump in daily changes of option-implied expected returns for forecast horizons of 182, 365, and 730 days, respectively. The "jump coefficient" is statistically significant at the 5% (10%) level for a forecast horizon of 730 (365) days. We document that the magnitude of the estimated discontinuity is larger than β estimated in Equation (4). This is likely due to how the polynomials predict changes in option-implied expected returns conditional on vote share.

To ensure that our results are not driven by overfitting, we visualize our RDD estimates. Figure (appendix) plots changes in option-implied expected returns on the day of the vote against the distance to the majority threshold for forecast horizon of 30 and 90 days, respectively. We also include fitted values estimated from our

polynomials on both sides of the threshold and explicitly emphasize the majority threshold (vertical dashed line). In line with results from above, we do not find evidence for a discontinuous jump around the majority threshold for option-implied expected returns with short-term forecast horizons of 30 and 90 days, respectively. Panels A and B show that changes in option-implied expected returns seem to be randomly distributed within the plot regardless of vote share. If anything, they have a tendency to increase for exceptionally high vote outcomes.

Plots appear noticeably different when replacing short-term maturities with forecast horizons of 182 days or longer. Figure (xy, not appendix) shows that at small margins below (above) the threshold, option-implied expected returns tend to increase (decrease) resulting in a discontinuous jump around the threshold. As before, we emphasize that the observed pattern is in line with the hypothesis that investors are on average not able to anticipate the outcome of close-vote proposals.

Figure 2: RDD on daily changes in option-implied expected returns.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \beta \sum_{n=1}^{N} pass_{i,t}^{n} + P_l\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma_h^{n,l}\right) + P_r\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma^{n,r}\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $pass_{i,t}^{n}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and α_y denotes year fixed effects. We fit polynomials in the vote share of order 3 on both side of the majority threshold (P_l; P_r). In each Panel, we plot predicted values from estimated coefficients on the polynomials at both sides of the threshold and visualize the discontinuous jump captured by β in the regression model from above for different forecast horizons. Observations are summarized and averaged within 2% buckets. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023.

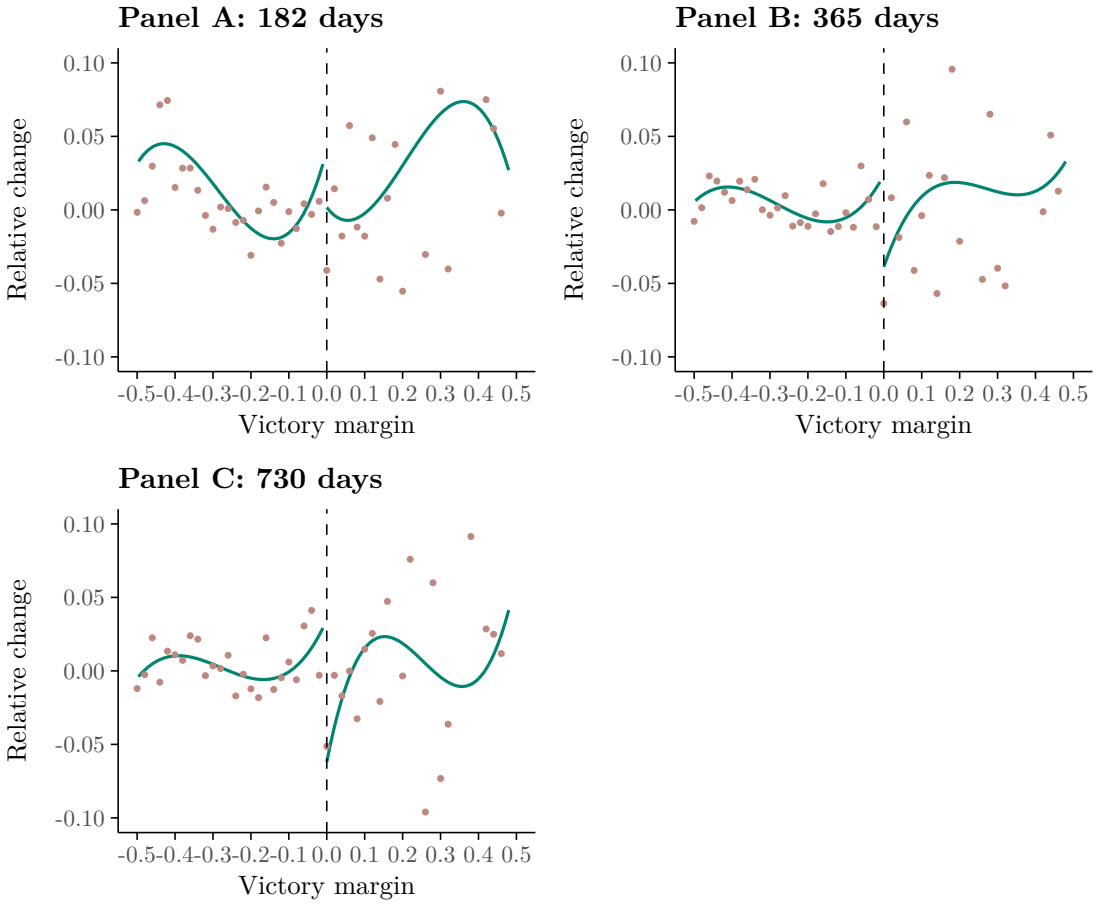


Table 2: Daily changes in option-implied expected returns around the majority threshold.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \alpha_y + \beta \times pass_{i,t} + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote constructed in the spirit of Martin and Wagner (2019) for different forecast horizons, $pass_{i,t}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and α_y denotes year fixed effects. In each specification, we restrict the inclusion of proposals conditional on their distance to the majority threshold. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: 182 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.011	0.023	0.028	0.021	0.019	-0.052**	-0.101***
	(0.514)	(0.999)	(1.08)	(0.539)	(0.414)	(-2.96)	(-3.60)
Observations	966	817	149	84	61	37	20
R^2	0.04	0.05	0.11	0.16	0.24	0.63	0.67

Panel B: 365 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	-0.002	0.008	0.011	0.002	-0.004	-0.061**	-0.098***
	(-0.102)	(0.369)	(0.532)	(0.046)	(-0.102)	(-2.54)	(-3.28)
Observations	966	817	149	84	61	37	20
R^2	0.03	0.04	0.17	0.17	0.24	0.64	0.51

Panel C: 730 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	-0.010	-0.005	0.003	-0.015	-0.023	-0.052**	-0.086**
	(-0.480)	(-0.168)	(0.211)	(-0.619)	(-0.853)	(-2.46)	(-3.02)
Observations	965	816	149	84	61	37	20
R^2	0.02	0.02	0.19	0.20	0.27	0.60	0.42

Table 3: RDD on daily changes in option-implied expected returns.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \beta \sum_{n=1}^{N} pass_{i,t}^{n} + P_l\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma_h^{n,l}\right) + P_r\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma^{n,r}\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $pass_{i,t}^{n}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and α_y denotes year fixed effects. We fit polynomials in the vote share of order 3 on both side of the majority threshold (P_l; P_r). In each specification, we run the RDD for option-implied expected returns with different forecast horizons. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023. Standard errors are in parenthesis and clustered at the year-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Pass	-0.539	0.107	-0.033	-0.069*	-0.093**
	(-1.47)	(1.11)	(-0.993)	(-1.89)	(-2.66)
γ_1^l	4.51	0.226	0.731**	0.352	0.431*
	(1.00)	(0.457)	(2.20)	(1.62)	(1.97)
γ_2^l	17.3	1.92	3.68**	1.79*	1.98**
	(0.876)	(0.947)	(2.40)	(1.97)	(2.15)
γ_3^l	18.4	2.48	4.49**	2.20*	2.41**
	(0.735)	(1.07)	(2.41)	(2.03)	(2.17)
γ_1^r	0.647	-0.597	-0.073	1.01**	1.34***
	(0.320)	(-0.337)	(-0.193)	(2.56)	(3.25)
γ_2^r	0.885	4.29	2.56	-4.00**	-6.26***
	(0.088)	(0.424)	(1.18)	(-2.32)	(-3.06)
γ_3^r	-1.61	-7.01	-4.60	4.81**	8.15**
	(-0.110)	(-0.488)	(-1.34)	(2.23)	(2.70)
Observations	972	971	972	972	972
R^2	0.14	0.04	0.05	0.04	0.02

5.3 Incorporating multiple periods in the RDD setup

We also take into account the possibility that proposal passage causes changes in option-implied expected returns over longer horizons than just the day of the vote. As noted earlier, we employ a panel data structure and collect (aggregated) changes in option-implied expected returns, whereby each observation refers to event horizon h. In Table 4, we report coefficients that capture horizons h equaling zero, one, and two to seven. These estimates measure the change in option-implied expected returns on the day of the vote, one day after the vote, and aggregated changes from day two to day seven after the vote, respectively. Following prior literature, we include firm-meeting, year, and distance-to-vote-date fixed effects.

The magnitude of coefficients capturing the reaction of option-implied expected returns on the day of the vote barely changes compared to earlier tests for all relevant forecast horizons. However, we document that for option-implied expected returns with a forecast horizon of 365 days, our estimate remains only marginally significant at the 15% level. Note that this finding should be interpreted with caution since we are wiping out a lot of variation by introducing a battery of additional fixed effects within our panel data structure. Changes in option-implied expected returns that refer to a forecast horizon of 730 days, in turn, are even more strongly significant in the setup at hand relative to our tests above. We also detect some reversion of initial changes in option-implied expected returns over days two to seven as captured by $Pass_{[t+2:t+7]}$ but these are not significant at conventional levels and only amount to small fractions of the initial reaction captured by $Pass_t$.

Table 4: RDD on daily changes in option-implied expected returns for multiple horizons.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t+h}\left[R_{i,t+h+1+\tau} - R_{f,t+h+1+\tau}\right] = \beta_h \sum_{n=1}^{N} pass_{i,t}^{n} + P_l\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma_h^{n,l}\right) + P_r\left(\sum_{n=1}^{N} v_{i,t}^{n}, \gamma^{n,r}\right) + \alpha_{i,t} + \alpha_h + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $pass_{i,t}^{n}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and $\alpha_{i,t}$, α_h and α_y denotes firm-meeting, distance to vote date and year fixed effects, respectively. We fit polynomials in the vote share of order 3 on both side of the majority threshold (P_l; P_r). In each specification, we run the RDD for option-implied expected returns with different forecast horizons and construct a panel to capture the potential effect of proposal passage/failure on option-implied expected returns with horizon consisting of multiple periods h. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023. Standard errors are in parenthesis and clustered at the year-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
$\text{Pass}_{[t+2,t+7]}$	0.002	-0.019	0.021	0.010	0.011
	(0.016)	(-0.677)	(1.25)	(1.31)	(1.58)
Pass_{t+1}	-1.54	-0.277	-0.071	-0.046	-0.017
	(-1.04)	(-1.20)	(-0.822)	(-1.08)	(-0.411)
Pass_{t}	-0.482	0.140	-0.035	-0.056	-0.091**
	(-1.08)	(1.27)	(-0.872)	(-1.41)	(-2.75)
Observations	9,919	9,918	9,921	9,921	9,921
R^2	0.13	0.10	0.11	0.09	0.08

5.4 The interplay between realized and expected returns

Pagano et al. (2023) develop a model in which realized and expected returns move into opposite directions as the probability of a disaster increases. The authors use the "fever period" from February 24, 2020 to March 20, 2020 prior to the COVID-19 outbreak and argue that expectations on the likelihood of disaster occurrence spiked massively during that time. They continue to show empirically that, in the "fever period", option-implied expected returns of non-resilient firms increased while realized returns decreased as they reflect changes in expected returns (i.e., stock prices primarily moved due to discount rate adjustments).

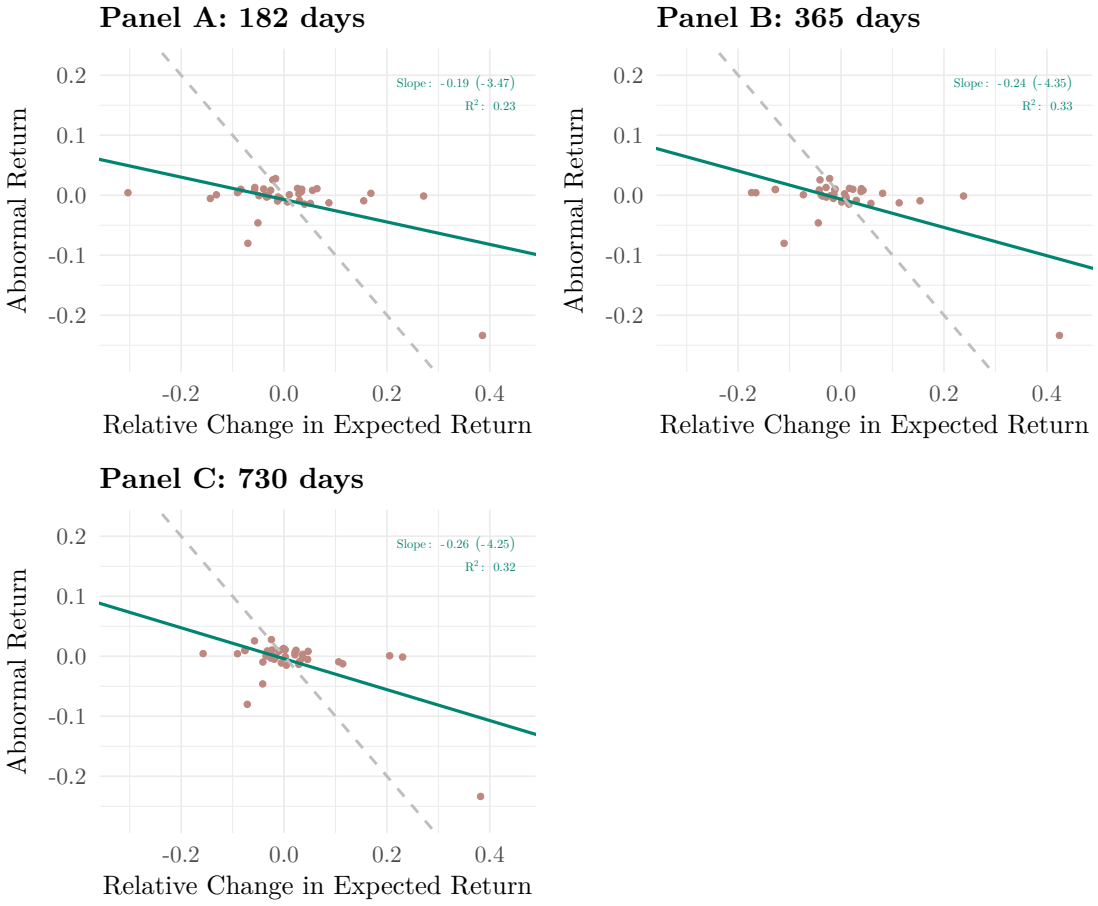
We argue that the framework in Pagano et al. (2023) is also applicable to our setting but instead of adjustments to the likelihood of a disaster, we deal with changes in the exposure - by passing an E-proposal and becoming greener - to a risk factor related to greenness. In short, close vote E-proposal passage reflects *negative* discount rate news and hence adds *positively* to realized returns. For each day with voting outcomes close to the majority threshold, we test our hypothesis formally by regressing realized returns on changes in option-implied expected returns in the spirit of Pagano et al. (2023). Results for forecast horizons of 182, 365 and 730 days conditional on the distance to the majority threshold being smaller or equal to five percentage points are in Figure 3.[13]

As predicted, we find a significantly negative relationship between realized returns and option-implied expected returns. When option-implied expected returns increase by one percentage point, realized returns adjust by - 0.2 to 0.26 percentage points depending on forecast horizon. The modest slope in Panels A-C is not surprising given that besides discount rate news (for a wide range of maturities), realized returns also reflect cashflow news of different maturities that might move in the same or inverse direction than changes in expected returns. To summarize, we find that changes in option-implied expected returns move asset prices to some degree. Since there are countless components influencing realized returns, we think it

[13]For brevity, we do not repeat the analysis for forecast horizons of 30 and 91 days. A comparison of realized and expected returns is not useful for the shortest forecast horizons because we do not identify a clear pattern in the analysis above due to noise and a potentially delayed effect of becoming greener upon proposal passage. We conclude that the effects on realized returns would also be ambiguous.

is natural that the explanatory power of expected returns with particular maturity can only be limited in this context.

Figure 3: Relationship between realized returns and changes in option-implied expected returns.
Panels A-C plot abnormal returns against relative changes in option-implied expected returns for different forecast horizons with distance to the majority threshold smaller or equal to 5 percentage points based on voting rules defined in corporate charters. We regress abnormal returns on relative changes in option-implied expected returns on the day of the vote and report slope coefficients, t-values and R^2 along with fitted values. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023.



6 Conclusion

In this paper, we ask whether there is difference in the expected returns of green versus brown securities (greenium) in US equity markets by employing a RDD that leverages E-proposal that are decided at small margins around the majority threshold. Our methodology exploits the quasi-random assignment of close vote proposal to passage or failure and identifies the causal effect of a small change in investors aggregated greenness perception on option-implied expected returns.

In our baseline specification, we document a significant drop in expected returns of roughly 9.3% (6.9%) when E-proposals narrowly pass compared to when they narrowly fail for a forecast horizon of 365 (730) days. We visualize our RDD estimates to address overfitting concerns and construct a panel data structure to account for the possibility that the voting outcome affects option-implied expected returns over multiple periods. Our results are robust to these adjustments. We also demonstrate that there is an inverse relationship between realized returns and changes in option-implied expected returns supporting the idea that the latter reflect discount rate adjustments that move asset prices.

Overall, our finding is consistent with theoretical work that predicts green securities to have relatively lower expected returns due to non-pecuniary benefits investors derive from holding them and because they serve as a relatively better hedge against risk related to climate change and the transition towards net-zero economies. It thus supports the notion of a negative greenium.

We identify three limitations of previous work that we aim to address in this study. First, we use forward-looking expected return proxies derived from options as opposed to realized returns which are likely contaminated by cashflow and discount rate news and hence do not accurately reflect expected returns. Second, we do not rely on provider-specific E-scores or pollution data to proxy for aggregate greenness perception of investors. Third, our RDD setup mitigates general endogeneity concerns that are present in conventional asset pricing test (e.g., in portfolio sorts or panel data analyses).

While our results provide strong evidence in favor of a negative greenium, there is a clear limitations with respect to sample size. In future extensions of this work,

we intend to increase our sample by incorporating additional shareholder proposal voting data from a different data provider and by covering European firms as well. We also plan to extend our framework to a fuzzy RDD where treatment is not defined by vote share but by spikes in implied volatility or option-implied expected returns prior to the voting date. These spikes proxy for investors' expectation of a large resolution of uncertainty upon voting which - following our theory - happens for close vote proposals. By relying solely on ex post vote shares, we may overlook proposals that were anticipated by the market to be close votes ex ante but ultimately passed or failed by wide margins.

Appendix

Table A-1: Summary statistics on E-proposals by type

This table provides summary statistics on ecology-related shareholder proposals by ID & description. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering a period from 2003 to 2024. Proposals are being classified as ecology-related based on He et al. (2023) who check and classify proposals manually. Weuse voting rules defined in corporate charters to determine the vote share receivedby a proposal. We report the total amount of (passed) proposals, those that aredecided close to the majority threshold (close votes) and the relative fraction ofpassed proposals along with averages and standard deviations of vote shares. Vote share metrics and the fraction of passed proposals are expressed in percentages.

		Proposals			Vote share		Close votes	
ID	Descrpition	Total	Passed	Passed (Rel.)	Mean	SD	5%	10%
S0206	Establish Environmental/Social Issue Board Committee	47	0	0.00	5.66	4.67	0	0
S0224	Require Environmental/Social Issue Qualifications for Director Nominees	23	0	0.00	14.29	7.89	0	0
S0708	Toxic Emissions	2	0	0.00	5.85	0.15	0	0
S0709	Nuclear Power - Related	29	0	0.00	6.79	3.27	0	0
S0711	Nuclear Safety (INACTIVE)	1	0	0.00	9.84		0	0
S0730	Report on Environmental Policies	44	1	2.27	15.49	13.66	0	0
S0731	Community- Environmental Impact	143	7	4.90	21.38	14.81	4	11
S0737	Toxic Substances (INACTIVE)	2	0	0.00	12.81	5.19	0	0
S0740	Environmental - Related Miscellaneous (INACTIVE)	25	0	0.00	9.10	4.03	0	0
S0742	Report on Climate Change	223	22	9.87	24.56	19.26	13	26
S0743	GHG Emissions	253	17	6.72	26.72	15.57	9	23
S0744	Hydraulic Fracturing	16	0	0.00	26.24	7.00	0	0
S0745	Climate Change Action	3	0	0.00	3.79	0.29	0	0
S0777	Report on Sustainability	172	9	5.23	26.49	14.81	8	19
S0778	Wood Procurement	8	0	0.00	10.83	8.22	0	0
S0779	Renewable Energy	45	0	0.00	17.88	11.46	1	2
S0780	Energy Efficiency	6	0	0.00	11.91	6.45	0	0
S0781	Recycling	80	2	2.50	24.98	16.41	3	7
S0782	Publish Two Degree Scenario Analysis	6	2	33.33	35.78	19.78	2	3

Table A-2: Daily changes in option-implied expected returns around the majority threshold (forecast horizons of 30 and 91 days).
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right] = \alpha_y + \beta \times pass_{i,t} + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{i,t}\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote constructed in the spirit of Martin and Wagner (2019) for different forecast horizons, $pass_{i,t}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and α_y denotes year fixed effects. In each specification, we restrict the inclusion of proposals conditional on their distance to the majority threshold. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Votings Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023. t-statistics are in parenthesis. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: 30 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	-0.154	-0.034	-0.109	-0.160	-0.234	-0.774	-2.43
	(-1.26)	(-0.314)	(-1.12)	(-1.21)	(-1.12)	(-1.20)	(-1.05)
Observations	945	798	147	83	60	37	20
R^2	0.14	0.14	0.07	0.09	0.10	0.26	0.56

Panel B: 91 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.064	0.047	0.124	0.142	0.176	0.012	-0.047
	(1.19)	(1.30)	(1.31)	(0.965)	(0.977)	(0.269)	(-1.10)
Observations	963	814	149	84	61	37	20
R^2	0.02	0.03	0.07	0.13	0.15	0.49	0.89

References

Aswani, J., Raghunandan, A., and Rajgopal, S. (2023). Are carbon emissions associated with stock returns?*. Review of Finance, 28(1):75–106.

Bach, L. and Metzger, D. (2018). How close are close shareholder votes? The Review of Financial Studies, 32(8):3183–3214.

Baker, M., Bergstresser, D., Serafeim, G., and Wurgler, J. (2022). The pricing and ownership of US green bonds. Annual Review of Financial Economics, 14:415–437.

Berg, F., Kölbel, J. F., and Rigobon, R. (2022). Aggregate confusion: The divergence of esg ratings*. Review of Finance, 26(6):1315–1344.

Bolton, P. and Kacperczyk, M. (2021). Do investors care about carbon risk? Journal of Financial Economics, 142(2):517–549.

Bolton, P. and Kacperczyk, M. (2023). Global pricing of carbon-transition risk. The Journal of Finance, 78(6):3677–3754.

Breeden, D. T. and Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices. The Journal of Business, 51(4):621–651.

Campbell, J. Y. (1991). A variance decomposition for stock returns. The Economic Journal, 101(405):157–179.

Campbell, J. Y. and Shiller, R. J. (1988a). The dividend-price ratio and expectations of future dividends and discount factors. The Review of Financial Studies, 1(3):195–228.

Campbell, J. Y. and Shiller, R. J. (1988b). Stock prices, earnings, and expected dividends. The Journal of Finance, 43(3):661–676.

Campbell, J. Y. and Vuolteenaho, T. (2004). Bad beta, good beta. The American Economic Review, 94(5):1249–1275.

Chabi-Yo, F., Dim, C., and Vilkov, G. (2023). Generalized bounds on the conditional expected excess return on individual stocks. Management Science, 69(2):922–939.

Chabi-Yo, F. and Loudis, J. (2020). The conditional expected market return. Journal of Financial Economics, 137(3):752–786.

Cuñat, V., Gine, M., and Guadalupe, M. (2012). The vote is cast: The effect of corporate governance on shareholder value. The Journal of Finance, 67(5):1943–1977.

Davis, J. L., Fama, E. F., and French, K. R. (2000). Characteristics, covariances, and average returns: 1929 to 1997. The Journal of Finance, 55(1):389–406.

Elton, E. J. (1999). Presidential address: Expected return, realized return, and asset pricing tests. The Journal of Finance, 54(4):1199–1220.

Eskildsen, M., Ibert, M., Jensen, T. I., and Pedersen, L. H. (2024). In search of the true greenium. Available at SSRN.

Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? a regression discontinuity approach. Management Science, 61(11):2549–2568.

He, Y. E., Kahraman, B., and Lowry, M. (2023). Es risks and shareholder voice. The Review of Financial Studies, 36(12):4824–4863.

Heinkel, R., Kraus, A., and Zechner, J. (2001). The effect of green investment on corporate behavior. Journal of Financial and Quantitative Analysis, 36(4):431–449.

Hsu, P.-H., Li, K., and Tsou, C.-Y. (2023). The pollution premium. The Journal of Finance, 78(3):1343–1392.

Kadan, O. and Tang, X. (2019). A bound on expected stock returns. The Review of Financial Studies, 33(4):1565–1617.

Knox, B. and Vissing-Jorgensen, A. (2022). A stock return decomposition using observables. Available at SSRN 4049300.

Martin, I. (2017). What is the expected return on the market?*. The Quarterly Journal of Economics, 132(1):367–433.

Martin, I. W. R. and Wagner, C. (2019). What is the expected return on a stock? The Journal of Finance, 74(4):1887–1929.

Pagano, M., Wagner, C., and Zechner, J. (2023). Disaster resilience and asset prices. Journal of Financial Economics, 150(2):103712.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2021). Sustainable investing in equilibrium. Journal of Financial Economics, 142(2):550–571.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. Journal of Financial Economics, 142(2):572–597.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2022). Dissecting green returns. Journal of Financial Economics, 146(2):403–424.

Zhang, S. (2025). Carbon returns across the globe. The Journal of Finance, 80(1):615–645.