In Search of the Causal Greenium*

Alexander Pasler † Moritz Rodenkirchen ‡
Patrick Weiss §

January 30, 2026

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 7.2% (9.6%) relative to proposals' failure, indicating the existence of a negative greenium in US equity markets. We introduce a battery of fixed effects, account for multiple periods around shareholder proposal voting dates, and remove confounding governance and social proposals, and find that our results are robust in these specifications.

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

* We thank (in alphabetical order) Joachim Grammig, Jan Harren (discussant), Rainer Jankowitsch, Theis Jensen, Otto Randl, Sebastian Stöckl (discussant), and Christian Wagner, as well as participants at AWG 2025 and DGF 2025 for helpful comments and suggestions. We provide an Internet Appendix here.
† WU Vienna, e-mail: alexander.pasler@wu.ac.at.
‡ WU Vienna & VGSF, e-mail: moritz.rodenkirchen@wu.ac.at.
§ Reykjavík University, e-mail: patrickw@ru.is.

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 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. In this setting, green firms enjoy lower cost of capital relative to their browner counterparts and hence end up with relatively more attractive investment projects. This, in turn, shifts the allocation of capital in equilibrium towards projects of green firms. Therefore, 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 in the spirit of Martin and Wagner (2019) 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 or fail close to the majority threshold are similar in nature. The only difference lies in the fact that some proposals pass and others fail by chance. It follows that we can interpret the impact of close vote proposal outcomes on changes in option-implied expected returns as causal.

Why do we need another (empirical) paper on the greenium? Despite the clear theoretical 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 specifically address within our setup.

First, we do not infer expected returns from realized returns but rather 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 cash flow 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 revisions in expected cash flows or discount rates to some degree (see, e.g., Elton, 1999). In this regard, Pástor et al. (2022) convincingly demonstrate that the high realized returns of green stocks in the 2010s were mainly driven by climate change concerns 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 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 [..]". In contrast, we do not rely on explicit greenness measures from data providers such as MSCI, Sustainalytics, Trucost, or the Environmental Protection Agency (EPA). Instead, we assume that the passage of E-proposals leads to an implicit increase in the aggregate greenness perception of investors.

Finally, we believe that all existing studies share a common caveat: their results

[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. We provide richer details on related literature in our review in Section 2.

[2] Berg et al. (2022) show that greenness measures diverge substantially across providers. Hence, even if any provider-specific measure can represent aggregate greenness perception among investors in the market, the question remains which provider's score is the correct one.

might suffer from endogeneity. When conducting portfolio sorts or panel analyses, it is not possible to 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 that the econometrician either cannot control for or is not aware of. It follows that this factor is potentially driving return premia if uncontrolled for, rather than a firm's greenness.

In our baseline setup, we find a *negative* discontinuous jump around the majority threshold of passing relative to failing E-proposals, which corresponds to 9.6 (7.2) percentage points when considering option-implied expected returns with a forecast horizon of 730 (365) days. Our estimates are statistically significant at conventional levels, and we use polynomials of order three in the vote share. Intuitively, option-implied expected returns on the next 730 (365) days drop by roughly 9.6% (7.2%) when passing relative to failing an E-proposal around the majority threshold. Given that option-implied expected returns around shareholder proposal voting dates with forecast horizons of 365 and 730 days amount to approximately 5.5% p.a. on average in our sample, a reduction of 0.4 (365 days) to 0.5 (730 days) percentage points in expected returns is attributable to E-proposal passage relative to failure.

We plot our RDD estimates to visualize the discontinuous jump and account for the potential effect of proposal passage and failure on option-implied expected returns over multiple periods by introducing a panel data structure. Note that this setup allows us to apply additional fixed effects (firm-meeting, distance-to-vote-date) to our data.

We also account for the potential effect of confounding close vote governance (G-proposals) and social proposals (S-proposals), which were on the same ballot as E-proposals. In separate specifications, we exclude confounding proposals with a distance to the majority threshold of 5%, 10%, and 20% and document that our results become even stronger in both the full RDD setup as well as when accounting for multiple periods and additional fixed effects. This finding is particularly noteworthy since the exclusion of certain proposal subsets leads to a considerable reduction in sample size, which, in turn, increases the hurdle to maintain statistical significance.

Finally, we document an inverse relation between realized returns and changes in

option-implied expected returns, consistent with the interpretation that the latter reflect discount rate adjustments (Pagano et al., 2023). Depending on the forecast horizon, we estimate a slope that amounts to roughly -0.25 to -0.20 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 voting.

We provide further support for a causal interpretation of our results in two ways. First, we check for potential "bunching" around the threshold. Specifically, we run a McCrary (2008) test and find that the null of a continuous density of the vote share around the threshold cannot be rejected (p-value = 0.4172), suggesting that firms are unable to self-select into (proposal passage) or out of treatment (proposal failure) by manipulating the vote outcome. Second, we investigate pre-existing differences in variables known to predict returns that might be associated with option-implied expected returns. We do not detect a discontinuous jump in any of these variables at the majority threshold, indicating that changes in option-implied expected returns are driven by proposal passage or failure rather than by pre-existing differences in characteristics.

Assuming that a firm becomes greener by a small magnitude upon E-proposal passage and given that option-implied expected returns, on average, react negatively (positively) to proposal passage (failure), we provide causal evidence for the existence of a negative 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. In this context, we document that firms in our sample tend to operate in industries with large climate impact, i.e., firms whose business models involve high carbon emissions (e.g., Petroleum and Natural Gas & Utilities).

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 our data in Section 3. Section 4 provides details on our methodology. We present our results in Section 5, while Section 6 concludes.

2. Literature

In this section, 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 regard to expected return differentials between green and brown securities (greenium).

The theoretical asset pricing literature began by incorporating non-financial preferences (e.g., non-pecuniary benefits from investing in environmentally friendly or socially responsible assets) into investors' utility functions to address this question. The foundational model in Heinkel et al. (2001) demonstrates that, given that a considerable fraction of investors derives additional utility from holding sustainable assets, excess demand raises the 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 strengthen 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 to address the long-term risks posed by climate change and the transition to 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.

Depending on the parameter choice, the greenium is either negative or bounded at zero in the models mentioned above. To the best of our knowledge, there is no theoretical work that claims 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 (the authors use firm size), 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. 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 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 examining the link between greenness and expected returns. First, we do not rely on third-party E-scores or pollution data, which are likely not representing the 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.

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 on 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 of the expected excess return on 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 on 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 on 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 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] 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.

3. Data

To identify the effect of passing or failing E-proposals around the majority threshold, we primarily combine shareholder proposal voting outcome data with expected return proxies derived from options data. Furthermore, we gather information such as stock characteristics, accounting variables or industry affiliation from several other data sources.

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.[4] 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 denoted in line with the three pillars of ESG (environmental, social, and governance). We refer to this more granular categorization and additionally rely on He et al. (2023), who manually check and classify proposals to ensure that we correctly capture those related to ecological issues.

Figure 1 presents the number of E-proposals by vote share. Note that we compute vote share using the voting rules defined in corporate charters. Unlike the so-called "simple majority rule", these rules might also include withheld votes. The figure shows that most proposals fail and that they usually do so by large margins. Since the potential effect of passing relative to failing close vote E-proposals on option-implied expected returns lies at the heart of our empirical analyses, it follows naturally that our investigations will be based on a relatively small number of

[4] We describe how to prepare ISS voting data for further analyses in a contribution to the Tidy Finance webpage and provide ready-to-use programming code. The blog post is accessible via https://www.tidy-finance.org/blog/iss-shareholder-proposals/.

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 has been 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 of our analyses. It follows that our findings will be mainly driven by 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-3 reports summary statistics by proposal type. The most common themes addressed by shareholders include "GHG Emissions", "Report on Climate Change", and "Report on Sustainability", suggesting that shareholders primarily seek greater transparency regarding environmental issues through better reporting and likely expect firms to take action on GHG emissions reduction.

To merge proposals with information from other data sources, we first match ISS CUSIPs to 8- and 6-digit CUSIPs from CRSP. If there is no appropriate match using CUSIPs, we continue the matching procedure using standardized company names and tickers. We check for potential backward filling in the ISS data 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 plots the total number of E-proposals by vote share. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering the 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.

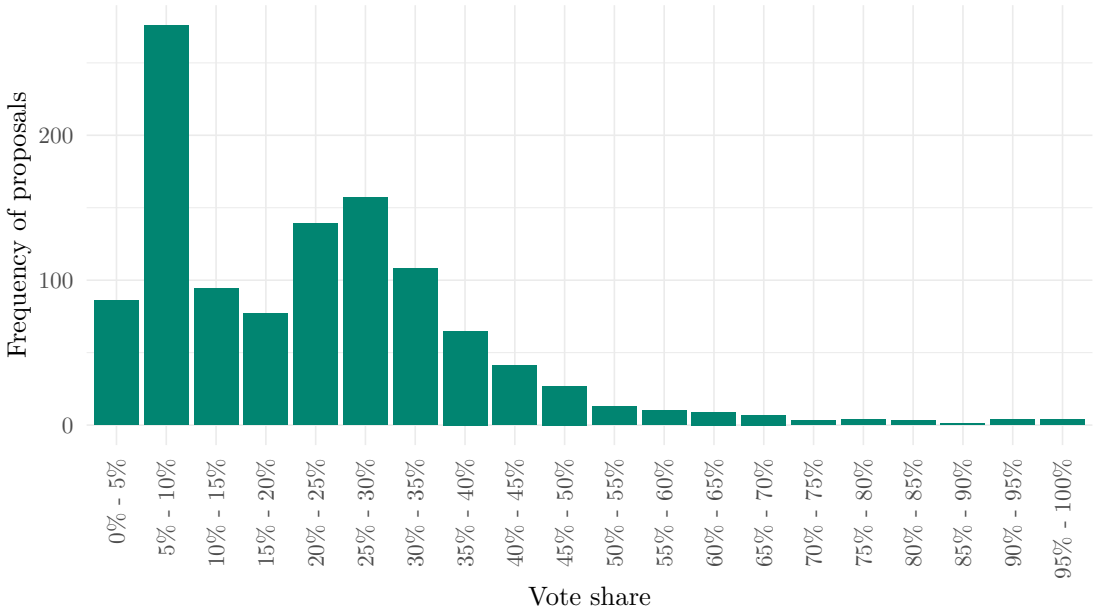


Table 1: E-Proposal voting patterns over time.
This table provides summary statistics on E-proposals by year. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering the period from 2003 to 2024. Proposals are classified as ecology-related based on He et al. (2023), who manually check and classify them. 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 for put and call options across different maturities and strikes. The computation of option-implied expected returns also requires a measure of the risk-free rate as input. We use the zero curve file from OptionMetrics and interpolate to obtain risk-free rates for pre-specified target maturities.[5] Finally, we use the security price file and combine it with the risk-free rate to compute forward prices. More information on constructing option-implied expected returns using OptionMetrics data is provided in Section 4.

To match OptionMetrics with ISS, we first rely on a linking table that matches the primary identifiers in OptionMetrics (SECIDs) with PERMNOs from CRSP available through Wharton Research Data Services (WRDS).[6] Then, we define appropriate matches between CRSP and ISS by exploiting our matching procedure outlined in Section 3.1.

3.3. Other data sources

We obtain stock characteristics and accounting figures from the Global Factor Data (GFD) based on Jensen et al. (2023) through WRDS.[7] From the MSCI ESG database, we retrieve E-scores, which we transform following Pástor et al. (2022) to obtain a third-party evaluation of firms' environmental performance for some parts of our analyses. Table A-1 in the Appendix presents summary statistics on GFD variables widely studied in previous literature and E-scores. For a given shareholder proposal, we always use the latest monthly record available in the databases corresponding to a specific vote date. In the case of GFD, we refer the reader to the authors' documentation for precise definitions of variables.

[5] 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.

[6] The linking table is called "Option Metrics CRSP History Link (opcrsphist)". We keep links with matching scores ranging from one to five.

[7] Factor returns can be downloaded directly from the authors' webpage: https://jkpfactors.com/. However, the more granular data we refer to needs to be fetched from WRDS.

We fetch total returns and SIC industry codes from the CRSP daily stock file and convert SIC codes into Fama-French industries following the mapping on Kenneth French's webpage. Table A-2 in the Appendix presents the industry composition of our sample, limited to 20 industries with the highest amount of voted proposals. Within each industry, we report the total number of shareholder proposals, the fraction of passed proposals relative to all proposals, as well as the number of close votes at 5% and 10% margins, respectively.

In our sample, firms operating in industries with large climate impact (e.g., those with business models that involve high carbon emissions) receive the highest shares of proposals. Similar to the overall pattern in the ISS data, most E-proposals fail in these industries. Despite high failure rates, close vote proposals are concentrated among the industries we report in Table A-2. Out of 37 observations, we classify as close vote outcomes with a distance to the majority threshold of up to 5%, 34 show up in one of the 20 industries we report.

Lastly, we obtain daily US factor returns from Kenneth French's webpage to compute abnormal returns under the Carhart (1997) four-factor model in a later part of our study.

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). Explaining changes in these variables on shareholder proposal voting days as a function of vote share lies at the heart of our empirical analyses. We continue with a summary of our identification strategy in the second part of this section.

4.1. Option-implied expected return

In what follows, we focus on the empirical construction of option-implied expected returns for asset i at time t, referring to theoretical concepts derived in Martin (2017) and Martin and Wagner (2019) as needed. To begin, we fetch volatility surface and security price data for the entire universe of stocks covered by Option-

Metrics 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[8]

$$SVIX^2_{i,t} = \frac{2}{R_{f,t+1}S^2_{i,t}} \left\{ \int_0^{F_{i,t}} put_{i,t}(K)dK + \int_{F_{i,t}}^{\infty} call_{i,t}(K)dK \right\}, \tag{1}$$

where $R_{f,t+1}$ is the risk-free rate from t to $t+1$, $S_{i,t}$ and $F_{i,t}$ are the security's spot price and forward price from t to $t+1$, respectively, and $put_{i,t}$ and $call_{i,t}$ are prices of OTM put and call options with strike price K written on the security under consideration expiring at time $t+1$.

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. We require at least two out-of-the-money put and call options for the spanning formula to be estimated. To define the "cutoff" for OTM put and call options, Equation (1) additionally requires forward prices, which we compute as $F_{i,t} = S_{i,t}e^{rT}$.

One comment on our definition of forward prices is in order. OptionMetrics itself provides "off-the-shelf" forward prices for standardized maturities, including dividend projections and borrowing rates.[9] However, since options are written on capital gain returns only, we consistently neglect dividends and borrowing costs in the construction of forward prices. This procedure is consistent with the original studies (Martin, 2017; Martin and Wagner, 2019), and a more complex procedure is, in many cases, not feasible as reconstructing OptionMetrics' computations is not

[8] 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 limit our analyses to maturities of 30, 91, 182, 365, and 730 days.

[9] We refer to the "IvyDB US file and data reference manual" as of February, 2024 for details. "Off-the-shelf" forward prices can be retrieved from the "standardized options" file.

sufficiently transparent.

We use the zero yield curve file to construct risk-free rates. The file provides zero-coupon yields for different non-standardized 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 with the most recent prior date with available data.

Martin and Wagner (2019) define the expected excess return of a stock by extending 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 several derivations, the authors derive the following expression for the expected return on a stock:

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

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 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[10]

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

[10] For our baseline results, we are using the expected return as given by Equation (2). However, in the Internet Appendix, we rerun our analyses using option-implied expected returns over the market.

Before we close this section, we introduce some notation that will prove useful in investigating daily changes in option-implied expected returns. Let $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \frac{\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]}{\mathbb{E}_{t-1}\left[R_{i,t-1+\tau} - R_{f,t-1+\tau}\right]} - 1$ 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.[11] 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 scaling term.

Martin (2017) and Martin and Wagner (2019) demonstrate why forward-looking expected return proxies derived from option prices are a crucial innovation: there seems to be more time variation, more volatility, and more skewness in expected returns than acknowledged by previous literature.

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 not the proper choice if the econometrician wishes to analyze daily changes in expected returns. Consider, for example, an arbitrary factor model to estimate expected returns. The procedure requires computing factor risk premia and 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 change only slightly. 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, are that only combinations of option prices and strikes matter. Since these reflect risk-neutral expectations of investors that are observable in real-time, one can derive a lower bound on expected returns under the physical (real-world) probability measure on a daily basis, thereby overcoming some of the limitations of more conventional methods.

[11] We use these relative changes in expected returns as the dependent variable in our main analyses. In Section D of the Appendix, we also provide results using changes in expected returns in levels, i.e., $\Delta\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] - \mathbb{E}_{t-1}\left[R_{i,t-1+\tau} - R_{f,t-1+\tau}\right]$.

Table 2 presents summary statistics on option-implied expected returns around shareholder proposal voting dates for different forecast horizons in days. For a given shareholder proposal, we collect observations within a window of two business days prior to the meeting and seven business days after the meeting [-2;+7] and average all available observations. Across all forecast horizons, we are able to compute option-implied expected returns on approximately 9.8 days, which is close to the ideal coverage of 10 days per event window.

The number of included shareholder proposals is relatively lower for the two shortest forecast horizons because, in some cases, relative changes in option-implied expected returns on the day of the vote cannot be computed due to negative values. There is large variation in expected returns across all horizons, but extreme tail observations seem to be especially present at the shortest forecast horizons of 30 and 91 days. In untabulated results, we compute the average standard deviation *within* event windows and find considerably more variation in daily option-implied expected returns for the shortest forecast horizons. Standard deviations amount to 1.20% (30 days) and 0.60% (91 days) before dropping to approximately 0.40% for the remaining measures.[12] Compared to previous literature investigating the properties of risk premia in equity markets, average levels of 5.3% to 6.2% p.a. seem fairly realistic.

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 outcomes, and Flammer (2015), who extends the initial framework to CSR proposals. However, instead of using abnormal stock returns as the main dependent variable, we refer to daily changes in option-implied expected returns and analyze proposals exclusively related to ecological issues. We argue that option-implied expected returns are a suitable choice for investigating the properties of the greenium in equity markets because they reflect the dynamics of forward-looking return expectations for individual stocks at a daily frequency.

[12] We identify this finding as one of two reasons why we do not detect a discontinuous jump around the majority threshold for the shortest forecast horizons. Option-implied expected returns with forecast horizons of 30 and 91 days are too noisy to uncover a significant relation between close vote proposal passage or failure and changes in expected returns.

Table 2: Option-implied expected returns around shareholder proposal voting dates.
We compute option-implied expected returns in the spirit of Martin and Wagner (2019) for different forecast horizons in days from 1996 to 2023. For a given shareholder proposal, we collect observations within a window of two business days prior to seven business days after the meeting [-2;+7] and average across all available observations. We then report the mean and standard deviation as well as the 1%, 5%, 25%, 50%, 75%, 95% and 99% percentiles across all available shareholder proposals for which we have sufficient data to compute changes in option-implied expected returns on the day of the voting. We obtain information on shareholder meetings from the Institutional Shareholder Services (ISS) US Vote Results database spanning the period from 2003 to 2024. All numbers are annualized and expressed in percentages.

Horizon	Proposals	Mean	SD	P5	P25	P50	P75	P95
30	915	6.21	13.61	0.42	1.33	2.67	6.05	21.84
91	970	5.25	9.71	0.56	1.45	2.75	5.35	16.77
182	978	5.26	9.00	0.87	1.73	2.93	5.30	16.05
365	981	5.37	9.66	1.06	1.96	3.03	5.15	15.39
730	981	5.61	10.73	1.20	2.07	3.08	5.03	15.05

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 can be informative about changes in expected returns. The challenge is to isolate the component of realized stock returns that reflects revisions in expected returns. In this regard, a key advantage of our approach is that we do not need to run complex estimation procedures such as vector autoregressions (VAR) to tease out (short-term) discount rate news.[13] Instead, we directly identify discount rate news from changes in observable option prices.[14]

[13] Implementations of this approach can be found in Campbell (1991) and Campbell and Vuolteenaho (2004), among others.

[14] Our rationale 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.

The identifying assumption of our design is that near the majority threshold (usually, but not necessarily, at a cutoff of 50%), proposal passage is "as-good-as-random". 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.

Cross-sectional pass indicator regressions. We begin with a simple cross-sectional exercise, estimating the impact of proposal passage relative to failure 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 zero otherwise. We then run regressions of the following form using OLS:

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

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ 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. We cluster standard errors at the year level. 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., ±15%, ±10%, ±7.5%, ±5%, and ±2.5%). Focusing on these "close-call" proposals allows us to get a consistent and unbiased estimate of the causal effect of passing relative to failing an E-proposal on the change in option-implied expected returns.

Full RDD setup. Following prior literature, we next include all shareholder pro-

posals, 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.[15] Put differently, the RDD estimates a continuous relationship between $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ 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

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

Again, β is our variable of interest and captures the discontinuous jump in daily option-implied expected returns changes. It hence provides an estimate of 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.

Multiple Periods. As pointed out in Cuñat et al. (2012) and Flammer (2015), 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.

Therefore, we adopt an approach that incorporates multiple periods of changes in option-implied expected returns. We allow for a multi-period impact of voting outcomes by implementing a panel structure that tracks changes in expected returns in periods surrounding 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

[15] In the Internet Appendix, we also provide results using polynomials of order two and four. The findings are qualitatively similar to our baseline estimates.

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.

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

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

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

5. Results

In this section we present our findings on dynamics in option-implied expected returns around shareholder proposal voting dates with a particular focus on *close vote* proposal related to ecological issues. We classify proposals as "ecology-related" by relying on a scheme in He et al. (2023), who manually check and classify proposals, as ISS classifications have been shown to be 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 the voting rules specified in corporate charters to determine whether a proposal is passed or failed. The difference is that firm-specific voting rules may include abstentions, while the simple

majority is computed as Votes For / Votes Against.[16]

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 and failure for close vote proposals. It follows that upon voting, uncertainty is resolved and expected returns adjust accordingly. We capture this adjustment through β in Equations (4), (5) and (6). Assuming a firm becomes greener by a small magnitude upon E-proposal passage and that a negative (positive) greenium exists in financial markets, option-implied expected returns should decrease (increase) following the vote. Hence, we predict a negative (positive) sign on β.

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

Table 3 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 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 and failure when voting outcomes are, on average, far from the majority threshold. Put differently, investors can anticipate the 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 proposals 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 relative to failing 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, respec-

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

tively. We report estimates for a shorter forecast horizon of 30 and 91 days in Table A-5 in the Appendix and do not find a significant effect of proposal passage or failure on option-implied expected returns in this set of specifications.

We view the observed pattern as 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. As mentioned in Section 4.1, daily changes in option-implied expected returns are highly volatile around shareholder meetings in our sample, especially for forecast horizons of 30 or 91 days. Even if there is an effect of proposal passage on short-term expected returns, we have little hope of capturing it because of considerable noise in daily changes in short-term option-implied expected returns.

Table 3: Daily changes in option-implied expected returns around the majority threshold.
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered by year. ***, **, 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	0.015	0.031	0.028	0.021	0.019	-0.052**	-0.101***
	(0.714)	(1.41)	(1.08)	(0.538)	(0.413)	(-2.96)	(-3.61)
Observations	978	829	149	84	61	37	20
R^2	0.03	0.04	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	0.017	0.011	0.001	-0.004	-0.061**	-0.098***
	(0.090)	(0.923)	(0.529)	(0.044)	(-0.104)	(-2.53)	(-3.27)
Observations	981	832	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	-0.006	0.004	0.003	-0.015	-0.023	-0.052**	-0.086**
	(-0.272)	(0.144)	(0.209)	(-0.624)	(-0.861)	(-2.45)	(-3.01)
Observations	981	832	149	84	61	37	20
R^2	0.01	0.02	0.19	0.20	0.27	0.60	0.41

5.2. Full RDD setup

Our earlier findings are based on estimating Equation (4) for a battery of specifications, with each specification separately accounting 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 three to the left and right sides of the threshold, respectively. Table 4 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 1% (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. Additionally, the estimated effect is robust to controlling for various firm characteristics, as shown in Table A-7 in the Appendix.

We also visualize our RDD estimates. Figure A-2 plots changes in option-implied expected returns on the day of the vote against the distance to the majority threshold for forecast horizons of 30 and 91 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 the results above, we do not find visual evidence of a discontinuous jump around the majority threshold in option-implied expected returns for short-term forecast horizons of 30 and 91 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 tend 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 2 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 consistent with the hypothesis that, on average, investors are unable to anticipate the outcome of close vote proposals and with a negative greenium.

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

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

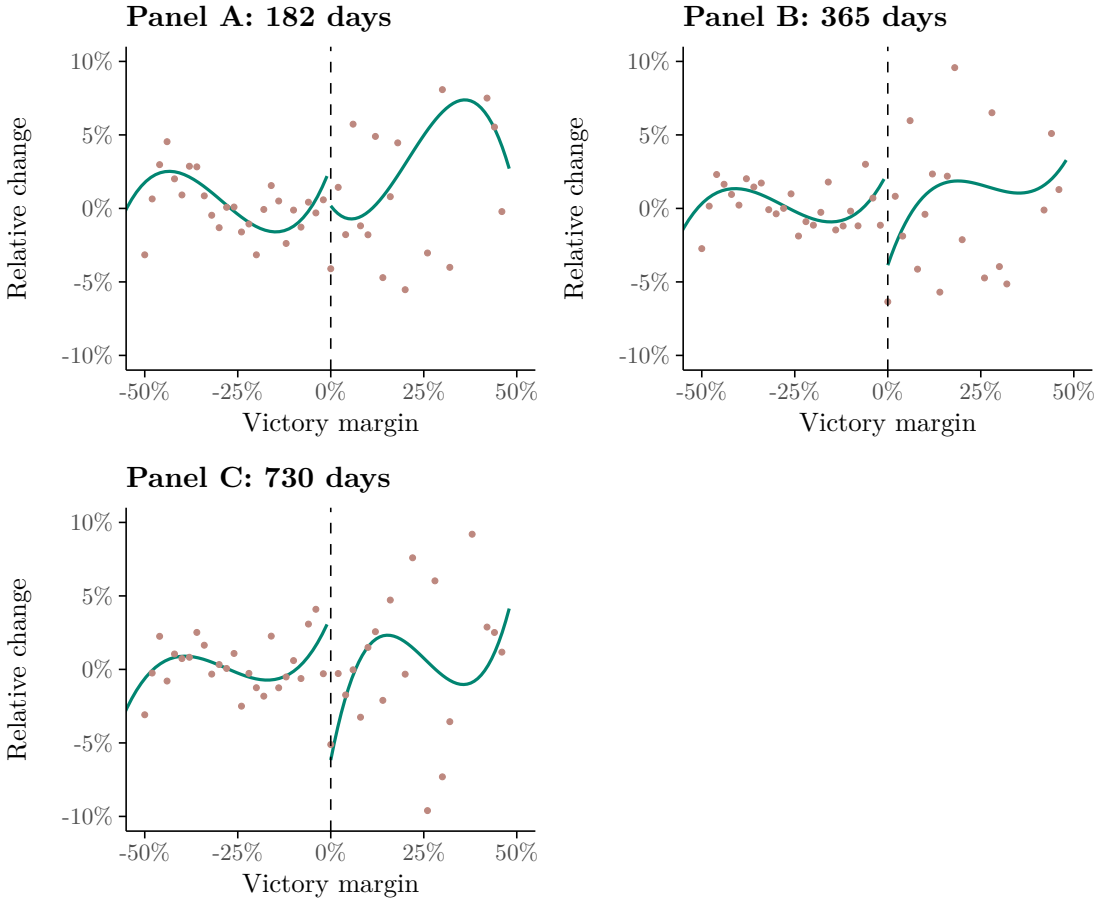
where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ is an indictor variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters and α_y denotes year fixed effects. We fit polynomials in the vote share of order three on both sides 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are 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	-0.656	0.098	-0.032	-0.072*	-0.096***
	(-1.61)	(1.03)	(-0.997)	(-2.08)	(-2.86)
γ_1^l	6.70	0.374	0.588**	0.406*	0.496**
	(1.51)	(0.884)	(2.46)	(2.07)	(2.45)
γ_2^l	27.4	2.39	2.82**	1.95**	2.19**
	(1.50)	(1.38)	(2.80)	(2.38)	(2.51)
γ_3^l	30.8	2.93	3.32**	2.36**	2.63**
	(1.37)	(1.49)	(2.80)	(2.37)	(2.44)
γ_1^r	2.46	-0.550	-0.056	1.04**	1.37***
	(1.08)	(-0.313)	(-0.149)	(2.80)	(3.47)
γ_2^r	-8.41	4.09	2.49	-4.10**	-6.32***
	(-0.827)	(0.406)	(1.16)	(-2.54)	(-3.21)
γ_3^r	10.7	-6.78	-4.52	4.91**	8.20**
	(0.753)	(-0.474)	(-1.33)	(2.42)	(2.78)
Observations	915	970	978	981	981
R^2	0.16	0.04	0.04	0.04	0.02

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

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ is an indicator variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters. We fit polynomials in the vote share of order three on both sides of the majority threshold (P_l; P_r). In each Panel, we plot predicted values from estimated coefficients on the polynomials on 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 Voting Analytics - US Vote Results database and the sample period runs from January 2003 to August 2023.



For a given shareholder meeting, there are usually multiple proposals with different resolution types on the ballot. As we seek to estimate the effect of close vote E-proposal passage or failure on expected returns, governance-related (i.e., G) and social-related (i.e., S) proposals that are decided "far away" from the majority threshold do not pose a serious challenge to our empirical design. However, close vote G- and S-proposal outcomes might cause changes in option-implied expected returns and thus affect the link between expected returns and greenness we established above.

We account for this possibility by excluding shareholder meetings with close vote G- and S-proposals from the full RDD setup and report our results in Table 5. In different specifications, we exclude confounding proposals with a distance to the majority threshold of 5%, 10%, and 20%, and report results for forecast horizons of 365 and 730 days. Consistent across all specifications, we find that our estimates increase in magnitude and become even more significant in most cases. This set of results is particularly noteworthy because we incur large reductions in sample size when excluding confounding proposals, which, in turn, poses a hurdle to maintaining significant results.

Table 5: RDD on daily changes in option-implied expected returns excluding confounding governance and social proposals.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the voting in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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. We fit polynomials in the vote share of order three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. We include E-proposals following the classification in He et al. (2023) and present results for forecast horizons of 365 and 730 days, excluding meetings with close vote governance and/or social proposals. In different specifications, we exclude confounding proposals with distances to the majority threshold of 5%, 10%, and 20%, respectively. Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the year-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	365 days			730 days		
	5%	10%	20%	5%	10%	20%
Pass	-0.079*	-0.103**	-0.120***	-0.099**	-0.121***	-0.124***
	(-1.98)	(-2.78)	(-2.92)	(-2.49)	(-3.05)	(-2.97)
Observations	868	760	587	868	760	587
R^2	0.04	0.05	0.07	0.03	0.04	0.08

5.3. Incorporating multiple periods in the RDD setup

We also consider the possibility that proposal passage causes changes in option-implied expected returns over horizons longer than just the day of the vote. Therefore, we employ a panel data structure and collect changes in option-implied expected returns, whereby each observation refers to event horizon h. In Table 6, 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 the aggregate change 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 the coefficients capturing the reaction of option-implied expected returns on the day of the vote changes little relative to earlier tests across all relevant forecast horizons. However, we document that, for option-implied expected returns with a forecast horizon of 365 days, our estimates are no longer significant at conventional levels. Note that this finding should be interpreted with caution, as we are effectively removing substantial 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 stronger in magnitude than in previous tests.[17] We also detect some small, insignificant reversals of initial changes in expected returns over days two to seven.

We also repeat our analyses, additionally accounting for confounding close vote G- and S-proposals from Section 5.2, in the multi-period setup at hand. Table A-6 reports the results. Analogous to Table 5, coefficients become larger in magnitude and turn statistically significant at the 5% level for changes in option-implied expected returns with a forecast horizon of 365 days.

Note that in our baseline setup, we estimate a proposal-level RDD and use each proposal's majority threshold to interpret the pass indicator as the local effect of passing relative to failing an E-proposal on changes in option-implied expected returns. Cuñat et al. (2012) and Flammer (2015), however, also account for multiple E-proposals in a given meeting. In the Internet Appendix, we run an (ideal) textbook RDD setup in which we only keep shareholder meetings with one unique

[17] The results are robust to controlling for various firm characteristics (see Table A-8).

E-proposal on the ballot, which supports our baseline results.[18]

Table 6: RDD on daily changes in option-implied expected returns for multiple horizons.
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, α_h and α_y denote firm-meeting, distance-to-vote-date and year fixed effects, respectively. We fit polynomials in the vote share of order three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	0.294	0.138	0.002	-0.069	-0.115**
	(0.429)	(1.23)	(0.035)	(-1.38)	(-2.35)
One day after, $t+1$	-0.707	-0.272*	-0.044	-0.056	-0.041
	(-0.413)	(-1.74)	(-0.766)	(-1.51)	(-1.16)
Days $t+2$ to $t+7$	1.09*	0.027	0.044	0.070	0.079
	(1.74)	(0.240)	(0.584)	(1.11)	(1.32)
Observations	4,609	4,870	4,906	4,919	4,918
R^2	0.59	0.21	0.30	0.22	0.20

[18] We provide an extended discussion on multiple E-proposals in a given meeting in the Internet Appendix, as well as a comparison of our results of the textbook RDD setting with results using the same approach chosen by Cuñat et al. (2012) and Flammer (2015), aggregating proposals at the meeting level.

5.4. The interplay between realized and expected returns

Pagano et al. (2023) develop a model in which realized and expected returns move in 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, during 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).

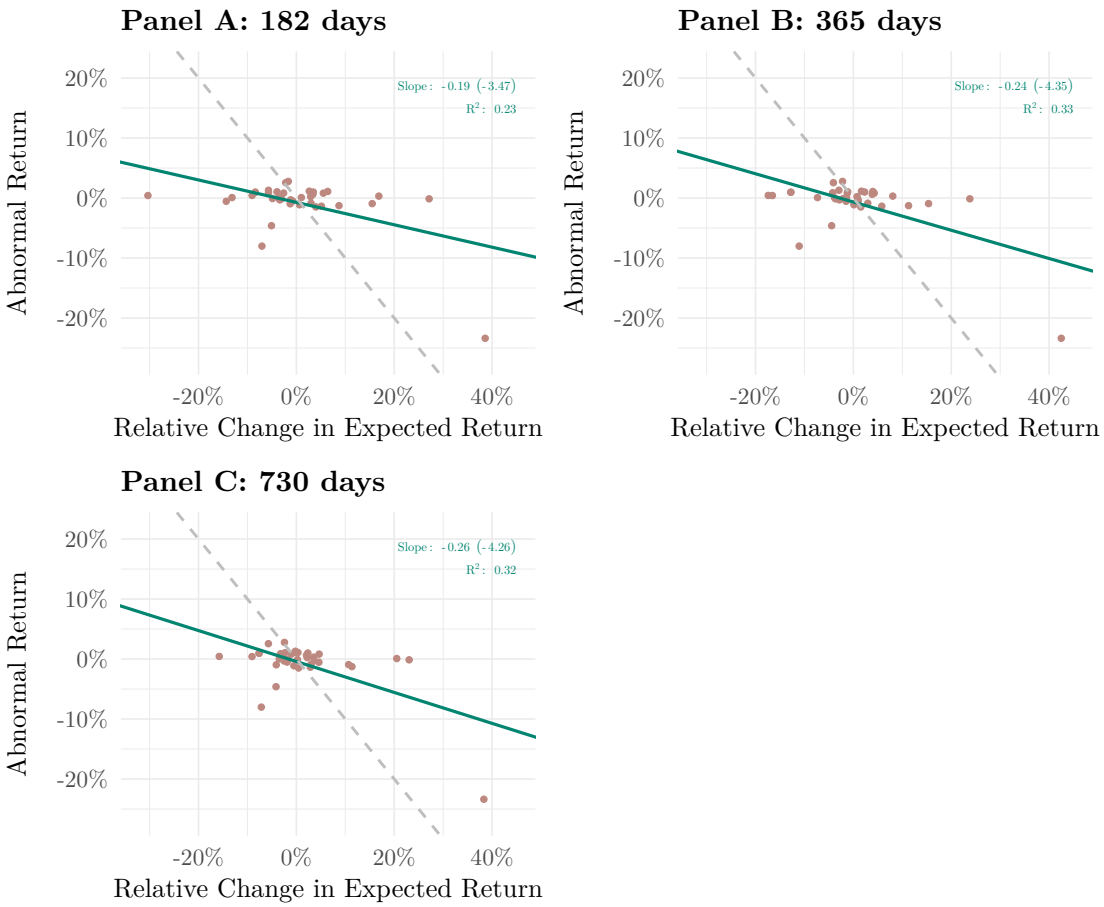
We argue that the framework in Pagano et al. (2023) is also applicable to our setting, but instead of adjustments to the likelihood of a disaster, we deal with changes in the exposure, by passing an E-proposal and becoming greener, to a risk factor related to greenness. In short, close vote E-proposal 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 formally test our hypothesis 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 than or equal to five percentage points, are in Figure 3.[19]

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 the forecast horizon. The modest slope in Panels A to 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 to 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, it is natural that

[19] 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.

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

Figure 3: Relation between realized returns and changes in option-implied expected returns.
Panels A to C plot abnormal returns under the Carhart (1997) four-factor model against relative changes in option-implied expected returns for different forecast horizons with distance to the majority threshold smaller than or equal to 5% 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023.



5.5. Addressing potential concerns with the RDD

To make a causal claim in our setting, we need to address the concerns of manipulation around the threshold, i.e., we need to rule out the possibility that firms self-select into (proposal passage) or out of treatment (proposal failure). Such behavior would indicate that proposals around the threshold do not pass or fail by chance and thus would violate a crucial assumption of making causal inference via RDD. To address the concern of potential "bunching" around the threshold, we run a McCrary (2008) test on vote share and present our results in Figure A-1 in the Appendix. Our tests do not detect manipulation around the threshold, i.e., the null of a continuous distribution of vote share around the majority threshold cannot be rejected (p-value of 0.4172).

Another concern is that firms with passed proposals close to the majority threshold differ systematically from those with close vote failed proposals. In this scenario, changes in option-implied expected returns are not driven by the passage or failure of close vote proposals, but rather by pre-existing differences in firm characteristics. In Table A-4 in the Appendix, we apply simple indicator regressions and the full RDD setup with various firm fundamentals as the dependent variable. Here, the set of characteristics represents variables known to predict returns, thus potentially also affecting option-implied expected returns.

Although there are some systematic differences in observable firm characteristics for firms that pass relative to fail E-proposals in the full sample (e.g., log market equity, E-score, or liquidity scaled by assets) and when moving to increasingly narrowed bandwidths around the majority threshold of 10%, 5% and 2.5% (E-score, tangibility, book leverage, liquidity scaled by lagged market assets), we do not detect a discontinuous jump of any of the investigated variables in the full RDD setup. Hence, we conclude that other variables known in the literature to predict returns do not drive our results.

6. Conclusion

In this paper, we investigate whether there is a difference in the expected return of green versus brown US stocks (i.e., a greenium) by employing an RDD that leverages E-proposals that are decided at small margins around the majority threshold. Our methodology exploits the quasi-random assignment of close vote proposals 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 7.2% (9.6%) when E-proposals narrowly pass compared to when they narrowly fail for a forecast horizon of 365 (730) days. We visualize our RDD estimates 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 document 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 findings are consistent with theoretical work that predicts green securities to have relatively lower expected returns due to the non-pecuniary benefits that investors derive from holding them, as well as their role as a relatively better hedge against climate-related physical and regulatory risks. Our results thus support 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. 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 tests (e.g., in portfolio sorts or panel data analyses).

In future work, we plan to investigate the relation between expected returns and close vote E-proposals in a European setting. This extension not only increases the number of close vote proposals that our inference ultimately relies on, but the effect of close vote proposal passage or failure on expected returns may also differ due to heterogeneity in physical and regulatory risk exposure across regions.

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.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.

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.

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.

Jensen, T. I., Kelly, B., and Pedersen, L. H. (2023). Is there a replication crisis in finance? *The Journal of Finance*, 78(5):2465–2518.

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.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2):698–714. The regression discontinuity design: Theory and applications.

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.

Appendix

A. Additional summary statistics

Table A-1: Summary statistics on accounting variables and stock characteristics by shareholder proposal.
We report summary statistics on accounting variables and stock characteristics sourced from the Global Factor Data based on Jensen et al. (2023). For a given shareholder proposal, we always use the latest monthly record available in the database corresponding to a specific vote date. Information on shareholder meetings is obtained from the Institutional Shareholder Services (ISS) US Vote Results database spanning a period from 2003 to 2024. Abnormal return is the residual stock return on the day of the vote measured in percentages after controlling for the four factor model of Carhart (1997) and market capitalization as well as total assets are measured in logs of millions of USD. We refer to the Global Factor Data documentation for definitions of the remaining variables.

Variable	Proposals	Mean	SD	P5	P25	Median	P75	P95
Abnormal return	967	0.05	1.86	-1.92	-0.69	-0.02	0.71	2.27
B/M-ratio	942	0.61	0.69	0.10	0.29	0.52	0.75	1.36
Book leverage	942	4.48	28.85	1.39	1.73	2.26	3.17	8.82
Capital expenditures	967	0.07	0.05	0.00	0.03	0.06	0.09	0.16
Cash-to-assets	969	0.10	0.11	0.00	0.02	0.05	0.14	0.35
Log(market cap.)	969	10.33	1.70	7.58	9.17	10.30	11.65	12.93
Log(total assets)	969	2.32	0.17	2.03	2.22	2.33	2.46	2.56
E-score	673	-2.48	1.56	-5.07	-3.62	-2.55	-1.19	-0.19
Market beta (60m)	952	0.96	0.59	0.17	0.52	0.93	1.26	1.92
Net profit margin	969	0.06	0.17	-0.13	0.03	0.08	0.12	0.25
Operating profits-to-assets	969	0.14	0.11	0.02	0.08	0.13	0.20	0.32
Ret 12-1	968	0.10	0.35	-0.46	-0.08	0.10	0.26	0.62
Return on equity	942	0.10	1.49	-0.17	0.05	0.11	0.20	0.38
Sales growth	968	0.06	0.26	-0.35	-0.05	0.04	0.15	0.44
Total asset growth	968	0.07	0.17	-0.16	-0.01	0.05	0.11	0.33

Table A-2: Shareholder proposals by Fama-French 49 industries.
We aggregate shareholder proposals into 49 Fama-French industries and report the total number of observations, the percentage share relative to all available shareholder proposals in our sample, the fraction of passed proposals relative to all proposals (within industry) and the number of close votes (within industry). We focus on 20 industries with the largest amounts of proposals. Information on shareholder meetings is obtained from the Institutional Shareholder Services (ISS) US Vote Results database spanning a period from 2023 to 2024. SIC codes are retrieved from the CRSP and then converted into Fama-French industries.

		Proposals			Close votes	
Code	Description	N	Share (%)	Passed (%)	5%	10%
30	Petroleum and Natural Gas	270	28.10	7.04	14	26
31	Utilities	127	13.22	3.94	5	16
43	Retail	61	6.35	9.84	2	5
2	Food Products	50	5.20	2.00	0	1
36	Computer Software	35	3.64	0.00	1	1
44	Restaurants, Hotels, Motels	33	3.43	3.03	0	4
48	Trading	33	3.43	0.00	3	5
18	Construction	26	2.71	7.69	1	3
21	Machinery	25	2.60	12.00	1	3
46	Insurance	25	2.60	8.00	2	3
41	Transportation	24	2.50	20.83	3	3
17	Construction Materials	22	2.29	4.55	0	1
23	Automobiles and Trucks	22	2.29	4.55	1	2
45	Banking	22	2.29	0.00	1	1
14	Chemicals	21	2.19	9.52	0	1
3	Candy & Soda	16	1.66	0.00	0	1
42	Wholesale	14	1.46	28.57	0	0
34	Business Services	13	1.35	7.69	0	1
29	Coal	12	1.25	0.00	0	0
32	Communication	12	1.25	0.00	0	0

Table A-3: Summary statistics on E-proposals by type.
This table provides summary statistics on E-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). 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	
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

B. Adressing potential concerns with the RDD setup

Figure A-1: McCrary (2008) test on vote share using voting rules defined in corporate charters.
This figure presents the graphical results of a McCrary (2008) test on vote shares received by E-proposals we use in our analyses. We rely on US Vote Results data from Institutional Shareholder Services (ISS) covering the period from 2003 to 2024. Proposals are classified as ecology-related based on He et al. (2023). We use voting rules defined in corporate charters to determine the vote share received by a proposal. The null of a continuous density of the vote share around the threshold cannot be rejected (p-value = 0.4172).

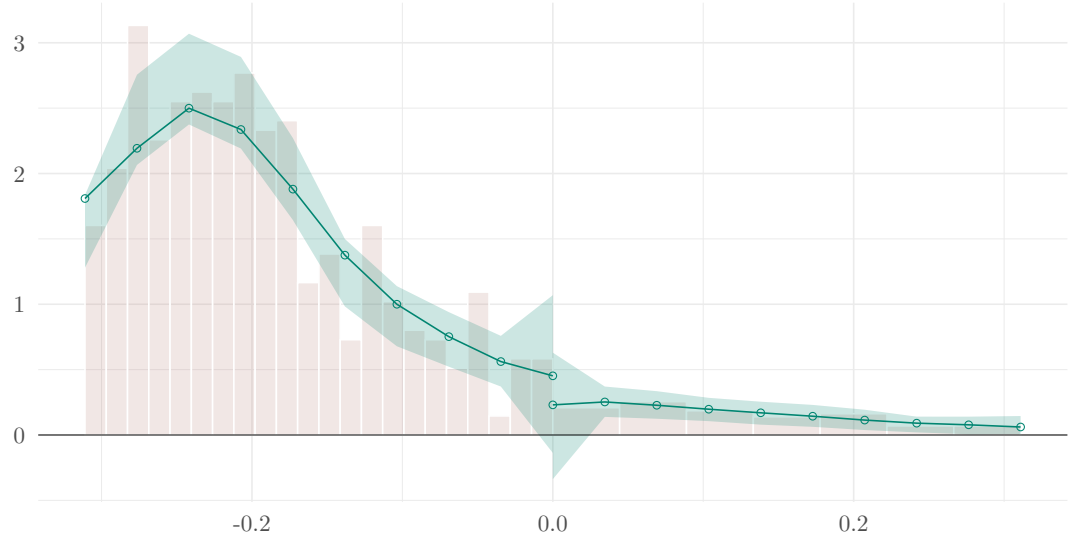


Table A-4: Pre-existing differences in variables that are known to predict returns.

We run indicator regressions without distance to majority restrictions (Full Sample), with increasingly narrow bandwidths around the majority threshold (i.e., ±10%, ±5%, and ±2.5%) and our full RDD setup. Variables that are known to predict returns serve as our dependent variables. We obtain these variables from the Global Factor Data based on Jensen et al. (2023), and always use the latest monthly record available in the database for each vote date. We refer to the Global Factor data documentation for precise definitions of the variables. E-score is defined in Section 3. Information on shareholder meetings is obtained from the Institutional Shareholder Services (ISS) US Vote Results database spanning the period from 2003 to 2024.

Characteristic	Full Sample	10%	5%	2.5%	RDD
B/M-ratio	0.310	0.252	-0.143	-0.257	0.138
	(1.26)	(0.77)	(-1.64)	(-1.62)	(0.64)
Log(market cap.)	-0.944***	-0.393	-0.192	-0.141	-0.575
	(-5.38)	(-1.31)	(-0.52)	(-0.14)	(-1.28)
Market beta (60m)	0.131	0.073	0.089	0.030	-0.077
	(1.48)	(0.54)	(0.48)	(0.14)	(-0.25)
Operating profits-to-assets	0.475	-0.005	0.010	-0.028	-0.287
	(1.34)	(-0.17)	(0.11)	(-1.05)	(-0.29)
Total asset growth	-0.023	-0.025	-0.018	0.108	0.150
	(-0.68)	(-0.68)	(-0.2)	(0.51)	(1.41)
E-score	-0.724***	-0.592	-0.607	-1.001***	-0.132
	(-3.86)	(-1.73)	(-1.44)	(-4.54)	(-0.5)
Liquidity scaled by book assets	-0.061**	-0.040	-0.010	-0.020	0.118
	(-2.28)	(-0.62)	(-0.14)	(-0.46)	(0.95)
Liquidity scaled by market assets	0.009	-0.071**	-0.027	0.045	-0.026
	(0.38)	(-2.49)	(-0.62)	(0.87)	(-0.32)
Tangibility	0.021	0.037	0.088	0.304***	0.055
	(0.62)	(0.48)	(1.1)	(25.17)	(0.68)
IVOL from CAPM (21 days)	0.003	0.003	-0.002	0.002	0.001
	(0.91)	(0.61)	(-0.79)	(0.4)	(0.17)
IVOL from CAPM (252 days)	0.003*	0.001	-0.001	0.006	-0.001
	(1.84)	(0.4)	(-0.24)	(0.68)	(-0.13)
IVOL from FF3 (21 days)	0.002	0.003	0.001	0.004	0.002
	(0.77)	(0.61)	(0.16)	(0.56)	(0.27)
IVOL from q-factors (21 days)	0.003	0.003	-0.001	0.002	0.002
	(0.88)	(0.56)	(-0.25)	(0.37)	(0.23)
Book leverage	11.404	-1.055	-2.026*	-2.807*	7.854
	(1.17)	(-1.47)	(-2.01)	(-2.21)	(1.09)
Operating leverage	0.049	-0.164	0.015	-0.152	-0.209
	(0.29)	(-0.98)	(0.06)	(-0.64)	(-0.58)

C. Additional Empirical Results

Figure A-2: RDD on daily changes in option-implied expected returns (30 and 91 days, respectively).
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \epsilon_{i,t},,$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ is an indicator variable that takes the value of one if vote share is equal or greater than the majority threshold as defined in corporate charters. We fit polynomials in the vote share of order three on both sides 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 forecast horizons of 30 (Panel A) and 91 (Panel B) days. 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023.

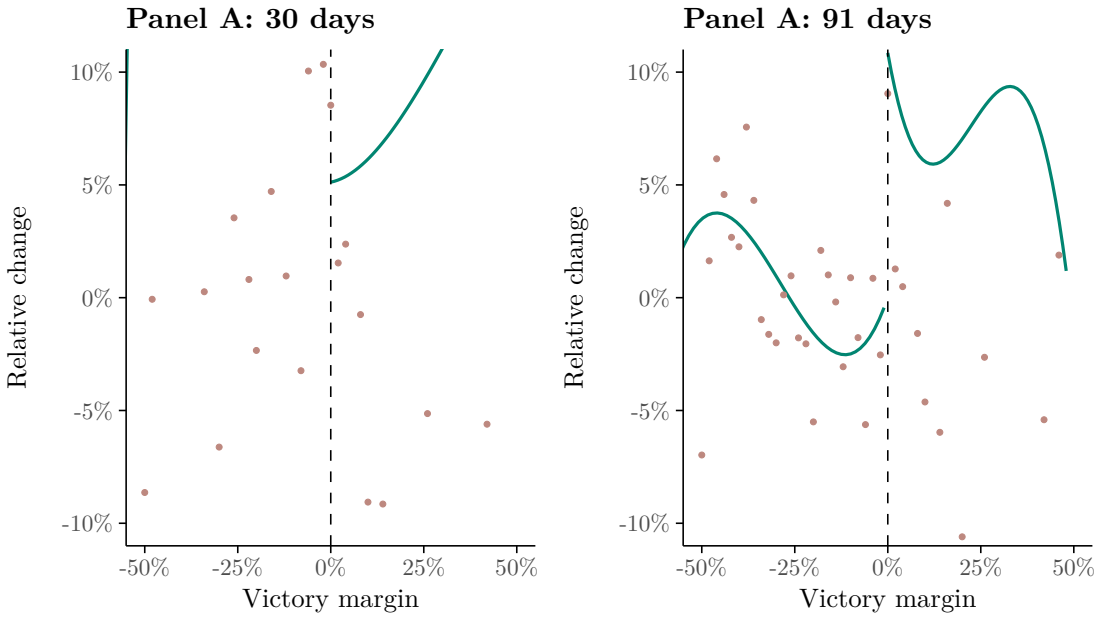


Table A-5: Daily changes in option-implied expected returns around the majority threshold (forecast horizons of 30 and 91 days).
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ 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 Voting 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: 30 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	-2.35	-0.028	-4.42	-7.34	-8.90	-0.774	-2.43
	(-1.02)	(-0.261)	(-1.03)	(-1.03)	(-1.04)	(-1.20)	(-1.05)
Observations	971	822	149	84	61	37	20
R^2	0.10	0.12	0.07	0.11	0.14	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	970	821	149	84	61	37	20
R^2	0.02	0.03	0.07	0.13	0.15	0.49	0.89

Table A-6: RDD on daily changes in option-implied expected returns for multiple horizons excluding confounding governance and social proposals.
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, α_h and α_y denote firm-meeting, distance-to-vote-date and year fixed effects, respectively. We fit polynomials in the vote share of order three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. In each specification, we run the RDD on option-implied expected returns for different forecast horizons and construct a panel to capture the potential effect of proposal passage/failure on option-implied expected returns at multiple horizons h. We include E-proposals following the classification in He et al. (2023) and present results for forecast horizons of 365 and 730 days, excluding meetings with close vote governance and/or social proposals. In different specifications, we exclude confounding proposals with distances to the majority threshold of 5%, 10%, and 20%, respectively. Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	365 days			730 days		
	5%	10%	20%	5%	10%	20%
Day of vote, t	-0.079	-0.111**	-0.126**	-0.124**	-0.142**	-0.135**
	(-1.42)	(-1.98)	(-2.16)	(-2.30)	(-2.50)	(-2.23)
One day after, $t+1$	-0.070*	-0.065	-0.078	-0.060	-0.062	-0.066
	(-1.77)	(-1.46)	(-1.56)	(-1.60)	(-1.46)	(-1.35)
Days $t+2$ to $t+7$	0.077	0.066	0.096	0.082	0.090	0.137*
	(1.18)	(0.899)	(1.13)	(1.29)	(1.22)	(1.70)
Observations	4,351	3,811	2,943	4,350	3,810	2,942
R^2	0.22	0.22	0.24	0.20	0.20	0.23

Table A-7: RDD on daily changes in option-implied expected returns with firm controls.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma_h^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \delta \mathbf{X}_{i,t} + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+1+\tau} - R_{f,t+1+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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, $\mathbf{X}_{i,t}$ is a set of firm characteristics, and α_y denotes year fixed effects. We fit polynomials in the vote share of order three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. In each specification, we run the RDD for option-implied expected returns with different forecast horizons. The set of firm characteristics includes all variables listed in Table A-1 excluding abnormal returns and E-scores. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. *t*-statistics are in parentheses, and standard errors are 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	-0.386	0.090	-0.043	-0.085**	-0.102**
	(-0.601)	(0.875)	(-1.22)	(-2.18)	(-2.67)
Observations	859	912	920	923	923
R^2	0.18	0.06	0.05	0.05	0.04

Table A-8: RDD on daily changes in option-implied expected returns for multiple horizons with firm controls.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right] = \beta_h \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma_h^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \delta \mathbf{X}_{i,t} + \alpha_{i,t} + \alpha_h + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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, $\mathbf{X}_{i,t}$ is a set of firm characteristics, 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 three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. The set of firm characteristics includes all variables listed in Table A-1 excluding abnormal returns and E-score. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	0.222	0.120	-0.012	-0.080	-0.122**
	(0.314)	(1.06)	(-0.243)	(-1.60)	(-2.44)
One day after, $t+1$	0.873	-0.326*	-0.064	-0.062	-0.047
	(1.42)	(-1.93)	(-1.08)	(-1.64)	(-1.28)
Days $t+2$ to $t+7$	1.07*	-0.014	0.030	0.069	0.064
	(1.69)	(-0.118)	(0.387)	(1.04)	(1.04)
Observations	4,326	4,580	4,616	4,629	4,628
R^2	0.62	0.22	0.30	0.22	0.21

D. Level Changes in Option-Implied Expected Returns

Table A-9: Daily level changes in option-implied expected returns around the majority threshold.
We estimate the following regression model using OLS:

$$\Delta\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \alpha_y + \beta \times Pass_{i,t} + \epsilon_{i,t},$$

where $\Delta\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the change in basis points 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses and standard errors are clustered by year. ***, **, 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	-0.003	-0.002	-0.002	-0.001	-0.002	-0.003	-0.004
	(-0.431)	(-0.138)	(-0.629)	(-0.348)	(-0.337)	(-0.882)	(-1.25)
Observations	982	833	149	84	61	37	20
R^2	0.02	0.02	0.18	0.25	0.27	0.30	0.52

Panel B: 91 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.0002	0.005**	-0.0006	-0.003	-0.004	0.0002	-0.002
	(0.106)	(2.38)	(-0.183)	(-0.810)	(-0.904)	(0.219)	(-0.895)
Observations	981	832	149	84	61	37	20
R^2	0.02	0.02	0.14	0.19	0.19	0.58	0.78

Table A-9 (continued): Daily level changes in option-implied expected returns around the majority threshold.

Panel C: 182 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.0004	0.003*	-0.0002	-0.001	-0.002	-0.002	-0.006
	(0.416)	(1.80)	(-0.128)	(-0.678)	(-0.929)	(-1.48)	(-0.996)
Observations	982	833	149	84	61	37	20
R^2	0.03	0.02	0.22	0.24	0.28	0.40	0.50

Panel D: 365 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.002	-0.0001	0.003	0.003	0.003	-0.004	-0.009
	(0.860)	(-0.044)	(1.24)	(1.04)	(0.953)	(-1.52)	(-0.951)
Observations	982	833	149	84	61	37	20
R^2	0.05	0.07	0.05	0.05	0.05	0.31	0.54

Panel E: 730 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	-0.003	-0.005	-0.002	-0.003	-0.005	-0.003	-0.006
	(-0.957)	(-0.606)	(-0.648)	(-0.893)	(-1.14)	(-1.45)	(-0.935)
Observations	982	833	149	84	61	37	20
R^2	0.05	0.06	0.17	0.18	0.24	0.39	0.58

Table A-10: RDD on daily level changes in option-implied expected returns.
We estimate the following regression model using OLS:

$$\Delta\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the change in basis points in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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. We fit polynomials in the vote share of order three on both sides 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are 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	-0.007	-0.0008	-0.004	-0.003	-0.007
	(-0.953)	(-0.137)	(-0.846)	(-0.703)	(-0.961)
γ_1^l	0.072*	0.012	0.017	0.001	-0.015
	(1.73)	(0.607)	(0.992)	(0.068)	(-0.388)
γ_2^l	0.379*	0.093	0.096	-0.0009	-0.062
	(1.83)	(0.967)	(1.12)	(-0.009)	(-0.315)
γ_3^l	0.497*	0.140	0.137	-0.006	-0.067
	(1.79)	(1.11)	(1.15)	(-0.049)	(-0.251)
γ_1^r	0.149	-0.066	0.008	0.164	0.151
	(0.886)	(-0.557)	(0.210)	(1.04)	(1.56)
γ_2^r	-1.25	0.626	0.171	-0.971	-0.997
	(-0.761)	(0.794)	(1.02)	(-1.12)	(-1.13)
γ_3^r	2.23	-1.02	-0.354	1.40	1.54
	(0.779)	(-0.842)	(-1.22)	(1.15)	(1.01)
Observations	982	981	982	982	982
R^2	0.03	0.03	0.04	0.06	0.06

Table A-11: RDD on daily level changes in option-implied expected returns for multiple horizons.
We estimate the following regression model using OLS:

$$\Delta\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma_h^l\right) + P_r\left(v_{i,t}, \gamma_h^r\right) + \alpha_{i,t} + \alpha_h + \alpha_y + \epsilon_{i,t},$$

where $\Delta\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right]$ denotes changes in basis points in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, 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 three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	-0.010	-0.004	-0.005	-0.004	-0.010*
	(-1.08)	(-0.495)	(-1.31)	(-0.547)	(-1.88)
One day after, $t+1$	0.013	-0.001	0.0008	-0.003	0.002
	(1.08)	(-0.218)	(0.172)	(-0.990)	(0.628)
Days $t+2$ to $t+7$	0.005	0.008	0.005	0.008*	0.010*
	(0.495)	(1.16)	(1.18)	(1.94)	(1.87)
Observations	4,925	4,923	4,925	4,925	4,925
R^2	0.20	0.14	0.15	0.16	0.13

Internet Appendix to "In Search of the Causal Greenium"

We provide complementary results to our findings in the main body. In Section I, we extend our baseline setup by aggregating multiple E-proposals in a given meeting following Cuñat et al. (2012) and Flammer (2015) and compare it to an ideal (textbook) setting in which there is only one E-proposal on the ballot for a given shareholder meeting. Section II explores the sensitivity of our baseline RDD estimates to the polynomial order chosen to fit changes in option-implied expected returns through the vote share. Lastly, in Section III, we consider changes in option-implied expected returns over the market as the outcome variable.

I. Multiple Proposals

Cuñat et al. (2012) note that there are possibly multiple E-proposals on the ballot of a given meeting. In all our analyses in the main body, we estimate a proposal-level RDD and use each proposal's majority threshold to interpret the pass indicator as the local effect of passing an E-proposal relative to failing it on changes in option-implied expected returns. This proposal-level design keeps the estimand transparent and tied to a single discontinuity, aligning with the regression discontinuity logic and avoiding arbitrary weighting of distinct proposals. Nevertheless, we check the robustness of our baseline results by applying two alternative approaches.

First, we follow the approach taken in Cuñat et al. (2012) and Flammer (2015). Here, multiple E-proposals in a given meeting are summarized into a single observation. For that, per meeting, the vote shares of the individual proposals, as well as the passage dummies, are respectively summed up to form a single variable. Table IA-1 and IA-2 show the RDD estimates using this aggregation scheme. Compared to Cuñat et al. (2012) and Flammer (2015), we do not find significant effects in the aggregated setting when changes in option-implied expected returns are used as the response variable.

We note that the approach of Cuñat et al. (2012) and Flammer (2015) requires strong structural assumptions. Their aggregation treats heterogeneous proposals as

being additively and linearly priced, and assumes that the sum of vote shares is the relevant smooth control.

For this reason, we adapt a setup that we think represents the cleanest way possible with respect to the core assumption of RDD, namely that each unit of observation (here, an individual firm-meeting combination) has one and only one value of the running variable (here, vote share) that determines its assignment to treatment. We estimate an RDD in which we only keep shareholder meetings with one unique E-proposal on the ballot. The results shown in Table IA-3 and IA-4 using this ideal (textbook) RDD setup confirm our baseline results.

Table IA-1: RDD on daily changes in option-implied expected returns. We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ 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 three on both sides 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are 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	-0.337	0.073	0.007	-0.006	0.007
	(-1.35)	(1.27)	(0.257)	(-0.251)	(0.267)
γ_1^l	1.24	-0.106**	-0.053	-0.043*	-0.034
	(1.10)	(-2.36)	(-1.59)	(-1.86)	(-1.46)
γ_2^l	-0.561	0.154	0.102	0.046	0.023
	(-0.280)	(1.44)	(1.30)	(0.625)	(0.387)
γ_3^l	-2.05	-0.072	-0.038	0.004	0.018
	(-1.12)	(-0.502)	(-0.362)	(0.049)	(0.232)
γ_1^r	-0.558	0.487	0.331	0.229	-0.187
	(-0.322)	(0.821)	(1.14)	(0.970)	(-0.963)
γ_2^r	1.80	-1.34	-0.653	-0.528	0.465
	(0.408)	(-0.915)	(-0.925)	(-0.931)	(1.07)
γ_3^r	-1.21	0.707	0.282	0.284	-0.278
	(-0.469)	(0.842)	(0.700)	(0.881)	(-1.17)
Observations	717	760	767	770	770
R^2	0.06	0.05	0.05	0.05	0.03

Table IA-2: RDD on daily changes in option-implied expected returns for multiple horizons.
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau}-R_{f,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, 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 three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	-0.015	0.116**	0.021	-0.006	0.003
	(-0.068)	(2.07)	(0.970)	(-0.251)	(0.151)
One day after, $t+1$	-0.239	-0.031	-0.015	-0.0008	-0.011
	(-0.542)	(-0.954)	(-0.708)	(-0.055)	(-0.575)
Days $t+2$ to $t+7$	0.049	-0.036	-0.028	-0.045**	-0.035**
	(0.268)	(-1.12)	(-1.26)	(-2.12)	(-2.16)
Observations	3,629	3,824	3,855	3,868	3,867
R^2	0.68	0.22	0.31	0.23	0.20

Table IA-3: RDD on daily changes in option-implied expected returns excluding shareholder meetings with multiple E-proposals on the ballot. We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 three on both sides 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) and exclude shareholder meetings with multiple E-proposals on the ballot. Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are 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	-0.442*	0.090	-0.053	-0.109**	-0.112**
	(-1.83)	(0.739)	(-1.09)	(-2.24)	(-2.29)
γ_1^l	2.74	0.581	0.777**	0.627**	0.782***
	(1.40)	(1.01)	(2.52)	(2.71)	(3.09)
γ_2^l	12.7	3.49	3.61***	2.83***	3.31***
	(1.52)	(1.62)	(3.04)	(3.26)	(2.96)
γ_3^l	14.2	4.23*	4.20***	3.31***	3.85**
	(1.37)	(1.85)	(3.33)	(3.52)	(2.77)
γ_1^r	4.97	0.534	0.456	1.76**	1.33*
	(0.965)	(0.180)	(0.542)	(2.15)	(1.78)
γ_2^r	-26.0	-3.77	-1.15	-8.39**	-7.55*
	(-1.02)	(-0.229)	(-0.269)	(-2.12)	(-1.84)
γ_3^r	38.4	5.66	1.36	11.2**	11.2*
	(1.10)	(0.244)	(0.220)	(2.10)	(1.84)
Observations	595	630	636	639	639
R^2	0.04	0.06	0.06	0.06	0.04

Table IA-4: RDD on daily changes in option-implied expected returns for multiple horizons excluding shareholder meetings with multiple E-proposals on the ballot.
We estimate the following regression model using OLS:

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

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{f,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, 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 three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. We include E-proposals following the classification in He et al. (2023) and exclude shareholder meetings with multiple E-proposals on the ballot. Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	0.733	0.101	-0.029	-0.133**	-0.162**
	(0.809)	(0.737)	(-0.432)	(-2.12)	(-2.57)
One day after, $t+1$	-1.76	-0.357	-0.048	-0.056	-0.056
	(-0.626)	(-1.58)	(-0.766)	(-1.30)	(-1.42)
Days $t+2$ to $t+7$	1.36	-0.050	-0.012	0.022	0.042
	(1.42)	(-0.370)	(-0.124)	(0.276)	(0.521)
Observations	3,023	3,176	3,202	3,215	3,214
R^2	0.78	0.23	0.32	0.24	0.22

II. Alternative polynomial orders

In the main body, we decide to use polynomials in the vote share of order three. In this subsection, we investigate the robustness of our findings with respect to other polynomial orders and focus on the full RDD setup in the spirit of Equation (5) and Table 4. Table IA-5 compares results for polynomials of order two, three, and four with changes in option-implied expected returns with forecast horizons of 365 days and 730 days serving as dependent variables. We find a negative "jump coefficient" in all specifications, but results are only significant at conventional levels for polynomials of order three and four for both forecast horizons.

Table IA-5: RDD on daily changes in option-implied expected returns with different polynomial orders.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{f,t+\tau}\right]$ is the relative change in option-implied expected returns on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 different specifications, we fit polynomials in the vote share of order two, three and four on both sides of the majority threshold (P_l; P_r) and for option-implied expected returns with forecast horizons of 365 and 730 days, respectively. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the year-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	365 days			730 days		
	2	3	4	2	3	4
Pass	-0.028	-0.072*	-0.073**	-0.034	-0.096***	-0.101***
	(-0.889)	(-2.08)	(-2.25)	(-1.44)	(-2.86)	(-3.12)
γ_1^l	-0.017	0.406*	0.112	0.025	0.496**	0.615
	(-0.164)	(2.07)	(0.252)	(0.282)	(2.45)	(1.22)
γ_2^l	0.077	1.95**	-0.156	0.095	2.19**	3.04
	(0.377)	(2.38)	(-0.055)	(0.561)	(2.51)	(0.894)
γ_1^r	0.434*	1.04**	1.51**	0.352	1.37***	1.40*
	(1.95)	(2.80)	(2.26)	(1.26)	(3.47)	(1.75)
γ_2^r	-0.675	-4.10**	-8.74	-0.598	-6.32***	-6.66
	(-1.49)	(-2.54)	(-1.41)	(-1.06)	(-3.21)	(-0.945)
γ_3^l		2.36**	-3.14		2.63**	4.86
		(2.37)	(-0.469)		(2.44)	(0.579)
γ_3^r		4.91**	20.7		8.20**	9.35
		(2.42)	(1.03)		(2.78)	(0.429)
γ_4^l			-4.76			1.92
			(-0.922)			(0.282)
γ_4^r			-16.9			-1.23
			(-0.812)			(-0.056)
Observations	981	981	981	981	981	981
R^2	0.04	0.04	0.04	0.02	0.02	0.02

III. Changes in Option-Implied Expected Returns over the Market

Equation (3) in the main body introduces the notion of option-implied expected returns over the market. Recall that one can easily obtain this measure by subtracting $SVIX_t^2$ from both sides of Equation (2) and interpret it as the event study analogue of an abnormal return under the market model, but in terms of expected returns. In our empirical setup, changes in option-implied expected returns due to close vote E-proposal passage or failure should be driven primarily by changes in the firm-level component of Equation (2), i.e., $\frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX}_t\right)$ or even by the risk-neutral variance term $SVIX_{i,t}^2$ in isolation. In this section, we investigate changes in $\frac{1}{2}\left(SVIX_{i,t}^2 - \overline{SVIX}_t\right)$ as opposed to $SVIX_{i,t}^2$ since the interpretation of $SVIX_{i,t}^2$ as an expected return proxy is tied to additional assumptions we do not consider here.[1]

Results that involve relative changes in option-implied expected returns over the market as the dependent variable are mixed. In Table IA-6, we find a negative effect of passing relative to failing E-proposals close to the majority threshold for a forecast horizon of 365 days, consistent with our baseline results. In the full RDD setup, the "jump coefficients" for both 365 days and 730 days are negative and statistically significant at the 10% level for the former. We do not find a significant effect after accounting for multiple periods around shareholder proposal voting dates and after introducing additional fixed effects.

As already mentioned in Section 4.1 in the main body, high volatility in option-implied expected returns at a daily frequency is a serious threat to identification in our setting. Expected returns in excess of the market seem to suffer even more from this issue as one stabilizing component, the risk-neutral variance of the market ($SVIX_t^2$), is taken out of the equation. This fact makes it difficult to establish a robust link between E-proposal passage or failure and changes in option-implied expected returns over the market.

[1] See Kadan and Tang (2019) for assumptions under which $SVIX_{i,t}^2$ can be interpreted as an expected return proxy.

Table IA-6: Daily changes in option-implied expected returns over the market around the majority threshold.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{m,t+\tau}\right] = \alpha_y + \beta \times Pass_{i,t} + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{m,t+\tau}\right]$ is the relative change in option-implied expected returns over the market 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered by year. ***, **, 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	-0.594	-0.253	-1.46	-2.01	-2.36	-2.57	-6.99
	(-1.51)	(-0.553)	(-1.44)	(-1.42)	(-1.41)	(-1.42)	(-1.60)
Observations	448	361	87	49	34	24	13
R^2	0.11	0.21	0.10	0.12	0.15	0.14	0.24

Panel B: 91 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.005	0.149	-0.038	-0.018	0.035	0.133	0.010
	(0.096)	(1.48)	(-1.13)	(-0.633)	(0.603)	(1.30)	(1.20)
Observations	424	345	79	45	31	21	11
R^2	0.05	0.06	0.30	0.34	0.46	0.50	0.37

Table IA-6 (continued): Daily changes in option-implied expected returns over the market around the majority threshold.

Panel C: 182 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
Pass	0.352	0.946	0.050	0.035	0.029	0.011	-0.072
	(0.918)	(1.04)	(0.816)	(0.453)	(0.492)	(0.475)	(-0.607)
Observations	415	338	77	45	31	21	11
R^2	0.04	0.12	0.31	0.27	0.73	0.82	0.85

Panel D: 365 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
pass	-0.050	-0.014	-0.026	-0.092	-0.091	-0.094	-0.251
	(-0.806)	(-0.160)	(-0.407)	(-1.78)	(-1.58)	(-1.38)	(-0.835)
Observations	401	330	71	42	29	19	9
R^2	0.12	0.12	0.31	0.46	0.68	0.76	0.52

Panel E: 730 days

	All	Non-close	15%	10%	7.5%	5%	2.5%
pass	-0.049	-0.047	0.006	-0.021	-0.033	0.029	0.048^{***}
	(-0.601)	(-0.319)	(0.105)	(-0.271)	(-0.359)	(0.610)	(1.5×10^{16})
Observations	392	326	66	38	25	15	7
R^2	0.05	0.07	0.44	0.66	0.77	0.95	0.99

Table IA-7: RDD on daily changes in option-implied expected returns over the market.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{m,t+\tau}\right] = \beta \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma^l\right) + P_r\left(v_{i,t}, \gamma^r\right) + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_t\left[R_{i,t+\tau} - R_{m,t+\tau}\right]$ is the relative change in option-implied expected returns over the market on the day of the vote in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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. We fit polynomials in the vote share of order three on both sides 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 Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are 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	-2.41	0.054	1.94	-0.216*	-0.141
	(-1.22)	(0.333)	(1.50)	(-1.85)	(-1.03)
γ_1^l	20.1	0.310	-3.59	1.59	-1.05
	(0.773)	(0.176)	(-1.13)	(1.50)	(-0.539)
γ_2^l	82.6	3.08	-11.1	7.40*	-3.17
	(0.833)	(0.375)	(-0.894)	(1.76)	(-0.428)
γ_3^l	98.7	5.07	-10.1	9.11*	-2.99
	(0.853)	(0.453)	(-0.698)	(1.87)	(-0.342)
γ_1^r	10.5**	-2.45	-60.4*	1.51	4.01
	(2.21)	(-0.875)	(-1.74)	(0.654)	(1.52)
γ_2^r	-39.2*	16.3	399.8*	-7.02	-18.3
	(-2.00)	(1.13)	(1.76)	(-0.574)	(-1.63)
γ_3^r	45.2*	-22.6	-604.7*	11.2	22.7
	(1.95)	(-1.10)	(-1.82)	(0.646)	(1.65)
Observations	448	424	415	401	392
R^2	0.12	0.05	0.17	0.13	0.05

Table IA-8: RDD on daily changes in option-implied expected returns over the market for multiple horizons.
We estimate the following regression model using OLS:

$$\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{m,t+h+\tau}\right] = \beta_h \times Pass_{i,t} + P_l\left(v_{i,t}, \gamma_h^l\right) + P_r\left(v_{i,t}, \gamma_h^r\right) + \\ + \alpha_{i,t} + \alpha_h + \alpha_y + \epsilon_{i,t},$$

where $\Delta_{\%}\mathbb{E}_{t+h}\left[R_{i,t+h+\tau} - R_{m,t+h+\tau}\right]$ denotes relative changes in option-implied expected returns over the market from time $t+h-1$ to $t+h$ in the spirit of Martin and Wagner (2019), $Pass_{i,t}$ 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 $\alpha_{i,t}$, 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 three on both sides of the majority threshold (P_l; P_r). For brevity, we do not report coefficients on the polynomials. 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 across multiple periods h. We include E-proposals following the classification in He et al. (2023). Shareholder proposals are from the ISS Voting Analytics - US Vote Results database, and the sample period runs from January 2003 to August 2023. t-statistics are in parentheses, and standard errors are clustered at the meeting-level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	30 days	91 days	182 days	365 days	730 days
Day of vote, t	-0.881	0.126	0.951	-0.299	-0.467
	(-0.518)	(0.655)	(1.25)	(-1.31)	(-1.02)
One day after, $t+1$	1.94	0.009	0.017	-0.098	-0.411
	(1.56)	(0.043)	(0.053)	(-0.510)	(-1.04)
Days $t+2$ to $t+7$	0.381	0.341	-0.283	-0.291	-0.360
	(0.220)	(0.976)	(-0.361)	(-0.798)	(-0.739)
Observations	2,274	2,161	2,110	2,042	1,974
R^2	0.39	0.43	0.47	0.81	0.77