Unlocking ESG Premium from Options

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Abstract

We find that option expensiveness, measured by delta-hedged option returns, is higher for low-ESG stocks, indicating that investors pay a premium in the options market to hedge against ESG-related uncertainty. We estimate that this ESG premium is about 0.2% for 50 days. All three components of ESG contribute to option pricing. We find that investors pay the ESG premium to hedge against jump risks, but not volatility risks. The effect of ESG performance is more prominent during periods when attention to ESG is higher and for firms that are more subject to ESG-related risks.

Keywords: ESG, risk premium, delta-hedged option return

JEL classification: G12, G14, G41, M14

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1 Introduction

There is growing interest in whether corporate environmental, social, and governance (ESG) performance matters for financial markets and corporate behavior. Practitioners contend that ESG-related uncertainty is now a central focus because investors are concerned that poor ESG performance can cause substantial physical risks, transition risks, supply chain risks, and/or downside risks (Morningstar (2020) and PwC (2020)). There is also academic evidence that ESG performance affects firms' risks, including systematic, downside, and crash risks.[1] However, less is understood about the pricing of these risks.

In this paper, we study the pricing of uncertainty associated with ESG, by which we mean operational, reputational, and/or litigation uncertainty due to poor ESG performance. Our interest is not so much in studying the impact of ESG on various risk measures *per se* but rather in analyzing whether investors recognize these risks and pay a premium, which we call the "ESG premium," to potentially hedge against them. Note that while risks due to poor ESG performance are normally associated with bad outcomes, the directional impact of ESG-related uncertainty could be positive. Therefore, we view ESG-related uncertainty as having both an upside and a downside, and we conjecture that investors may be willing to pay to hedge against this uncertainty. Options markets are a natural place for us to uncover these insurance premia, if any.[2] Option returns (suitably delta-hedged) allow us to isolate the pricing impact of ESG-related uncertainty due to hedging from the ESG risk premia on the underlying stocks. Ilhan, Sautner, and Vilkov (2021) also use risk-neutral quantities extracted from options to study the pricing of carbon risks.

We are also inspired by Kelly, Pástor, and Veronesi (2016) and Pástor and Veronesi (2013), who show that options whose lives span political events tend to be more expensive, indicating that political uncertainty is priced. Similar to their arguments about political risks, it is unclear when ESG risks will materialize or how severe they will be. For example, despite increasing awareness of ESG issues, there remains uncertainty about when and how ESG-related regulatory policies will be implemented, about investors' divestment policies, and about firms' fluctuations in revenues. Therefore, options serve as a good vehicle to understand how such uncertainties are perceived and ultimately priced. In the context of

[1] See, e.g., Albuquerque, Koskinen, and Zhang (2019), Hoepner, Oikonomou, Sautner, Starks, and Zhou (2024), and Kim, Li, and Li (2014).

[2] A separate line of inquiry studies whether ESG risks are priced in the market in the sense that investors are compensated with higher expected returns for bearing these risks. However, the evidence on risk compensation from the stock market is mixed. For example, Edmans (2011) and Hong and Kacperczyk (2009) document opposite effects of corporate social performance (see also Chava (2014) and Chava, Kim, and Lee (2022)), and Pástor, Stambaugh, and Taylor (2021) and Pedersen, Fitzgibbons, and Pomorski (2021) show that the effect of ESG performance on stock prices is theoretically ambiguous.

climate change, Giglio, Maggiori, Rao, Stroebel, and Weber (2021) highlight the importance of alternative asset classes to estimate their impact. For example, these authors use the real estate market to understand the term structure of discount rates for investments in climate change abatement. Somewhat similarly, we study another alternative asset market, the equity options market, to study the risks associated with ESG.

Our conjecture is that investors are willing to pay a premium to hedge against ESG-related uncertainty. We start our empirical investigation by analyzing how firms' ESG scores are related to their option expensiveness, measured using delta-hedged option and straddle returns. These returns insulate the effect of the underlying return (for which evidence of ESG pricing is ambiguous) and allow us to focus on the object of interest, the premium due to ESG-related uncertainty. Dew-Becker, Giglio, and Kelly (2021) and Dew-Becker, Giglio, Le, and Rodriguez (2017) also use option returns (specifically straddle and strangle returns) to study the pricing of macroeconomic risk and volatility risk, respectively.

We pick one call and one put option on each optionable stock that has a time to maturity of about one and a half months and are closest to being at the money (ATM)—these options are the most frequently traded and hence are the most liquid. For each optionable stock and in each month, we evaluate the return until the maturity of a portfolio that buys one call (or put), delta-hedged with the underlying stock. To investigate the impact of ESG performance on option returns and gauge the economic magnitude of the ESG premium, we sort all options into quintiles based on the ESG scores of the underlying stocks. We calculate three types of option returns. The first is daily rebalanced delta-hedged returns, following Bakshi and Kapadia (2003) and Cao and Han (2013), so that the portfolio is not sensitive to stock price movements. Second, we calculate daily compounded delta-hedged returns as an alternative measure (Bali and Murray (2013)). Third, we calculate the returns of the zero-beta straddle portfolio until maturity following Coval and Shumway (2001). We calculate the returns and factor model alphas using the stock market factors of Fama and French (2018) and the option market factor of Coval and Shumway (2001). We find that both returns and alphas increase almost monotonically from quintile one (lowest ESG score) to quintile five (highest ESG score), and this finding is robust across the three types of option returns. The difference in the average delta-hedged option returns on low- and high-ESG stocks can be regarded as the ESG premium that investors are willing to pay in the options market to hedge against their perceived uncertainty for low-ESG stocks. The magnitude of the risk premium using the daily rebalanced delta-hedged gain is around 0.2% held until maturity. Using daily compounded delta-hedged returns, the 7-factor monthly alpha for H−L spread portfolio is 0.27% for calls and 0.25% for puts, both of which are statistically significant. Beta-neutral straddle returns yield an estimate of the ESG premium of about 2.97%.[3]

Do all three components of ESG contribute to the relation between ESG scores and option returns? To investigate this question, we separate environmental (E), social (S), and corporate governance (G) scores and study their individual impacts on delta-hedged option returns. Using portfolio sorts as before, we find that all three aspects of ESG contribute to the positive relationship between delta-hedged option returns and ESG performance, although the E-score and the S-score are stronger determinants of option returns than the G-score.[4] The fact that our results are weaker using the G-score also suggests that corporate governance risks are more idiosyncratic in nature than those related to environmental and social issues. There are various potential sources of systematic ESG risks. For example, pro-environmental regulations may subsidize high-ESG products or handicap low-ESG products, leading to a larger difference in customer demand between high-ESG firms and low-ESG firms. The risks could also come from social movements such as #MeToo, which may change public awareness and investors' perceptions.

Delta-hedged option returns and straddle returns embed various types of risk premia, such as the volatility risk premium, jump risk premium, and tail risk premium. Many studies document the existence of a nonzero volatility premium (Bakshi and Kapadia (2003), Buraschi and Jackwerth (2001) and Coval and Shumway (2001)) and the risk of unforeseen tail events (Bakshi and Kapadia (2003) and Jackwerth and Rubinstein (1996)). It is, therefore, of interest to examine which risk premia contribute to the positive relationship between ESG scores and option returns. To directly test whether volatility and tail risk premia are related to ESG scores, we construct straddle returns following Cremers, Halling, and Weinbaum (2015). Through portfolio sorts, we find a positive relationship between ESG and returns to gamma-positive, vega-neutral straddles (portfolios exposed to tail risk), while the relationship between ESG and returns to vega-positive, gamma-neutral straddles (portfolios exposed to volatility risk) is not significant. These results show that jump risks related to ESG performance are strongly priced in the options, while the impact of volatility risks is limited.

If our hypothesis that investors pay a premium to hedge against uncertainty is correct, then the effect of ESG on option pricing should increase when public ESG awareness/attention increases, when the perceived uncertainty for low-ESG stocks is expected to be more important. To support our argument, we conduct three tests to examine how the

[3]For the remaining tests, we mainly focus on the daily rebalanced delta-hedged option gains.

[4]The result for the G-score is significant for average returns but is not insignificant for the 6-factor and 7-factor models.

ESG premium changes with public ESG awareness/attention over time. First, we divide our sample into two subperiods based on the monthly change in the Google search volume of "ESG," and we find that the alpha for the H−L spread portfolio is significantly higher during the period with heightened Google search volume. Second, we find that the effect of the ESG score on the delta-hedged option return is significantly stronger during the Paris Agreement period (January 2016 to June 2017), when the Paris Agreement was in effect and likely to impose stringent regulations on firms with poor ESG performance. Third, using aggregate ESG news in the market as a proxy for ESG awareness, we find that the ESG premium is much higher when there is more ESG news.

A natural question is whether the ESG premium comes from the quantity of risk or the price of risk. We find that low-ESG stocks are riskier, with risk measured as the risk of increasing volatility (Cao, Vasquez, Xiao, and Zhan (2023)) or jump intensity (Bollerslev, Li, and Zhao (2020)). This is consistent with the quantity of risk driving the higher risk premium on options on low-ESG stocks. At the same time, we also find that the quantity of risk does not change during times when ESG awareness is high. Coupled with evidence that the risk premium does increase during these times, we conclude that the market price of risk increases when investors pay more attention to ESG-related uncertainty. Therefore, both the quantity and the price of risk drive the ESG premium.

Next, we use Fama and MacBeth (1973) regressions (FM regressions henceforth) to test the impact of ESG performance on the option level. Controlling for various firm characteristics, option characteristics, and risk measures, we find that lower ESG scores are associated with lower delta-hedged option returns. For example, we find that the delta-hedged option returns for calls increase by 0.32% each month if we move from the lowest to the highest quartile of ESG scores (similar to the return spread from portfolio sorts). To disentangle the effect of carbon tail risk (Ilhan, Sautner, and Vilkov (2021)) from broader ESG risks, we run FM regressions of delta-hedged option returns on both the ESG score and carbon emission intensity. We find that the ESG score plays an important role even when we control for carbon emission intensity, which indicates that our results are not merely driven by the carbon emission intensity of the firm but also depend on other aspects of the ESG score.

ESG scores are likely to be correlated with other characteristics of the firm, which may also be important for option returns. To mitigate these endogeneity concerns, we use the RepRisk Index (RRI) to identify sudden increases in ESG risk and investigate how the options market reacts to these shocks. We use such exogenous variations in time as quasi-natural experiments and rely on multiple shocks to firm ESG risk to alleviate concerns about omitted variables. For each treated stock (for which RRI increases), we identify control stocks via propensity score matching. A difference-in-differences (DiD) analysis shows that after a sudden increase in ESG risk, the call option return until maturity of treated firms drops by 0.295% compared with that for the control group. The results are very similar for put options. A parallel trend analysis serves as a validity test of the DiD analysis and shows no visible trends before the shocks to ESG. We acknowledge that we do not have a cleaner exogenous shock to rule out all sources of endogeneity, and therefore we take these results only as suggestive causal evidence.

Given the complexity of measuring ESG information, ESG ratings from different providers disagree substantially, and the validity of these ratings has been critically debated. We perform three robustness tests to mitigate the concern that our empirical results are only significant for a particular ESG data provider. First, we used the ESG scores of four alternative data providers, and we find that all are significant. Second, we create a combined ESG score using the information from five data providers and show that the results are robust. Third, using a noise-correction procedure (Berg, Koelbel, Pavlova, and Rigobon (2024)), we again find consistent patterns.

Next, we consider several channels through which the link between the ESG score and the option market is strengthened or weakened. The first channel is different business models and product market competition. The proximity of industries to end consumers has been documented to influence the impact of the ESG score on firm fundamentals because private end consumers show more social concerns in their consumption (Baron, Harjoto, and Jo (2011) and Curcio and Wolf (1996)). We conjecture that the effect of ESG on option prices might be more important in industries that depend more heavily on the trust of end consumers. The second channel influencing the ESG premium is cross-sectional variations in investors' attention to ESG. We proxy this by the political leaning (Democratic versus Republican) of the state where the company is headquartered (Di Giuli and Kostovetsky (2014) and Hong and Kostovetsky (2012)), or the portion of the quarterly earnings conference call transcripts that are devoted to environmental-related political topics (Hassan, Hollander, van Lent, and Tahoun (2019)). As a third channel, we conjecture that corporate hedging policy can also affect the relationship between ESG performance and option pricing. We find evidence consistent with all of these channels.

To the best of our knowledge, our paper is the first to formally investigate the effect of ESG performance on risk premia in the options market. Previous studies (see, e.g., Edmans (2011), Flammer (2021), and Hong and Kacperczyk (2009)) focus on stock and bond markets to explore the pricing of ESG risks only in the underlying.[5] Since the seminal study of Bakshi

[5]Focusing on the stock market, Edmans (2011) and Hong and Kacperczyk (2009)) document opposite effects of corporate social performance (see also Chava (2014)). Flammer (2021) documents the positive effects of corporate social responsibility (CSR) and green bond issuances on firm value.

and Kapadia (2003), variance risk premia have been known to be negative—an increase in volatility is typically regarded as corresponding to bad states. The literature on the cross-sectional variation of these risk premia is sparse (see Buraschi, Trojani, and Vedolin (2014) and González-Urteaga and Rubio (2016)). We investigate how these risk premia are related to ESG. We conjecture and find evidence that investors are willing to pay to insure against ESG risks. Importantly, our study not only explores the relation between ESG and general variance risk premia but also drills down to risk premia related to jump risk.

We also contribute to the growing body of literature on option pricing. Goyal and Saretto (2009), Bali and Murray (2013), Cao and Han (2013), Zhan, Han, Cao, and Tong (2022), Christoffersen, Goyenko, Jacobs, and Karoui (2018), and Ramachandran and Tayal (2021) explore the impacts of various stock and volatility-related characteristics on option returns. Our paper is the first to examine the effects underlying firms' ESG performance on option pricing and to explore several potential underlying economic channels.

The study most closely related to ours is Ilhan, Sautner, and Vilkov (2021). These authors find that the cost of protection against downside tail risks is higher for firms with more carbon-intensive business models. Our paper differs from theirs in two major aspects. First, we focus on the risks associated with general ESG performance, not just the carbon policy risks. As discussed above, we show that our results are not due to the impact of carbon risks or only environmental risks, but rather derive from all of the components (E, S, and G) of ESG (our results are robust to controlling for carbon emission measures). The evidence from other cross-sectional analyses also shows that the social component is non-negligible, as it amplifies the impact of ESG on option pricing. Second, Ilhan, Sautner, and Vilkov (2021) mainly focus on downside risk (hence their focus on deep out-of-the-money (OTM) options). In contrast, we study the pricing of general uncertainty related to ESG performance (and, therefore, ATM options). Ilhan, Sautner, and Vilkov (2021) report that carbon risks also affect variance risk premia. We find results consistent with theirs. Importantly, we also show that the ESG premium embedded in option prices goes beyond that related to volatility risk only and includes premia related to jump risks. Because our interest is in the general ESG premium, we quantify it using returns (on delta-hedged options and straddles in our case) rather than prices *per se*. Dew-Becker, Giglio, and Kelly (2021) also advocates the use of option returns to study the pricing of macroeconomic risk.[6]

[6]Another minor difference between Ilhan, Sautner, and Vilkov (2021) and our study relates to the identification analysis. Given Ilhan, Sautner, and Vilkov (2021) focus on corporate carbon emission, their identification strategy is limited to the one-time shocks of the Paris Agreement and Trump's first election. Our focus on ESG allows us to identify firm-level stocks from news of E, S, and G separately. These granular shocks occur to different firms at different times, providing a better identification.

The rest of the paper proceeds as follows. Section 2 describes our data and measures. Section 3 quantifies the ESG premium and investigates the sources of this premium. We present the Fama-Macbeth results in Section 4. We discuss potential underlying economic channels that affect the cross-section relationship between ESG performance and option pricing in Section 5 and conclude in Section 6.

2 Data and variables

2.1 Data and sample coverage

We collect data on firms' ESG performance from ASSET4. These data provide objective, relevant, and systematic ESG information based on 250+ key performance indicators and 750+ individual data points from three pillars (E, S, and G). ASSET4 provides data on more than 3,000 firms globally, covering major indexes. In the US, ASSET4 only covered firms in the S&P 500 index at the beginning of the sample period and expanded to firms in the Russell 1000 index later.[7]

We obtain data on individual US stock options from OptionMetrics. The data set includes the daily closing bid and ask quotes, trading volume, and open interest of each option. Options' delta and other Greeks are computed by OptionMetrics based on standard market conventions.

Stock returns, prices, and trading volumes are obtained from the Center for Research on Security Prices (CRSP). The accounting data are collected from COMPUSTAT. We obtain institutional holdings (13F) data from Thomson Reuters and analyst coverage data from I/B/E/S. The daily and monthly Fama-French factors and risk-free rates are from Kenneth French's data library. The sample period is January 2004 to December 2018.

At the end of each month and for each optionable stock, we collect a pair of options (one call and one put) that are closest to being ATM and that expire on the third Friday/Saturday of the month after the next. For example, on June 30, 2011, we select options expiring on August 20, 2011. For a given month, all options that we study have the same expiration day, and our cross-sectional analysis is not influenced by the difference in maturities. We focus on these options because short-term ATM options are traded more frequently and

[7] ASSET4 was acquired by Thomson Reuters in 2009, and it now goes by the name Thomson Reuters ESG Scores. However, because the name ASSET4 is widely known, we use this name for simplicity. The raw ASSET4 score ranges from 0 to 100. To simplify the interpretation of the regression coefficients, we divide the raw ASSET4 score by 100. We also report that the ASSET4 ESG score is negatively associated with subsequent risk events, proxied by the number of negative ESG incidents from RepRisk (a news-based data provider).

with lower effective transaction costs than long-term options or expiring options. We apply several filters to the option data. First, our main analyses use options whose stocks do not have a planned dividend payment with ex-dividend dates prior to option expiration (i.e., we only exclude an option if the underlying stock has announced, at the time of establishing the portfolio, a dividend payment during the remaining life of the option). Second, to avoid microstructure-related bias, we retain only options that have positive trading volume in the last month. Third, we keep common stocks with stock prices larger than $5 in the previous month. Fourth, we exclude stocks with missing ESG scores from ASSET4 data and only retain stocks with both call and put options available after filtering. To ensure that our tests do not suffer from potential look-ahead bias as outlined in Duarte, Jones, Khorram, Mo, and Wang (2024), all the filters mentioned above are based on available real-time information, so future information is not used in our portfolio formation process.

Our final sample contains 69,058 option-month observations for both call and put options on individual stocks. Table 1 shows that the average moneyness of the sample options is 1, with a small standard deviation of 0.03. The time to maturity is between 46 and 52 calendar days, with an average of 50 days. These short-term ATM options have relatively smaller bid-ask spreads and provide more reliable pricing information related to investors' perceptions of risk and uncertainty.

Appendix Table A1 reports the sample coverage details of 899 unique underlying stocks. The average number of stocks in our sample per month is 384. On average, our sample contains only 5.58% of the total number of stocks in CRSP but comprises 34% of the total market capitalization. In addition, 73% of our sample stocks are traded on the NYSE/AMEX and 72.7% are included in the S&P500 index. Compared to the full CRSP sample, the average size percentile and the book-to-market ratio percentile of these stocks in our sample are 90% and 36%, respectively. In addition, the average institutional ownership is 80%, and the average number of analysts following is 16.43. The industry distribution of these stocks does not deviate substantially from that of the full CSRP sample. Given the characteristics of our sample firms, the results are less likely to be confounded by market frictions, such as small, illiquid, less transparent stocks, stocks with low attention, or bias toward a few industries. For example, Table 1 shows that the quoted call option bid-ask spread has a mean (median) of 0.15 (0.11), which is less than 0.12 (0.08) in previous related studies such as Cao and Han (2013) and Zhan, Han, Cao, and Tong (2022). A lower bid-ask spread also indicates that option prices adjust faster to investors' flow of information as well as to changes in perceived uncertainty.

2.2 Delta-hedged option return

We rebalance the delta-hedged option on each trading day, and calculate the delta-hedged call option return until maturity following Bakshi and Kapadia (2003) and Cao and Han (2013). We define the daily rebalanced delta-hedged option gain as the change in the value of a self-financing portfolio that consists of a long call position hedged by a short position in the underlying stock. Such a portfolio is not sensitive to stock price movements, with the net investment earning the risk-free rate.[8] Specifically, consider a call option that is hedged discretely N times over a period $[t, t+1]$. The rebalancing times are t_n (where $t_0 = t$ and $t_N = t+1$). The delta-hedged call option gain is

$$\Pi_{t+1} = C_{t+1} - C_t - \sum_{n=0}^{N-1} \Delta_{c,t_n} \left(S_{t_{n+1}} - S_{t_n} \right) - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365} \left(C_{t_n} - \Delta_{c,t_n} S_{t_n} \right), \tag{1}$$

where Δ_{c,t_n} is the call delta of the call option on date t_n, r_{t_n} is the annualized risk-free rate on date t_n, and a_n is the number of calendar days between t_n and t_{n+1}.[9] The delta-hedged put option gain is defined similarly. Note that since we hold options to maturity, $C_{t+1} = \max(S_{t+1} - K, 0)$ and $P_{t+1} = \max(K - S_{t+1}, 0)$. With a zero-net-investment initial position, the delta-hedged option gain Π_{t+1} is the excess dollar return of the delta-hedged option. Because the option price is homogeneous of degree one in the stock price and the strike price, Π_{t+1} is proportional to the initial stock price. To make it comparable across stocks, we scale the dollar return by $\Delta_{c,t} S_t - C_t$ for call options and $P_t - \Delta_{p,t} S_t$ for puts.[10]

Panels A and B of Table 1 present the summary statistics of the delta-hedged option returns until maturity for the call and put options, respectively. Consistent with the findings of Cao and Han (2013), the average delta-hedged returns of individual equity options are negative for both calls and puts. On average, the delta-hedged gain for calls (puts) is -0.21% (-0.27%) until maturity. There is substantial cross-sectional variation in these gains. For example, the lower and upper quartiles of delta-hedged call gains are $-$ 1. 95% and 1. 03%, respectively.

[8] At the end of each trading day, we require the option to have positive bid quotes, the midpoint of bid and ask quotes to be at least \$1.25, and the option price to not violate obvious no-arbitrage conditions such as $S \geq C \geq \max(0, S - Ke^{-rT})$, where C is the call option midpoint price, S is the underlying stock price, K is the strike price, T is the time to maturity, and r is the risk-free rate. If these criteria are not met for a portfolio, we do not rebalance it on that day. Please note that these filters do not suffer from the potential look-ahead bias since we monitor delta-hedged option portfolios on a daily basis.

[9] Stock prices are adjusted for stock splits. If the delta for an option is missing from the OptionMetrics data on a given day, we use the current stock price and the most recent non-missing implied volatility to estimate the option delta based on the Black-Scholes formula.

[10] We obtain similar results when we scale the delta-hedged option gains by the initial price of the underlying stocks or that of options.

We report the stock-related summary statistics in Panel C of Table 1. Ln(ME) is the logarithm of market capitalization and Ln(BM) is the logarithm of the book-to-market ratio (Fama and French (1992)). RET1 is the stock return in the prior month. RET212 is the cumulative stock return from the prior second through twelfth months. As in Ang, Hodrick, Xing, and Zhang (2006), idiosyncratic volatility (IVOL) is computed as the standard deviation of the residuals of the Fama and French (1993) three-factor model estimated using the daily stock returns over the previous month. Ln(AMIHUD) is the logarithm of the Amihud (2002) stock illiquidity measure, calculated as the average of the daily ratio of the absolute stock return to dollar volume over the previous month. The ESG score has a mean of 0.62 and a standard deviation of 0.26. Such a large cross-sectional variation of ESG scores is useful to estimate the effect of ESG performance on the options market. Panel D of Table 1 reports the time-series average of the cross-sectional correlations among these stock variables. The ESG score tends to have high correlations with Ln(ME) and Ln(AMIHUD), which we further control in the multivariate regression analyses.

3 ESG premium

3.1 Portfolio sort results

To understand the pricing implications of ESG performance, we start our analysis using portfolio sorts to quantify the ESG premium. We use three types of option returns to calculate this premium. First, we rely on the daily rebalanced delta-hedged option gains, as described in Section 2.2.

Second, we use daily compounded delta-hedged option return, following Cao and Han (2013) and Choy and Wei (2023). Specifically, at the end of each day, t_n in the portfolio holding period, for delta-hedged call options, we buy one contract of the call option hedged by a short position in delta shares of the underlying stock, where delta is the hedge ratio under the Black-Scholes model. We adjust the hedge position at the end of each day to make it delta-neutral, and calculate the portfolio return for each day t_n:

$$R_{t_{n+1}} = \frac{\left(C_{t_{n+1}} - \Delta_{c,t_n} S_{t_{n+1}}\right) \text{ or } \left(P_{t_{n+1}} - \Delta_{p,t_n} S_{t_{n+1}}\right)}{H_{t_n}} - 1, \tag{2}$$

where the absolute value of initial investment cost H_{t_n} is $(\Delta_{c,t_n} S_{t_n} - C_{t_n})$ for call options and $(P_{t_n} - \Delta_{p,t_n} S_{t_n})$ for put options, and Δ_{c,t_n} and Δ_{p,t_n} are the Black-Scholes option call and put deltas, respectively, on day t_n.[11] Then, we calculate the daily compounded delta-hedged option return until maturity by compounding the daily returns as:

$$R_{t+1} = \prod_{n=0}^{N-1} (1 + R_{t_{n+1}}) - 1. \tag{3}$$

The third option return is a zero-beta straddle portfolio return, which is also not sensitive to stock returns. Dew-Becker, Giglio, and Kelly (2021) also use straddle returns to study whether investors hedge macroeconomic risks. We select a call option and a put option with a maturity of 50 days and are closest to ATM, as in the main tests. Following Coval and Shumway (2001), we form zero-beta straddles by solving the equations below:

$$\begin{aligned} r_v &= \theta r_c + (1-\theta) r_p \\ \theta\beta_c &+ (1-\theta)\beta_p = 0, \end{aligned} \tag{4}$$

where r_v is the straddle return, θ is the fraction of the straddle's value in call options, and β_c and β_p are the market betas of the call and put, respectively. β_c is calculated as follows:

$$\beta_c = \frac{S}{C}\Delta_c\beta_s, \tag{5}$$

where β_s is the rolling beta of the stock, which is estimated using weekly returns over the past year. We hold this portfolio until maturity.

To measure the ESG premium, we sort all stocks into quintiles based on the ESG score at the end of each month and then calculate the equal-weighted portfolio return for the quintiles and the H−L spread portfolio using the three option returns. In addition, we report the risk-adjusted return based on two different factor models. The first is a 6-factor model from Fama and French (2018) that includes the market factor, size factor, value factor, profitability factor, investment factor, and momentum factor. The second is a 7-factor model that includes these six factors plus a market volatility factor proxied by the zero-beta straddle return on the S&P 500 index (Carr and Wu (2009) and Coval and Shumway (2001)), to examine whether the portfolio return can be further explained by the systematic volatility risk factor. The portfolio sort results for daily rebalanced delta-hedged option gains, daily compounded delta-hedged option return, and straddle returns are reported in Panels A, B,

[11] To mitigate the concern that our results are model-dependent, we also estimate hedge ratios using a model-free approach developed in Bates (2005). Bates (2005) shows that if the price of a European or American claim is homogeneous of degree one in stock price and exercise price, then the model-free option delta and gamma are uniquely determined. We estimate these deltas using his recommended approach. We find that the model-free delta has a high correlation with the Black-Scholes delta, and consequently, there is no material change to our results when using the model-free option delta.

and C of Table 2, respectively. Panels A and B show the results separately for delta-hedged calls and delta-hedged puts. Delta-hedged call and put positions are, in essence, volatility positions and thus should behave similarly. To increase the power of some of our tests, we also pool both calls and puts in the results in Panels A and B.

The returns and alphas from the factor models exhibit patterns consistent with our conjecture that options on low-ESG stocks are more expensive. Both the returns and alphas increase monotonically from quintile one (lowest ESG score) to quintile five (highest ESG score), and these results are robust across the three types of option returns. For example, in Panel A of Table 2, where we consider daily rebalanced delta-hedged option gains, when we group call and put options together, the 6-factor alpha of the quintile one (five) portfolio is −0.40% (−0.23%), leading to a H−L portfolio alpha of 0.17%, which is statistically significant at the 1% level. The H−L 7-factor alpha is a bit lower at 0.13% but is still significant at the 1% level. The call option returns and put option returns demonstrate similar patterns, although the magnitude of the H−L portfolio alphas is slightly higher for put options than for call options.

The average daily compounded delta-hedged option return increases monotonically from the lowest ESG options to the highest ESG options, as shown in Panel B of Table 2. The H−L spread is 0.34% for call options and 0.33% for put options. These magnitudes are approximately a quarter of the H−L spread of 10 anomalies that can significantly predict option returns (Zhan, Han, Cao, and Tong (2022)).[12] Given the fact that our sample with non-missing ESG scores includes options of relatively large stocks, the economic magnitude of the ESG premium is nontrivial.

Panel C of Table 2 shows that beta-neutral straddle returns also increase as ESG scores increase, with a 7-factor alpha of −4.29% for the quintile one portfolio and −1.32% for the quintile five portfolio, yielding a H−L portfolio alpha of 2.97%. Overall, the portfolio-sorting results show that there is an ESG premium in the cross-section of option returns, supporting the hypothesis that investors pay a significant premium to hedge against uncertainties associated with poor ESG performance. The magnitude of the ESG premia is around 0.2% for daily rebalanced delta-hedged gains, around 0.3% for daily compounded delta-hedged returns, and around 3.5% for straddle returns.

As a further robustness check, we analyze variance swaps, which provide a straightforward strategy to place a directional bet on future variances. We follow Carr and Wu (2009) to

[12] For example, Zhan, Han, Cao, and Tong (2022) document that for the call option, the EW H−L option return spread of cash flow variance (CFV) is 1.58%, and it is 1.38% for total external financing (TEF).

create synthetic variance swaps from options.[13] We then investigate whether the variance swap rate and the variance risk premium are related to the ESG scores. Because the variance swap rate is akin to *prices*, we analyze the *contemporaneous* relation between the ESG scores and variance swap rate in this analysis. The results are reported in Appendix Table A2. We find that the synthetic variance swap rate with the same maturities as the options in our sample (approximately 50 days) is higher for low-ESG stocks (Panel A), and the variance risk premium is also higher for low-ESG stocks (Panel B), indicating that investors are willing to pay a higher premium to hedge against the variance risks associated with low-ESG stocks. Although we acknowledge that there are approximation errors inherent in the procedure of synthesizing variance swaps from vanilla options (Carr, Lee, and Wu (2012)), the evidence using variance swaps nonetheless corroborates the evidence using delta-hedged options.

3.2 E, S, or G

In this subsection, we examine the effects of environmental (E-score), social (S-score), and corporate governance (G-score) performance on option pricing separately. This investigation allows us to understand whether some components of ESG are relatively more important for option pricing. We repeat the portfolio sort analyzes similarly to those in Table 2, using the E-score, the S-score, and the G-score as the sorting variables separately. Table 3 shows the results for the daily rebalanced delta-hedged option gains for the call and put options

[13] We choose a horizon that is the same as the maturity of options (approximately 50 days) for the synthetic variance swap rates. Specifically, at the end of each month for each stock, we choose the two nearest maturities T_1 and T_2 (except when the shortest maturity is within eight days). Then, at each maturity, we first linearly interpolate the implied volatilities at different moneyness levels to obtain a fine grid of implied volatilities. For moneyness below the lowest (highest) available moneyness level in the market, we use the implied volatility at the lowest (highest) strike price. Using this interpolation and extrapolation procedure, we generate a fine grid of 2,000 implied volatility points with a strike range of ± 8 standard deviations from the current spot price. Given the fine grid of implied volatilities, we compute the OTM call option prices using the Black-Scholes formula and replicate the variance swap rate according to the following equation:

$$SW_{t,T_1} = \frac{2}{T_1 - t} \sum_{K_n = S_t}^{K_n = K_{max}} \frac{C(K_n, T_1)}{e^{-r_f (T_1 - t)} (K_n)^2} (K_{n+1} - K_n),$$

for maturity T_1 and similarly for maturity T_2. Then we interpolate the synthetic variance swap rates at the two maturities to obtain the variance swap rate at a fixed horizon that is the same as the maturity of options:

$$SW_{t,T} = \frac{1}{T - t} \frac{SW_{t,T_1}(T_1 - t) + SW_{t,T_2}(T_2 - t)}{T - T_1},$$

where T_1 and T_2 denote the two maturity dates and T denotes the interpolated maturity date such that $T - t$ is the maturity of options. The variance risk premium is defined as the difference between the variance swap rate and the ex-post realized variance.

together.[14] When sorting on the E-score, Panel A shows that the H−L portfolio alpha is 0.12% (0.10%) based on the 6-factor (7-factor) model, which is significant at the 5% level. The H−L spread for the S-score has a larger magnitude than that for the E-score, with a 6-factor (7-factor) alpha of 0.20% (0.16%), which is significant at the 1% level. The average return of H−L drops to 0.10% for the G-score and becomes insignificant when we use the 6-factor and 7-factor models. Comparisons of the three scores show that the E-score and S-score are stronger determinants of option returns than the G-score. Taken together, the results in Table 3 show that option pricing depends on all three kinds of risks. Although environmental (or climate) risks have drawn considerable attention in recent academic literature, social and governance performance as well as environmental performance are important drivers of our results.

The results also suggest that ESG risks are likely to be systematic, especially environmental and social risks. There are different potential sources of systematic ESG risks. For example, pro-environmental regulations may subsidize high-ESG products or handicap low-ESG products, leading to a greater difference in customer demand between high-ESG firms and low-ESG firms. The impact of regulation shocks on individual firms depends on their ESG risk exposure, which is proxied by ESG performance. It could also come from social movements, which may change public awareness and investors' perceptions. For example, #MeToo is a social movement against sexual abuse and sexual harassment.[15] After #MeToo, firms performing badly on workplace harassment were exposed to significant monetary penalties and reputational harm. This shock affects the whole market systematically, while the impact depends on the firm's ESG risk exposure (i.e., performance on workplace harassment). At the same time, it is possible that some ESG risks are idiosyncratic. This is most likely the case with governance risks. We do find that the risk premium associated with the G-score is smaller and less significant.

3.3 Sources of risk premia

Delta-hedged option returns and straddle returns embed various kinds of risk premia, such as volatility risk and tail risk premia. Many studies document a non-zero volatility risk premium (see, e.g., Buraschi and Jackwerth (2001) and Coval and Shumway (2001)). Bakshi and Kapadia (2003) show that priced volatility risk is an important source of underperformance of delta-hedged portfolios. Similarly, option prices reflect the risk of potential unforeseen tail

[14] The results are similar when we use buy-and-hold delta-hedged option returns or zero-beta straddle returns.

[15] #MeToo began to spread rapidly as a hashtag on October 15, 2017, after actress Alyssa Milano asked followers on Twitter to share their stories of sexual harassment and assault using the hashtag #MeToo.

events (Bakshi and Kapadia (2003) and Jackwerth and Rubinstein (1996)). Accordingly, in this subsection, we investigate whether the positive relationship between ESG and the delta-hedged option return is driven by exposure to these various kinds of risks.

A delta-hedged option position is essentially a volatility position whose payoff is based on the volatility of the underlying stock (similar to, albeit not exactly the same as, a variance swap, as noted in Section 3.1). Since the seminal study of Bakshi and Kapadia (2003), variance risk premia have been known to be negative—an increase in volatility is typically regarded as corresponding to bad states. If an increase in the volatility of low-ESG firms corresponds to an increase in aggregate volatility, then these positions pay off when the world is in a bad state, and investors are willing to pay for this insurance. We find evidence consistent with this. Specifically, we calculate the volatility betas of firms by regressing the physical volatility of stocks (or changes in volatility) against aggregate volatility (or its changes), where volatility is calculated as the standard deviation of daily returns over the past month, and we use the past year to estimate the betas. In unreported results, we find that the volatility betas of low-ESG firms are higher than those of high-ESG firms (the difference is statistically significant). This rationalizes the insurance premia in options on low-ESG firms.

To further directly test whether risk premia associated with volatility and jump risks are related to ESG scores, we use tradable portfolios. We follow Cremers, Halling, and Weinbaum (2015) and use two beta-neutral straddles with different maturities to construct a jump risk portfolio and a volatility risk portfolio. In particular, the jump risk portfolio is a beta-neutral, vega-neutral, and gamma-positive strategy consisting of (i) a long position in one beta-neutral ATM straddle with maturity T_1 and (ii) a short position in y market-neutral ATM straddles with maturity T_2, where $T_2 > T_1$ and y is chosen to make the overall portfolio vega-neutral. Similarly, the volatility risk portfolio is a market-neutral, gamma-neutral, and vega-positive strategy consisting of (i) a long position in one market-neutral ATM straddle with maturity T_2, and (ii) a short position in y market-neutral ATM straddles with maturity T_1, where $T_2 > T_1$ and y is chosen to make the gamma of the overall strategy zero. Considering option liquidity, we choose T_2 to be 80 days and T_1 to be 50 days. The rest of the procedure is the same as described in Section 3.1, and we hold these portfolios for 50 days without additional rebalancing. Higher portfolio returns indicate lower exposure to volatility risk or jump risk.

We use these two straddle returns as dependent variables in the portfolio sort analysis, similar to those in Table 2. The results are reported in Table 4. Somewhat surprisingly, we find weaker evidence for the pricing of volatility risks, as the H$-$L spread returns or alphas are not significantly different from zero for straddle portfolios exposed to only volatility risk (gamma-neutral and vega-positive) in Panel A. In contrast, the H−L spread returns and alphas are large in economic magnitude and highly statistically significant for straddle portfolios exposed to only jump risks in Panel B (gamma-positive and vega-neutral). The H−L jump straddle portfolio is 3.26% using the 7-factor alpha, which is even higher than the corresponding number of 2.97% for the beta-neutral straddle spread return in Panel C of Table 2.

Overall, this subsection shows strong evidence that options with higher ESG scores have lower jump risks, while the evidence for volatility risk is much weaker. We return to this issue in Section 4.5 to further understand the pricing of different risks.

3.4 The effect of public awareness: Time-series variation

The perceived uncertainty of low-ESG stocks is expected to be more important when public awareness of ESG issues is high. We corroborate our baseline results by further examining the role of public awareness of/attention to ESG, which is proxied by three measures: the Google search volume index (SVI), the announcement of the Paris Agreement, and aggregate ESG news in the market. We first construct the H−L portfolio based on the ESG score each month and then investigate how the H−L return spread changes with time series variation in public awareness/attention to ESG. Specifically, we run the following regression for different proxies of ESG public awareness/attention:

$$R_{t+1} = \alpha_0 + \alpha_1 D_t + \beta' F_{t+1} + \varepsilon_{t+1}, \tag{6}$$

where D_t is an indicator variable indicating the period of high-ESG public awareness/attention. Our variable of interest is α_1, which captures the average return/alpha differences between high-awareness and low-awareness periods. For the first proxy, Google SVI, we divide our sample into two sub-periods based on the logarithm of monthly change in the Google SVI (DGSVI) of "Environmental, Social and Corporate Governance." Periods with higher values are indicated as high-awareness periods.[16] For the second proxy, the Paris Agreement, we focus on the window around the announcement of the Paris Agreement (July 2014 to December 2018), and designate the period from January 2016 to June 2017 as the high-ESG-awareness period.[17] We use the number of aggregate ESG news stories in the market as the

[16]We find similar results when using other topics such as "Global Warming" and "Socially Responsible Investing."

[17]On December 12, 2015, the Paris Agreement was announced at the 21st Conference of the Parties (or COP21) to the United Nations Framework Convention on Climate Change (UNFCCC) in Paris. The Paris Agreement is broadly considered to be a landmark step for global climate change mitigation and adaptation action, and more importantly, it came as a surprise. For the first time, most UN countries agreed on the need

last proxy for ESG awareness. Each month, we count the number of ESG news stories from RepRisk scaled by the total number of news stories in the market from RavenPack to get the relative amount of ESG news. Then, we divide our sample into two sub-periods based on the relative amount of ESG news, and the periods with higher values are identified as high-awareness periods.

Our null hypothesis is that when, for example, Google SVI is high in month t, which may be due to a political summit on environmental issues or social events related to equality, investors pay more attention to ESG risks and pay a higher price to hedge against these uncertainties. This makes options on low-ESG stocks more expensive at the end of month t, leading to a larger alpha of the H−L spread over the approximately 50 days following the end of month t.

We report the results for the Google SVI, the announcement of the Paris Agreement, and the aggregated ESG news in Panels A, B, and C, respectively, of Table 5. We find that the H−L return spread is more prominent when public ESG awareness/attention is higher. In Panel A, the H−L 7-factor alpha is 0.10% (t-statistic = 1.73) during the low-awareness period, while the H−L 7-factor alpha is 0.28% during the high-awareness period, and the difference between the two sub-periods is 0.18% (significant at the 5% level). Panel B shows that during the Paris Agreement period, the ESG premium is significantly higher than in the periods before the announcement of the Paris Agreement and after the US withdrawal. Panel C demonstrates similar patterns. We conclude that given higher awareness of ESG risks, investors are willing to pay a higher ESG premium.[18]

3.5 Quantity of risk versus price of risk

The risk premium is the product of the quantity of risk and the market price of risk. To investigate which of these two terms accounts for the higher premiums associated with options with low-ESG scores during the high-awareness period, we test whether the risk of rising volatility and jump intensity are higher for low-ESG stocks. To measure the risk of

to limit global temperature increase "well below 2°C" above pre-industrial levels (Art 2.1(a)) to strengthen countries' ability to deal with the impacts of climate change (Art 2.1(b)) and to commit to "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" (Art 2.1(c)). Another related event is the announcement of the withdrawal of the United States from the Paris Agreement. On June 1, 2017, President Donald Trump announced that the US would cease all participation in the 2015 Paris Agreement on climate change mitigation. Therefore, we designate the period from January 2016 to June 2017 as the high-ESG-awareness period.

[18] We also investigate the time-series variation of delta-hedged option returns separately for portfolios with the lowest and highest ESG scores. We find that α_1 is more significant and negative for options with the lowest ESG score than for options with the highest ESG score, which indicates that ESG awareness has a stronger impact on options with the lowest ESG performance.

increasing volatility, we follow Cao, Vasquez, Xiao, and Zhan (2023) and rely on intra-day trading data to calculate the volatility of volatility increases (VOV+), which is the standard deviation of the positive (percentage) change in volatility over option maturity, which is approximately 50 days.[19] Following Bollerslev, Li, and Zhao (2020), we proxy jump intensity by the relative signed jump (RSJ), which is the difference between the negative and positive realized semi-variance over the option maturity, scaled by the sum of the positive and negative realized semi-variance.[20]

We then define the risk spread as the VOV+ or the RSJ difference between the portfolio with the highest ESG score and the portfolio with the lowest ESG score, and we run the following regression to investigate how the risk spread varies with ESG attention:

$$Risk\ spread_{t+1} = \alpha_0 + \alpha_1 D_t + \varepsilon_{t+1}, \tag{7}$$

where D_t is defined the same way as in equation (6). The coefficient α_0 measures whether the quantity of risk is different between low- and high-ESG stocks on average. The coefficient α_1 measures how the quantity of risk varies with ESG-related events.

Table 6 shows that α_0 is generally negative (and statistically significant in almost all specifications), showing that low-ESG stocks have a higher jump intensity and a higher risk of increasing volatility. The fact that low-ESG stocks are "riskier" (insofar as risk is measured by VOV+ and RSJ) is consistent with the quantity of risk driving the higher risk premium on options on low-ESG stocks. However, this evidence is unconditional and does not rule out that the price of risk also varies systematically with ESG awareness.

We find that the coefficient α_1 in Table 6 is statistically insignificant in all our specifications. Thus, the quantity of risk does not vary with ESG-related events. Since Table 5 shows that the risk premium is higher in these periods, we conclude that the increase in the ESG premium during these periods comes from the increase in the market price of risks. For example, when Google SVI on ESG topics increases, investors pay more attention to ESG

[19]We use the historical tick-by-tick quote data from the TAQ database to record prices every five minutes starting at 9:30 EST and construct 5-minute log-returns for a total of 78 daily returns. We use the last recorded price within each 5-minute period to calculate the log return. To ensure sufficient liquidity, we require that a stock has at least 80 daily transactions to construct a daily measure of realized volatility. Then, we calculate the daily percentage change in volatility. We define the monthly VOV+ (positive VOV) measure as the standard deviation of the positive percentage change of volatility within each month.

[20]This measure is based on 5-minute intraday transaction prices and is defined as:

$$RSJ_{it} = \frac{\sum_{k=1}^{n}[r^2_{t-1+k/n} I(r_{t-1+k/n} < 0) - r^2_{t-1+k/n} I(r_{t-1+k/n} > 0)]}{\sum_{k=1}^{n}[r^2_{t-1+k/n} I(r_{t-1+k/n} > 0) + r^2_{t-1+k/n} I(r_{t-1+k/n} < 0)]}.$$

issues, and the market price of ESG risks increases while the difference in the quantity of risks between low- and high-ESG stocks does not change.

In summary, we find that both the quantity of risks and the market price of risks matter for the return spreads that we document.

4 ESG performance and delta-hedged option returns: Regression evidence

4.1 Baseline results

To better control for the confounding effects of other firm characteristics and option characteristics, we next study the effect of ESG performance on the cross-section of delta-hedged option returns using monthly FM regressions. The dependent variable is the daily rebalanced delta-hedged option gain until maturity as described in Section 2.2.

We tabulate the results in Table 7 for call options, put options, and call and put options together. In columns (1), (3), and (5), the control variables are market capitalization, book-to-market ratio, reversal, momentum, idiosyncratic volatility, and stock illiquidity. We also include two option-related variables as controls. Option open interest (OPTION IO) is the total number of option contracts that are open at the end of the previous month scaled by the stock trading volume of the previous month. The option bid-ask spread (OPTION BA) is the ratio of the difference between the bid and ask quotes of options to the midpoint of the bid and ask quotes at the end of the previous month. For call options, the coefficient on ESG is 0.238 (t-statistic = 3.05). This coefficient shows that delta-hedged call returns increase by 0.109% each month from the lower quartile of the ESG score (0.40) to the upper quartile of the ESG score (0.86). Given that the mean of delta-hedged call returns is −0.21%, the economic significance of ESG on option returns is substantial. Columns (3) and (4) report the results for put options, and columns (5) and (6) report the results for call and put options together. These results are largely similar to those for calls. In addition, we control for different types of risk measures, including lagged model-free option implied variance, skewness, and kurtosis in our baseline FM regressions, to examine whether these risks could explain the positive relationship between delta-hedged option returns and ESG scores. We find that the ESG score is still significant in explaining delta-hedged call option returns even when we control for volatility and jump risks. The coefficient estimate merely changes for delta-hedged option returns after the inclusion of lagged risk measures. These results indicate that investors perceive that stocks with lower ESG scores have higher risks beyond those stock characteristics, option characteristics, and risk proxies.[21]

Finally, to disentangle the effect of climate risks from broader ESG risks, we run FM regressions of delta-hedged option returns on both ESG performance and carbon intensity. Carbon intensity is the Scope 1 carbon emissions obtained from Trucost scaled by the market value of the firm.[22] We report the results of regressions controlling for the carbon emission score in Appendix Table A3. Consistent with higher tail risks documented by Ilhan, Sautner, and Vilkov (2021), we find that firms with the more carbon-intensive business model have more negative delta-hedged option returns. However, when we control for carbon intensity, the ESG score still plays an important role. This evidence indicates that our results are not purely driven by the carbon emission intensity of the firm but also depend on other aspects of the ESG score.

4.2 Possible endogeneity

ESG scores are likely to be correlated with other characteristics of the firm, which may also be important for option returns. Alternatively, firms may learn from option prices and adjust their ESG performance accordingly. To mitigate these endogeneity concerns, we use RepRisk, a news-based data provider, to identify sudden increases in ESG risk and investigate how the options market reacts to those shocks. RepRisk uses RepRisk Index (RRI) to estimate ESG risk. RepRisk screens over 90,000 public sources daily, including print and online media, government bodies, regulators, and other online sources. When there are material ESG risks, such as violations of international standards that can have reputational, compliance, and financial impacts on the company, RRI increases. We use the RRI trend, which is the difference in RRI between the current date and the 30 days before, to identify sudden increases in firms' ESG risk.[23]

Identification based on changes in RRI is not perfect because large jumps in RRI are due to severe ESG-related incidents, which are endogenous outcomes of firms' operations and strategies. Nevertheless, the exact timing of such ESG risk incidents cannot be predicted.

[21] According to Thomson Reuters Refinitiv, the Asset4 ESG scores "are based on the relative performance of ESG factors with the company's sector (for E and S) and country of incorporation (for G)." See https://www.refinitiv.com/en/sustainable-finance/esg-scores#methodology. Our results hold with little change in significance and magnitude if we control for industry fixed effects in the FM regressions.

[22] The results are not materially different when we scale raw carbon emissions using revenue or include Scope 2 carbon emissions.

[23] We use a cutoff of 16 to identify events with large increases in RRI. The results become stronger (weaker) if we use a relatively higher (lower) cutoff. We also use cutoffs of 12 and 20 to identify events with sudden increases in ESG risk. These results are qualitatively similar to those presented in this sub-section.

We use such exogenous variations over time as quasi-natural experiments and rely on multiple shocks to firms' ESG risk to alleviate omitted variable concerns. In particular, for each treated stock (for which RRI increases), we identify control stocks via propensity score matching according to size, book-to-market ratio, reversal, momentum, and idiosyncratic volatility. We expect that the options of treated firms that experience a sudden increase in ESG risk will become more expensive (as indicated by a drop in the delta-hedged option return) compared with those of matched control firms after the events. The main specification of the DiD test is as follows:

$$R_{it+1} = \alpha + \beta_1 TREATED_{it} \times POST_{it} + \beta_2 TREATED_{it} + \beta_3 POST_{it} + \beta_4 X_{it} + \gamma_t + \theta_i + e_{it+1}, \tag{8}$$

where R_{it+1} is the delta-hedged option return, $TREATED$ is an indicator variable that equals one for treated stocks and zero for control firms, and X is the same control variables as in Table 7. The event window is from five months before the event to six months after the event. $POST$ is an indicator variable that is equal to one after the events and zero otherwise. Because we have limited events each month, we rely on panel regressions instead of FM regressions. We add firm and time fixed effects and cluster standard errors by firm.

Table 8 shows the results. Column (1) shows that after a sudden increase in ESG risk, the call option returns of treated firms drop by 0. 295% compared to those of the control group. The results are very similar for put options in column (3) and call and put options combined in column (5).

To validate the robustness of our DiD matching model, we present evidence of parallel trends in columns (2), (4), and (6), corresponding to call options, put options, and a combined analysis of call and put options, respectively. Specifically, we construct a series of relative-time indicators for the months leading up to the sudden increase in ESG risks: EVENT represents the event month, while PRE1 and PRE2 denote one and two months before the event, respectively. Observations from three months prior to the event serve as the benchmark. The results indicate no significant pre-trend before the event, further supporting the exogeneity of the shocks.

We plot the point estimates and their 90% confidence intervals for the coefficients in Figure 1. This figure shows that the coefficient estimates for the relative-time indicators prior to the sudden increase in ESG risks are not statistically significant at the 10% level. This finding further confirms that our DiD matching model satisfies the parallel trends assumption.

To the extent that our propensity matching provides adequate control firms, our DiD analysis suggests that the relation between returns and ESG scores is not confounded by omitted variables. However, we acknowledge that we do not have a cleaner exogenous shock to rule out all sources of endogeneity. Therefore, we take the evidence from this subsection only as suggestive causal evidence.

4.3 Alternative ESG data providers

Given the complexity of measuring ESG information, the ESG ratings of different providers can differ substantially. The validity of these ratings has been debated critically (Eccles and Stroehle (2020), Christensen, Serafeim, and Sikochi (2022), Gibson, Krueger, and Schmidt (2021), Berg, Koelbel, Pavlova, and Rigobon (2024), and Berg, Koelbel, and Rigobon (2022)). For example, Berg, Koelbel, and Rigobon (2022) find that the correlation between the ESG ratings of six rating providers is quite weak. They decompose the divergence into contributions of scope, measurement, and weights, where measurement contributes most of the divergence. Their results indicate that research conclusions (including ours) are potentially dependent on the choice of rating providers.

In this subsection, we perform three robustness tests to mitigate the concern that our empirical results are only significant based on the ESG data from a particular provider. We use ESG data from four alternative ESG rating providers: KLD, MSCI, Sustainalytics, and RepRisk. (1) KLD scores measure firm-level social performance, including community relations, product characteristics, environmental impact, employee relations, workforce diversity, and corporate governance, which covers both the social benefits and harms of a firm.[24] (2) MSCI ESG rating identifies both ESG risks and opportunities that are most material to an industry. Within each industry, MSCI identifies industry leaders and laggards according to their exposure to ESG risks and how well they manage those risks relative to their peers, and then assigns ratings accordingly. (3) Sustainalytics identifies key ESG issues for different industry peer groups based on an analysis of the peer group and its broader value chain, a review of companies' business models, and key activities associated with environmental and/or social impacts. It collects data via corporate disclosure, media, and NGO reporting to analyze ESG information according to key ESG issues and assigns scores accordingly. (4) RepRisk is a news-based data provider. It screens over 90,000 public sources each day, including print and online media, government bodies, regulators, and other online sources. When there are material ESG risks, such as violations of international standards that can

[24]KLD, formerly known as Kinder, Lydenberg, Domini and Co., was acquired by RiskMetrics in 2009. MSCI bought RiskMetrics in 2010. The data set was subsequently renamed MSCI KLD Stats as a legacy database. We keep the original name of the data set to distinguish it from the MSCI data set.

have reputational, compliance, and financial impacts on the company, the RepRisk index increases.

All ratings are organized such that the higher the scores, the better the ESG performance (we invert the signs of the RepRisk scores, which are designed to measure risks). We include KLD because it is the data set that has been used most frequently in academic studies. We include RepRisk because it relies mainly on news and media reporting, which has markedly different information compared with other raters that rely on a blend of data sources (Berg, Koelbel, Pavlova, and Rigobon (2024)). ASSET4, MSCI, and Sustainalytics are widely recognized and used by sustainable finance professionals.[25]

We first repeat our baseline FM regression for call and put options together using four alternative ESG data sets. The results are reported in columns (1) to (4) of Table 9 for call and put options together. To save space, we only report the results with all the controls used in Table 7. We find that the coefficient on the ESG score is significant for the four alternative ESG data sets. Options with higher KLD scores, MSCI scores, Sustainalytics scores, and RepRisk scores have higher delta-hedged option returns. These results demonstrate that our results are not overly dependent on the choice of ESG rating providers.

An ESG score from a single rater has limited information and might be noisy. Therefore, our second robustness test is to construct a combined ESG score using a simple average of available ESG scores for a particular stock. Specifically, for each ESG data provider, we sort all of the stocks into deciles according to that ESG score and assign the rank to each stock. Then, we define the combined ESG score as the average of the rankings, requiring there to be at least three ESG ratings available for a particular stock. This approach aggregates ESG information from different data providers while maintaining a reasonably large sample. Using this combined ESG score, we show the results in column (5) of Table 9. Options with higher combined ESG scores have significantly higher delta-hedged option returns.

Following Berg, Koelbel, Pavlova, and Rigobon (2024), we use a noise-correction procedure as our third robustness test, in which we instrument ASSET4 ESG scores with ratings from other ESG rating agencies, as in the classical errors-in-variables problem. Specifically, we use two-stage least squares regression to tackle the measurement error problem in ESG scores. The first-stage regression uses the ESG scores of the four alternative data providers as instruments for the ASSET4 ESG score and includes the same controls as in Table 7:

$$ASSET4_{it} = \alpha + \beta_1 KLD_{it} + \beta_2 MSCI_{it} + \beta_3 Sus_{it} + \beta_4 RepRisk_{it} + \beta_4' X_{it} + e_{it}. \quad (9)$$

[25] These ESG data are featured in the 2019 and 2020 investor surveys "Rate the Raters by the SustainAbility Institute (see https://www.sustainability.com/globalassets/sustainability.com/thinking/pdfs/sustainability-ratetheraters2020-report.pdf).

We run the above regression each month, where $ASSET4_{it}$ is the ASSET4 ESG score for stock i in period t. We denote $\widehat{ASSET4}_{it}$ be the fitted value from estimating equation (9). Then, we run the second-stage regression using the standard FM regression. Column (6) in Table 9 shows the results for the combined call and put options. After correction of the ASSET4 ESG score using other ESG data providers, our results are still significant for both call and put options.

Taken together, these results indicate that our findings are not purely driven by a particular ESG data provider and are robust to alternative ESG data sources, although they may be noisy and contain different ESG information.

4.4 Robustness tests

Our main results are based on ATM options. To explore the effect of ESG performance on options with different levels of moneyness, we define out-of-the-money (OTM) and in-the-money (ITM) options based on the absolute value of delta. Options with an absolute delta value ranging from 0.2 to 0.4, 0.4 to 0.6, and 0.6 to 0.8 are classified into the OTM, ATM, and ITM option groups, respectively. We restrict options to have the same maturity as in our main tests, about 50 days. Next, we calculate the average value of the delta-hedged returns for all of the options in these three categories. FM regressions of delta-hedged returns on ESG performance and other controls are reported in the Appendix Table A4.[26] The effect of ESG on option returns is significant across the three moneyness groups. We observe the largest economic magnitude for the coefficient of ESG performance on OTM option returns, which is consistent with the argument that ESG is relevant to downside risks because OTM options are usually used to hedge downside risks.

We focus on short-term options because they are traded more frequently and with lower effective transaction costs than long-term derivatives. Therefore, their prices adjust more quickly to changes in perceived uncertainty and risks (Cont and Tankov (2004) and Ilhan, Sautner, and Vilkov (2021)). To investigate how our results might be affected by the maturity options, we also examine the longer-term options that are relatively liquid as a robustness check. Specifically, we define options with maturity between 90 days and 180 days (180 days to 360 days) as medium-term (long-term) options. For each stock at the end of each month, we calculate the average delta-hedged option returns of all mid- and long-term options separately. To mitigate the impact of liquid long-term options, we remove options with bid-

[26]The FM regressions in Table A4 are at the stock level. Option open interest is the average of the total number of option contracts divided by the stock trading volume. We calculate the option level bid-ask spread as the ratio of the bid-ask spread of option quotes over the midpoint of the bid and ask quotes, and then we take the average of the option level bid-ask spread into the stock level.

ask spreads greater than 50%. We then explore the relationship between the delta-hedged option returns of the mid- and long-term options and ESG performance. In unreported results, we find that the ESG premium also exists in longer-term options with maturities between 90 days and 360 days that are relatively liquid.

We also perform a placebo test. ESG investing has become increasingly important for investors only in the last two decades. We posit that prior to 2004, ESG investing influenced only a relatively small part of the investment industry, and thus its impact on the options market should be much less significant. We conduct two tests of this conjecture. First, we backfill ASSET4 ESG data from 2004 to the period from 1996 to 2003, as ASSET4 ESG data are not available for the earlier sample period. We find that ESG does not have a significant impact on delta-hedged option gains in this earlier sample period. Second, we use the KLD data from 1996 to 2003 to repeat the placebo test, and we again find insignificant results. These results support our conjecture that the significant impact of ESG on option pricing in the 2004-2018 period is related to the growing (perceived) risks associated with ESG issues.

4.5 ESG performance and different risk measures

In this subsection, we provide further evidence on how ESG performance is related to different option-implied risks. Following Ilhan, Sautner, and Vilkov (2021), we use four measures of risks implied by option prices, including VRP, MFIS, MFIK, and SlopeD.

VRP is computed as the difference between the risk-neutral expected variance and the realized variance (Carr and Wu (2009) and Bollerslev, Tauchen, and Zhou (2009)). As a proxy for the risk-neutral expected variance, we use the model-free implied variance $MFIV_{t,t+\tau}$ computed on day t for the period τ. The realized variance ($RV_{t,t+\tau}$) is computed from daily log returns over a future window from t to $t+\tau$, that is, with a length corresponding to the period of the options used for the risk-neutral variance. Following Ilhan, Sautner, and Vilkov (2021) and Kelly, Pástor, and Veronesi (2016), the variance risk premium $VRP_{t,t+\tau}$ for period t to $t+\tau$ is computed in the ex-post version on each day t as $(MFIV_{t,t+\tau} - RV_{t,t+\tau})$ and expressed in annual terms. It captures the cost of protection against general uncertainty-related volatility changes in downward and upward directions. MFIS and MFIK are constructed following Bakshi, Kapadia, and Madan (2003) and quantify the asymmetry of the risk-neutral distribution and heaviness of the tail in the risk-neutral distribution, respectively. By being normalized, MFIS and MFIK provide information about the expensiveness of protection against left tail events and extreme events. We follow Kelly, Pástor, and Veronesi (2016) and Ilhan, Sautner, and Vilkov (2021) to calculate SlopeD. Specifically, SlopeD is the slope coefficient from regressing the implied volatilities of OTM puts (deltas between -0.5 and

-0.1) on the corresponding deltas and a constant. A greater positive value of SlopeD indicates that deeper OTM puts are relatively more expensive, suggesting a relatively higher cost of protection against downside tail risks.

We then investigate how ESG performance is related to these risks implied from the options market, and we report the results in the Appendix Table A5. VRP, MFIK, and SlopeD are negatively related to ESG performance, significant at the 1% level. The results indicate that the options of low-ESG firms have higher costs of protection against uncertainty-related volatility changes, jump risks, and downside tail risks. We do not find significant results for MFIS, which captures information about the expensiveness of protection against left-tail events relative to right-tail events. One possibility is that the options of low-ESG firms may also have upside jump opportunities (Cohen, Gurun, and Nguyen (2024)).

5 Additional cross-sectional results

Thus far, we have documented that the ESG scores of the underlying firms affect the cross-section of option returns and that there is a significant ESG premium in the options market. In this section, we further explore heterogeneity between firms and investigate the impact of ESG conditional on different industries, product competition intensity, investors' awareness, and corporate hedging activity. We focus on the sample that contains call and put options together.

5.1 Different business models

The proximity to end-consumers potentially influences the impacts of ESG on the firm and on investors' perceptions. The intuition is that private end consumers or individuals show more social concern in their consumption. End consumers could simply choose not to buy the products if the firm has poor ESG performance. Such firms therefore face greater uncertainty when their ESG performance is poorer. Baron, Harjoto, and Jo (2011) and Curcio and Wolf (1996) find that there is a stronger impact of social performance on firms' financial performance in industries serving end consumers than in other industries. Lev, Petrovits, and Radhakrishnan (2010) also find that charitable contributions lead to significant sales growth only in consumer industries.

Following these studies, we hypothesize that the impact of ESG scores on delta-hedged option returns is stronger for firms that are closer to end consumers. To test this hypothesis, we follow Lev, Petrovits, and Radhakrishnan (2010) in using four-digit SIC industry codes and classifying our sample firms into two groups based on their proximity to end consumers. We provide details of the classification in the Appendix Variable Definitions. We then test whether the effect of social performance on option returns differs between these two groups via FM regressions of delta-hedged option returns.

Panel A of Table 10 reports the regression results. CONSUMER is an indicator variable that equals one if a firm is in industries classified as closer to end consumers, and zero otherwise. Our focus is on the interaction term CONSUMER×(ESG score), which captures the incremental impact of ESG performance on option returns for firms that are closer to consumers. We include the same control variables as those in Table 7 (column (6)) but do not report them in Table 10 to avoid clutter. The estimated coefficient on the interaction term is positive and statistically significant at the 1% level. Our results indicate that among firms that are closer to end consumers, the social performance of the firm has a larger impact on the cross-section of option returns in the sense that options on low-ESG firms, which are closer to end consumers, are relatively more expensive than options on high-ESG firms, which are farther from end consumers.

In addition to proximity to end-consumers, product/service differentiation can also influence our documented relationship between ESG scores and option returns. ESG performance is one strategy for firms to differentiate themselves from their competitors (McWilliams and Siegel (2001), Chih, Chih, and Chen (2010)), and Cao, Liang, and Zhan (2019)). By investing in corporate social goods and differentiating itself from others, a firm can benefit from higher profit margins and lower risk (Albuquerque, Koskinen, and Zhang (2019)). Such benefits are particularly important for firms operating in competitive industries, as they are more vulnerable to potential risks in the future than firms in concentrated industries. We therefore conjecture that when firms face more severe product competition, social performance will have a greater impact on perceived uncertainty and on option pricing.

We use product market fluidity (Hoberg, Phillips, and Prabhala (2014)) as a proxy for product market competition. This measure assesses the degree of competitive threat and product market change surrounding a firm using computational linguistics and analyzing individual firm business descriptions from 10-Ks. A higher FLUIDITY measure indicates more intense competition from peers offering similar products. Table 10 Panel A, column (2) reports the results of the FM regressions for delta-hedged returns. The coefficient of interest is the interaction term FLUIDITY×(ESG score). We find that this coefficient is positive and statistically significant at the 5% level. Consistent with the product market competition and product differentiation argument, we find that the impact of ESG performance on option pricing is stronger for firms facing heightened competition. In summary, the results in Panel

A of Table 10 indicate that the influence of ESG performance on perceived uncertainty and option pricing depends on the nature of a firm's business and its competitive landscape.

5.2 Cross-sectional variation in ESG attention

Evidence suggests that Democratic-leaning voters care more about CSR than Republican-leaning voters. For example, Di Giuli and Kostovetsky (2014) find that firms headquartered in Democratic-leaning states are more likely to spend resources on CSR. Gromet, Kunreuther, and Larrick (2013) demonstrate that more politically conservative individuals are less in favor of investment in energy-efficient technology than those who are more politically liberal (see also Costa and Kahn (2013)). When the electorate is more Democratic, companies may be more susceptible to pressure from activists to adopt CSR policies (Baron (2001)). We use the political affiliation of the state where the company is headquartered as a proxy for ESG attention.

Specifically, we divide all states into two groups based on whether the Democratic candidates won the state in the most recent presidential election. We then construct an indicator variable BLUE that equals one for the firms headquartered in these states if voters predominantly chose the Democratic candidate (referred to as "blue states") and zero for firms headquartered in other states. We include BLUE and the interaction term BLUE×(ESG Score) in FM regressions to investigate whether the effect of the ESG score on option pricing differs across firms that are subject to different levels of ESG awareness due to the political leanings of different states. Panel B of Table 10, column (1) shows the results. As expected, we find that the interaction term is positive and statistically significant at the 5% level for calls. This evidence suggests that when firms are headquartered in Democratic-leaning states, their option pricing is more influenced by their ESG performance than those in Republican-leaning states.

Our second proxy for firm-level variation in ESG attention is proposed by Hassan, Hollander, van Lent, and Tahoun (2019).[27] They textually analyze quarterly earnings conference calls and measure the portion of content devoted to environment-related political topics as CONFENV. Some firms with poor ESG performance may attract more attention from investors during conference calls, and one may think of this as an alternative measure of ESG performance. However, firms with good ESG performance may also draw more attention if there is ESG-related news. Empirically, we find that the correlation between CONFENV and ESG score is only -0.02. We run FM regressions of the delta-hedged option return on

[27] See also Sautner, van Lent, Vilkov, and Zhang (2023) for an alternative measure using a machine learning keyword discovery algorithm. Our results are robust to using their measure.

CONFENV and its interaction with the ESG score. Panel B of Table 10, column (2) shows that the coefficients on the interaction term are positive and statistically significant. These results suggest that when investors and firms discuss ESG-related topics more during conference calls, the effect of ESG performance on option pricing becomes stronger, as investors pay more attention to these issues and are willing to pay a higher premium to hedge against heightened perceived uncertainties.

5.3 Corporate hedging activities

Next, we examine whether corporate hedging policy reduces the effect of ESG performance on option pricing. Firms can actively manage risks related to various dimensions, such as interest rates, foreign exchange, and operations. Risks from poor ESG performance may mainly be related to firm operations, such as potential lawsuits and loss of revenue. Specific hedging policies for such risks are not readily available. However, one can infer a firm's ability to manage ESG risk from other hedging policies. For example, if a firm is concerned about financial risk and hedges such risk using derivatives, we conjecture that such a firm is more likely to manage ESG risks as well. We test this hypothesis by dividing firms into two groups based on whether they have nonzero hedge gains/losses according to income statement data from COMPUSTAT. We define an indicator variable, HEDGER, that equals one for firms with nonzero gains/losses from hedging, and zero otherwise.[28] We run FM regressions of the delta-hedged option return on HEDGER and its interaction with the ESG score. Panel C of Table 10 reports the results for calls and puts together. We find that the coefficients on HEDGER are positive. This suggests that these firms have relatively lower risk and their options are relatively cheaper. The coefficient of interest is again that on the interaction term. We find that it is negative and statistically significant. These results indicate that among firms with hedging activities, the effect of the ESG score on option pricing is weaker, consistent with the argument that these firms may actively manage ESG risk.

6 Conclusion

With increasing awareness of ESG issues in recent years, firms with poor ESG performance face higher uncertainty from different perspectives, such as when and how ESG-related regulatory policies will be implemented, investors' divestment policies, and fluctuations in rev-

[28]Firms with a hedging policy do not necessarily have gains or losses in their current income statement. Therefore, the information from the income statement is an under-identification of corporate hedging activities.

enues. Are such uncertainties and risks perceived by investors and priced in the options market?

Our analysis suggests that ESG-related uncertainty is priced in the options market and that option prices reflect the market consensus on this uncertainty. Via quintile portfolio sorts, we find the magnitude of the ESG premium to be about 0.2% over 50 days. These results are robust to alternative ESG data providers and methods of constructing option returns. All components of ESG contribute to option expensiveness. We find that this premium mainly derives from jump risks. The ESG risk premium in the options market increases when public attention to ESG issues increases. However, there is substantial heterogeneity between firms in multiple dimensions, such as proximity to end consumers, product market competition intensity, investors' awareness, and corporate hedging activities.

Appendix A: Variable Definitions

Option Variables	
Daily rebalanced delta-hedged option gain until maturity	The daily rebalanced delta-hedged option gain is the change (until option maturity) in the value of a portfolio consisting of one contract of a long option position and delta shares of the underlying stock, re-hedged daily. The call option delta-hedged gain is scaled by $\Delta_c S - C$, where Δ_c is the Black-Scholes option delta, S is the underlying stock price, and C is the price of the call option. The put option delta-hedged return is defined analogously except that we scale it by $P - \Delta_p S$.
Daily compounded delta-hedged option return until maturity	For each stock at the end of each month, we buy one contract of the call/put option against a long position of Δ shares of the underlying stock, where Δ is the Black–Scholes call/put option delta. We adjust the hedge position at the end of each day to make it delta-neutral and calculate the portfolio return for each day t according to equation (1). Then, we calculate the daily compounded delta-hedged option return until maturity by accumulating the daily return.
Beta-neutral straddle return	For each stock at the end of each month, following Coval and Shumway (2001), we select θ units of call options and $1 - \theta$ units of put options that are approximately ATM and have a maturity of around one month and a half (50 days). θ is determined to make the straddle beta-neutral. The position is held for one month to compute the buy-and-hold return.
Variance swap rate	We follow Carr and Wu (2009) to create synthetic variance swaps from options. Specifically, at the end of each month for each stock, we choose the two nearest maturities. For each maturity, we linearly interpolate the implied volatilities at different moneyness levels to obtain a fine grid of implied volatilities. We compute the out-of-the-money call option prices using the Black-Scholes formula and replicate the variance swap rate using a series of option prices. Then we interpolate the synthetic variance swap rates at the two maturities to obtain the variance swap rate at a fixed 30-day horizon.
Gamma-positive vega-neutral straddle return	For each stock at the end of the previous month, we take a long position in one beta-neutral ATM straddle with a maturity around one month and a half (50 days), and (ii) a short position in y beta-neutral at-the-money straddles with a maturity around two months and a half (80 days), and y is chosen to make the vega of the overall strategy zero.
Vega-positive gamma-neutral straddle return	For each stock at the end of the previous month, we take a long position in one beta-neutral ATM straddle with a maturity around two months and a half (80 days), and (ii) a short position in y beta-neutral at-the-money straddles with a maturity around one month and a half (50 days), and y is chosen to make the gamma of the overall strategy zero.
RSJ	The relative signed jump is the difference between the negative and positive realized semi-variance scaled by the sum of the positive and negative realized semi-variance (Bollerslev, Li, and Zhao (2020)).

VOV+	We follow Cao, Vasquez, Xiao, and Zhan (2023) to calculate the volatility of volatility increases as the standard deviation of the positive (percentage) change of volatility over a month. We use the historical tick-by-tick quote data from the TAQ database to record prices every five minutes starting at 9:30 EST and construct 5-minute log returns for a total of 78 daily returns. We use the last recorded price within each 5-minute period to calculate the log return. Then, we calculate the daily percentage change in volatility (volatility-return). We define the monthly VOV+ (positive VOV) measure as the standard deviation of the positive percentage change of volatility within each month.
IMPVAR / IMPSKEW / IMPKURT:	Following Bakshi, Kapadia, and Madan (2003), the model-free implied risk-neutral variance/skewness/kurtosis is calculated for options with expiration of 50 days at the end of each month, using the implied volatility of 30 days and 60 days from the Volatility Surface to perform the linear interpolation.
OPTION OI	The total number of option contracts that are open at the end of the previous month scaled by the stock trading volume of last month.
OPTION BA	The ratio of the difference between the bid and ask quotes of the option to the midpoint of the bid and ask quotes at the end of the previous month.
ESG Performance Measure	
ESG score	The ESG score is from the ASSET4 database and is based on 250+ key performance indicators (KPIs) and 750+ individual data points from three pillars (E, S, and G). The ESG score ranges between 0 and 1 after scaling by 100.
RRI trend	Difference in the RepRisk Index (RRI) between the current date and 30 days prior. The RepRisk data vendor recommends monitoring the development of the risk exposure of a company related to ESG issues or as an indicator of when a risk incident has appeared for a company.
Stock Characteristics	
Ln(ME)	The natural logarithm of the market value of the firm's equity at the end of the previous year.
Ln(BM)	The natural logarithm of book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).
RET212	The cumulative stock return from the prior second through twelfth months.
RET1	The stock return in the previous month.
Ln(AMIHUD)	The logarithm of the Amihud (2002) stock illiquidity measure of the previous month.
INSTOWN	The percentage of common stocks owned by institutions in the previous quarter.
ANLST	The number of analysts following the firm in the previous month.

IVOL	The standard deviation of the regression residual of individual stock returns on the Fama and French (1993) three factors using daily data in the previous month, as in Ang, Hodrick, Xing, and Zhang (2006).
BETA	Market beta of rolling 60-month FF-3 monthly return regressions.
CONSUMER	Indicator variable for stocks in the industry that are close to end consumers. Industry classifications are based on Sharpe (1982). The following four-digit SIC codes are assigned to each group. (1) Basic industries: 1000-1299, 1400-1499, 2600-2699, 2800-2829, 2870-2899, 3300-3399; (2) Capital goods: 3400-3419, 3440-3599 excluding 3523, 3670-3699, 3800-3849, 5080-5089, 5100-5129, 7300-7399; (3) Construction: 1500-1599, 2400-2499, 3220-3299, 3430-3439, 5160-5219; (4) Consumer goods: 0000-0999, 2000-2399, 2500-2599, 2700-2799, 2830-2869, 3000-3219, 3420-3429, 3523, 3600-3669, 3700-3719, 3751, 3850-3879, 3880-3999, 4813, 4830-4899, 5000-5079, 5090-5099, 5130-5159, 5220-5999, 7000-7299, 7400-9999; (5) Energy: 1300-1399, 2900-2999; (6) Finance: 6000-6999; (7) Transportation: 3720-3799 excluding 3751, 4000-4799; (8) Utilities: 4800-4829 excluding 4813, 4900-4999; (9) Others: all other SIC codes. Finally, firms in the consumer goods and finance sectors are classified as closer to end consumers.
FLUIDITY	The degree of competitive threat and product market change surrounding a firm, based on Hoberg, Phillips, and Prabhala (2014).
BLUE	Indicator variable (referring to blue states) refers to states where voters predominantly choose the Democratic Party.
CONFENV	Share of the conversations in the quarterly earnings conference calls centering on risks associated with environment-related political topics, proposed by Hassan, Hollander, van Lent, and Tahoun (2019).
HEDGER	Indicator variable equal to one if the firm has a nonzero record of cash flow hedge gains/losses in COMPUSTAT, and zero otherwise.

References

Albuquerque, Rui, Yrjo Koskinen, and Chendi Zhang, 2019, Corporate social responsibility and firm risk: Theory and empirical evidence, *Management Science* 65, 4451–4469.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *Review of Financial Studies* 16, 527–566.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and differential pricing of individual equity options, *Review of Financial Studies* 16, 101–143.

Bali, Turan G., and Scott Murray, 2013, Does risk-neutral skewness predict the cross-section of equity option portfolio returns? *Journal of Financial and Quantitative Analysis* 48, 1145–1171.

Baron, David P., 2001, Private politics, corporate social responsibility and integrated strategy, *Journal of Economics and Management Strategy* 10, 7–45.

Baron, David P., Maretno Agus Harjoto, and Hoje Jo, 2011, The economics and politics of corporate social performance, *Business and Politics* 13, 1–46.

Bates, David S., 2005, Hedging the smirk, *Finance Research Letters* 2, 195–200.

Berg, Florian, Julian F. Koelbel, Anna Pavlova, and Roberto Rigobon, 2024, ESG confusion and stock returns: Tackling the problem of noise, Working Paper.

Berg, Florian, Julian F. Koelbel, and Roberto Rigobon, 2022, Aggregate confusion: The divergence of ESG ratings, *Review of Finance* 26, 1315–1344.

Bollerslev, Tim, Sophia Zhengzi Li, and Bingzhi Zhao, 2020, Good volatility, bad volatility, and the cross section of stock returns, *Journal of Financial and Quantitative Analysis* 55, 751–781.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463–4492.

Buraschi, Andrea, and Jens Jackwerth, 2001, The price of a smile: Hedging and spanning in option markets, *Review of Financial Studies* 14, 495–527.

Buraschi, Andrea, Fabio Trojani, and Andrea Vedolin, 2014, When uncertainty blows in the orchard: Comovement and equilibrium volatility risk premia, *Journal of Finance* 69, 101–137.

Cao, Jie, and Bing Han, 2013, Cross section of option returns and idiosyncratic stock volatility, *Journal of Financial Economics* 108, 231–249.

Cao, Jie, Hao Liang, and Xintong Zhan, 2019, Peer effects of corporate social responsibility, *Management Science* 65, 5487–5503.

Cao, Jie, Aurelio Vasquez, Xiao Xiao, and Xintong Zhan, 2023, Why does volatility uncertainty predict equity option returns? *Quarterly Journal of Finance* 13, —.

Carr, Peter, Roger Lee, and Liuren Wu, 2012, Variance swaps on time-changed Lévy processes, *Finance and Stochastics* 16, 335–355.

Carr, Peter, and Liuren Wu, 2009, Variance risk premiums, *Review of Financial Studies* 22, 1311–1341.

Chava, Sudheer, 2014, Environmental externalities and cost of capital, *Management Science* 60, 2223–2247.

Chava, Sudheer, Jeong Ho Kim, and Jaemin Lee, 2022, Risk, return, and environmental and social ratings, Working Paper.

Chih, Hsiang-Lin, Hsiang-Hsuan Chih, and Tzu-Yin Chen, 2010, On the determinants of corporate social responsibility: International evidence on the financial industry, *Journal of Business Ethics* 93, 115–135.

Choy, Siu Kai, and Wei, Jason, 2023, Investor Attention and Option Returns, *Management Science* 69, 4845–4863.

Christensen, Dane M., George Serafeim, and Anywhere (Siko) Sikochi, 2022, Why is corporate virtue in the eye of the beholder? The case of ESG ratings, *Accounting Review* 97, 147–175.

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2018, Illiquidity premia in the equity options market, *Review of Financial Studies* 31, 811–851.

Cohen, Lauren, Umit G. Gurun, and Quoc H. Nguyen, 2024, The ESG-innovation disconnect: Evidence from green patenting, Working Paper.

Cont, Rama, and Peter Tankov, 2004, *Financial modelling with jumps*, New York: Chapman & Hall.

Costa, Dora L., and Matthew E. Kahn, 2013, Energy conservation "nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment, *Journal of the European Economic Association* 11, 680–702.

Coval, Joshua D., and Tyler Shumway, 2001, Expected option returns, *Journal of Finance* 56, 983–1009.

Cremers, Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate jump and volatility risk in the cross-section of stock returns, *Journal of Finance* 70, 577–614.

Curcio, Richard J., and Fran M. Wolf, 1996, Corporate environmental strategy: Impact upon firm value, *Journal of Financial and Strategic Decisions* 9, 21–31.

De Fontnouvelle, Patrick, Raymond P. H. Fishe, and Jeffrey H. Harris, 2003, The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999, *Journal of Finance* 58, 2437–2463.

Dew-Becker, Ian, Stefano Giglio, Anh Le, and Mariuss Rodriguez, 2017, The price of variance risk, *Journal of Financial Economics* 123, 225–250.

Dew-Becker, Ian, Stefano Giglio, and Bryan Kelly, 2021, Hedging macroeconomic and financial uncertainty and volatility, *Journal of Financial Economics* 142, 23–45.

Di Giuli, Alberta, and Leonard Kostovetsky, 2014, Are red or blue companies more likely to go green? Politics and corporate social responsibility, *Journal of Financial Economics* 111, 158–180.

Duarte, Jefferson, Christopher S. Jones, Mehdi Khorram, Haitao Mo, and Junbo Wang, 2024, Too good to be true: Look-ahead bias in empirical options research, Working Paper.

Eccles, Robert G., and Judith C. Stroehle, 2020, Exploring social origins in the construction of ESG measures, Working Paper.

Edmans, Alex, 2011, Does the stock market fully value intangibles? Employee satisfaction and equity prices, *Journal of Financial Economics* 101, 621–640.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Finance* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 2018, Choosing factors, *Journal of Finance* 128, 234–252.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Flammer, Caroline, 2021, Corporate green bonds, *Journal of Financial Economics* 142, 499–516.

Gibson, Rajna, Philipp Krueger, and Peter Steffen Schmidt, 2021, ESG rating disagreement and stock returns, *Financial Analyst Journal* 77, 104–127.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *Review of Financial Studies* 34, 3527–3571.

González-Urteaga, Anna, and Gonzalo Rubio, 2016, The cross-sectional variation of volatility risk premia, *Journal of Financial Economics* 119, 353–370.

Goyal, Amit, and Alessio Saretto, 2009, Cross-section of option returns and volatility, *Journal of Financial Economics* 94, 310–326.

Gromet, Dena M., Howard Kunreuther, and Richard P. Larrick, 2013, Political ideology affects energy-efficiency attitudes and choices, *Proceedings of the National Academy of Sciences* 110, 9314–9319.

Hassan, Tarek A., Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, 2019, Firm-level political risk: Measurement and effects, *Quarterly Journal of Economics* 134, 2135–2202.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product market threats, payouts, and financial flexibility, *Journal of Finance* 69, 293–324.

Hoepner, Andreas G. F., Ioannis Oikonomou, Zacharias Sautner, Laura T. Starks, and Xiaoyan Zhou, 2024, ESG shareholder engagement and downside risk, *Review of Finance* 28, 483–510.

Hong, Harrison, and Marcin Kacperczyk, 2009, The price of sin: The effects of social norms on markets, *Journal of Financial Economics* 93, 15–36.

Hong, Harrison, and Leonard Kostovetsky, 2012, Red and blue investing: Values and finance, *Journal of Financial Economics* 103, 1–19.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov, 2021, Carbon tail risk, *Review of Financial Studies* 34, 1540–1571.

Jackwerth, Jens Carsten, and Mark Rubinstein, 1996, Recovering probability distributions from option prices, *Journal of Finance* 51, 1611–1631.

Kelly, Bryan, Ľuboš Pástor, and Pietro Veronesi, 2016, The price of political uncertainty: Theory and evidence from the option market, *Journal of Finance* 71, 2417–2480.

Kim, Yongtae, Haidan Li, and Siqi Li, 2014, Corporate social responsibility and stock price crash risk, *Journal of Banking and Finance* 43, 1–13.

Lev, Baruch, Christine Petrovits, and Suresh Radhakrishnan, 2010, Is doing good good for you? How corporate charitable contributions enhance revenue growth, *Strategic Management Journal* 31, 182–200.

Mayhew, Stewart, 2002, Competition, market structure, and bid-ask spreads in stock option markets, *Journal of Finance* 57, 931–958.

McWilliams, Abagail, and Donald Siegel, 2001, Corporate social responsibility: A theory of the firm perspective, *Academy of Management Review* 26, 117–127.

Morningstar, 2020, ESG risk comes into focus. https://www.morningstar.com/features/esg-risk.

Newey, Whitney, and Kenneth D. West, 1987, A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2021, Sustainable investing in equilibrium, *Journal of Financial Economics* 142, 550–571.

Pástor, Ľuboš, and Pietro Veronesi, 2013, Political uncertainty and risk premia, *Journal of Financial Economics* 110, 520–545.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2021, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* 142, 572–597.

PwC, 2020, Six key challenges for financial institutions to deal with ESG risks, PwC Insights-and-Publications. https://www.pwc.nl/en/insights-and-publications/services-and-industries/financial-sector/six-key-challenges-for-financial-institutions-to-deal-with-ESG-risks.html.

Ramachandran, Lakshmi Shankar, and Jitendra Tayal, 2021, Mispricing, short-sale constraints, and the cross-section of option returns, *Journal of Financial Economics* 141, 297–321.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, Firm-level climate change exposure, *Journal of Finance* 78, 1449–1498.

Zhan, Xintong, Bing Han, Jie Cao, and Qing Tong, 2022, Option return predictability, *Review of Financial Studies* 35, 1394–1442.

Figure 1: Dynamic impact of sudden increase in ESG risks on delta-hedged option gains

This figure plots the regression coefficient estimates of DiD analysis about the impact of sudden increase in ESG risks on delta-hedged option gains. The event window is from five months before the event to six months after the event. We construct a series of relative-time indicators for the months around sudden increase in ESG risks: $t = 0$ represents the event month, and $t = -1$ and -2 denote one and two months before the event, respectively. $t = +1, +2$, and $+3$ denote one, two, and three months after the event, respectively. Observations from three months prior to the event serve as the benchmark. All regressions control for year and firm fixed effects. For each coefficient estimate, we plot the point estimate in dark squares and the 90% confidence interval in vertical lines clustered at the firm level.

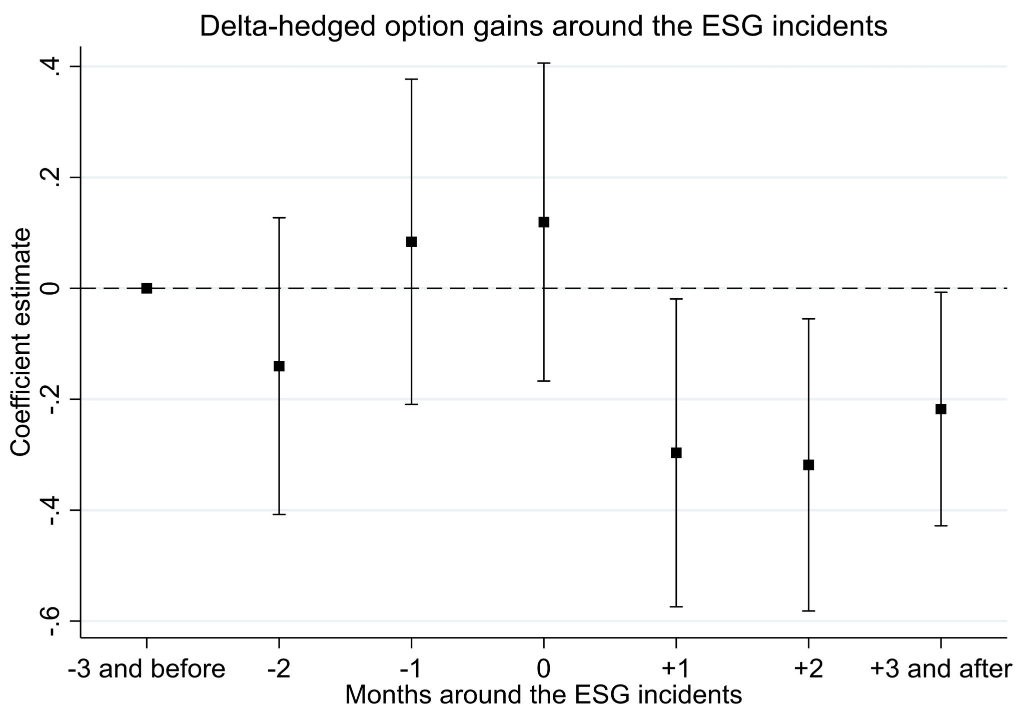

Table 1: Summary statistics

This table reports the descriptive statistics of the delta-hedged option returns and stock characteristics. In Panel A (Panel B), the call (put) option delta-hedged gain is the change until maturity in the value of a portfolio consisting of one contract of a long call (put) position and a proper amount of the underlying stock, re-hedged daily so that the portfolio is not sensitive to stock price movements. The call option delta-hedged gain is scaled by $(\Delta_C \times S - C)$, where Δ is the Black-Scholes option delta, S is the underlying stock price, and C is the price of call option. The put option delta-hedged gain is scaled by $(P - \Delta_P \times S)$, where P is the price of the put option. The resulting ratios are reported in percentage per month. Moneyness is the ratio of the stock price to the option strike price. Days to maturity is the number of calendar days until the option expires. Option bid-ask spread is the ratio of the difference between the bid and ask quotes of the option to the midpoint of the bid and ask quotes at the end of the previous month. Panel C reports the time-series average of the cross-sectional statistics of the stock characteristics. The ESG score is the monthly updated raw score from the ASSET4 database scaled by 100. Ln(ME) is the logarithm of market capitalization. Ln(BM) is the logarithm of the book-to-market ratio. IVOL is the annualized idiosyncratic volatility computed as in Ang, Hodrick, Xing, and Zhang (2006). RET1 is the stock return in the previous month. RET212 is the cumulative stock return from the prior second through twelfth months. Ln(AMIHUD) is the logarithm of the Amihud (2002) illiquidity measure of stock over the previous month. INSTOWN is the percentage of common stocks owned by institutions in the previous quarter. Analyst coverage is the number of analysts following the firm in the previous month. Panel D reports the time-series average of the cross-sectional correlations. The Pearson correlations are shown below the diagonal together with the Spearman correlations above the diagonal. The sample period is from January 2004 to December 2018.

	Mean	Standard deviation	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
Panel A: Call options (69,058 observations)							
Delta-hedged gain until maturity	−0.21%	3.90%	−3.64%	−1.95%	−0.49%	1.03%	3.21%
Moneyness	1.00	0.03	0.97	0.99	1.00	1.01	1.03
Days to maturity	50	2	46	49	50	51	52
Option bid-ask spread	0.12	0.15	0.03	0.05	0.08	0.14	0.23
Panel B: Put options (69,058 observations)							
Delta-hedged gain until maturity	−0.27%	3.15%	−3.31%	−1.86%	−0.57%	0.86%	2.97%
Moneyness	1.00	0.03	0.97	0.99	1.00	1.01	1.03
Days to maturity	50	2	46	49	50	51	52
Option bid-ask spread	0.12	0.15	0.03	0.05	0.08	0.14	0.24

Panel C: Stock characteristics summary							
	Mean	Standard deviation	10th percentile	Lower quartile	Median	Upper quartile	90th percentile
ESG score	0.62	0.26	0.26	0.40	0.63	0.86	0.94
Ln(ME)	9.06	1.17	7.70	8.21	8.91	9.77	10.65
Ln(BM)	−0.97	0.78	−1.92	−1.43	−0.93	−0.43	−0.05
IVOL	0.24	0.15	0.12	0.15	0.21	0.29	0.41
INSTOWN	0.80	0.16	0.60	0.71	0.82	0.90	0.97
ANLST	16.43	7.43	7.11	11.02	15.87	21.14	26.53

Panel D: Correlations									
	ESG score	Ln(ME)	Ln(BM)	RET1	RET212	IVOL	Ln(AMIHUD)	INSTOWN	ANLST
ESG score		0.505	−0.020	0.004	0.023	−0.287	−0.476	−0.260	0.202
Ln(ME)	0.497		−0.171	−0.015	0.043	−0.371	−0.899	−0.383	0.517
Ln(BM)	−0.006	−0.167		0.001	−0.013	0.031	0.173	−0.008	−0.177
RET1	−0.005	−0.027	0.004		0.012	−0.005	−0.006	0.007	−0.006
RET212	−0.022	0.000	−0.021	0.019		−0.088	−0.114	0.008	−0.028
IVOL	−0.248	−0.335	0.024	0.056	−0.036		0.323	0.250	−0.051
Ln(AMIHUD)	−0.462	−0.906	0.182	0.007	−0.097	0.294		0.273	−0.566
INSTOWN	−0.191	−0.351	−0.003	0.001	−0.015	0.144	0.210		−0.069
ANLST	0.191	0.503	−0.167	−0.014	−0.046	−0.053	−0.553	−0.045	

Table 2: ESG premium

At the end of each month, we rank all of the stocks in our sample into quintiles by the ESG scores and calculate the equal-weighted average of the option return for a portfolio of stocks. The ESG score is the monthly updated ESG performance measure from ASSET4. In Panel A, the option return is the daily rebalanced delta-hedged option return until maturity. In Panel B, the option return is the daily compounded delta-hedged option return until maturity. For each stock at the end of the previous month, we buy one contract of the call/put option against a long position of Δ shares of the underlying stock, where Δ is the Black-Scholes call/put option delta. The position is rebalanced daily until maturity to compute the buy-and-hold return. In Panel C, the option return is the zero-beta straddle return until maturity. For each stock at the end of the previous month, following Coval and Shumway (2001), we select θ units of call options and $1-\theta$ units of put options that are approximately ATM and have maturity around one and a half months. θ is determined to make the straddle beta-neutral. The position is held until maturity to compute the buy-and-hold return. The 6-factor alpha is calculated from the Fama and French (2018) 6-factor model. The 7-factor alpha is calculated from the Fama and French (2018) 6-factor and market volatility factor proxied by the zero-beta straddle return on the S&P 500 index (Coval and Shumway (2001)). All of the returns are in percentage per month and t-statistics are in parentheses. The sample period is from January 2004 to December 2018.

ESG score rank	Low	2	3	4	High	H−L
Panel A: Daily rebalanced delta-hedged option gains until maturity						
	Call options					
Average return	−0.37	−0.21	−0.20	−0.15	−0.15	0.22
	(−2.53)	(−1.47)	(−1.45)	(−1.09)	(−1.17)	(4.06)
6-factor alpha	−0.39	−0.22	−0.23	−0.16	−0.18	0.21
	(−2.96)	(−1.78)	(−1.89)	(−1.29)	(−1.74)	(3.95)
7-factor alpha	−0.18	−0.05	−0.06	0.01	−0.02	0.16
	(−1.20)	(−0.34)	(−0.45)	(0.09)	(−0.20)	(2.73)
	Put options					
Average return	−0.44	−0.27	−0.23	−0.23	−0.25	0.18
	(−2.75)	(−1.77)	(−1.52)	(−1.53)	(−2.03)	(3.58)
6-factor alpha	−0.43	−0.26	−0.24	−0.23	−0.27	0.15
	(−3.08)	(−1.94)	(−1.76)	(−1.75)	(−2.62)	(2.94)
7-factor alpha	−0.24	−0.09	−0.07	−0.07	−0.13	0.10
	(−1.58)	(−0.65)	(−0.50)	(−0.43)	(−1.11)	(1.90)
	Call + put options					
Average return	−0.40	−0.24	−0.22	−0.19	−0.20	0.20
	(−2.64)	(−1.66)	(−1.51)	(−1.32)	(−1.62)	(4.09)
6-factor alpha	−0.40	−0.24	−0.24	−0.19	−0.23	0.17
	(−3.02)	(−1.91)	(−1.86)	(−1.53)	(−2.20)	(3.64)
7-factor alpha	−0.21	−0.07	−0.07	−0.03	−0.08	0.13
	(−1.37)	(−0.53)	(−0.50)	(−0.17)	(−0.67)	(2.39)

ESG score rank	Low	2	3	4	High	H−L
Panel B: Daily rebalanced buy-and-hold delta-hedged option returns						
	Call options					
Average return	−1.18	−0.97	−1.20	−1.11	−0.85	0.34
	(−8.07)	(−6.01)	(−3.93)	(−4.00)	(−6.29)	(3.92)
6-factor alpha	−1.22	−0.97	−1.27	−1.09	−0.91	0.31
	(−8.42)	(−6.05)	(−3.55)	(−4.14)	(−6.43)	(3.86)
7-factor alpha	−0.98	−0.75	−1.09	−0.77	−0.72	0.27
	(−5.89)	(−4.00)	(−2.84)	(−2.90)	(−4.69)	(3.94)
	Put options					
Average return	−0.84	−0.65	−0.55	−0.57	−0.51	0.33
	(−4.85)	(−3.96)	(−3.15)	(−3.46)	(−3.47)	(5.71)
6-factor alpha	−0.80	−0.61	−0.52	−0.54	−0.49	0.31
	(−5.88)	(−4.85)	(−3.90)	(−4.67)	(−4.76)	(5.25)
7-factor alpha	−0.61	−0.46	−0.35	−0.39	−0.36	0.25
	(−4.33)	(−3.36)	(−2.49)	(−3.10)	(−3.24)	(3.95)
	Call + put options					
Average return	−1.00	−0.82	−0.88	−0.84	−0.68	0.33
	(−6.57)	(−5.22)	(−4.45)	(−4.33)	(−5.31)	(5.36)
6-factor alpha	−1.00	−0.80	−0.90	−0.81	−0.70	0.30
	(−7.45)	(−5.90)	(−4.25)	(−4.77)	(−6.24)	(5.13)
7-factor alpha	−0.79	−0.61	−0.72	−0.58	−0.54	0.25
	(−5.36)	(−4.07)	(−3.22)	(−3.23)	(−4.43)	(4.26)
Panel C: Zero-beta straddle returns						
Average return	−8.27	−6.19	−4.59	−4.20	−4.30	3.97
	(−2.88)	(−2.09)	(−1.59)	(−1.40)	(−1.57)	(2.68)
6-factor alpha	−7.29	−5.54	−4.35	−3.64	−4.45	2.84
	(−2.24)	(−1.61)	(−1.38)	(−1.05)	(−1.49)	(1.86)
7-factor alpha	−4.29	−2.88	−1.32	0.01	−1.32	2.97
	(−0.99)	(−0.62)	(−0.30)	(0.00)	(−0.33)	(2.06)

Table 3: Separate effects of the E-score, S-score, and G-score

At the end of each month, we rank all of the stocks in our sample into quintiles by the E-score, S-score, and G-score and calculate the equal-weighted average of the daily rebalanced delta-hedged option return (calls and puts together) for a portfolio of stocks in Panel A, Panel B, and Panel C, respectively. The E-score, S-score, and G-score are the monthly updated ESG performance measures from ASSET4. The 6-factor alpha is calculated from the Fama and French (2018) 6-factor model. The 7-factor alpha is calculated from the Fama and French (2018) 6-factor and market volatility factor, proxied by the zero-beta straddle return on the S&P 500 index (Coval and Shumway (2001)). The sample period is from January 2004 to December 2018.

ESG score rank	Low	2	3	4	High	H−L
			Panel A: E-score			
Average return	−0.32	−0.29	−0.26	−0.20	−0.20	0.12
	(−2.14)	(−1.90)	(−1.80)	(−1.49)	(−1.51)	(2.91)
6-factor alpha	−0.33	−0.29	−0.27	−0.22	−0.21	0.12
	(−2.51)	(−2.22)	(−2.14)	(−1.84)	(−1.88)	(2.68)
7-factor alpha	−0.16	−0.12	−0.09	−0.03	−0.06	0.10
	(−1.10)	(−0.79)	(−0.66)	(−0.27)	(−0.47)	(2.07)
			Panel B: S-score			
Average return	−0.39	−0.25	−0.22	−0.21	−0.19	0.20
	(−2.73)	(−1.71)	(−1.49)	(−1.42)	(−1.55)	(5.49)
6-factor alpha	−0.41	−0.24	−0.23	−0.22	−0.21	0.20
	(−3.25)	(−1.90)	(−1.81)	(−1.64)	(−2.07)	(5.26)
7-factor alpha	−0.22	−0.08	−0.06	−0.04	−0.06	0.16
	(−1.61)	(−0.54)	(−0.44)	(−0.26)	(−0.56)	(3.93)
			Panel C: G-score			
Average return	−0.30	−0.30	−0.23	−0.24	−0.20	0.10
	(−1.93)	(−2.12)	(−1.54)	(−1.74)	(−1.56)	(2.14)
6-factor alpha	−0.30	−0.31	−0.23	−0.25	−0.22	0.08
	(−2.17)	(−2.58)	(−1.82)	(−2.02)	(−2.09)	(1.62)
7-factor alpha	−0.11	−0.14	−0.06	−0.08	−0.08	0.03
	(−0.69)	(−1.10)	(−0.43)	(−0.55)	(−0.64)	(0.58)

Table 4: Volatility risk premium, jump risk premium, and ESG performance

This table reports the portfolio sorting results for the volatility risk premium and the jump risk premium based on ESG performance. Panels A and B report the portfolio sorting results of vega-positive, gamma-neutral straddle returns until maturity (volatility risk sensitive) and gamma-positive, vega-neutral straddle returns until maturity (jump risk sensitive), respectively. The ESG score is the monthly updated ESG performance measure from ASSET4. We report the raw returns and alphas from the 6-factor and 7-factor models. The sample period is from January 2004 to December 2018.

ESG score rank	Low	2	3	4	High	H−L
Panel A: Vega-positive, gamma-neutral (volatility risk sensitive) straddle returns						
Average return	−1.21	−0.93	−0.43	−2.04	−1.69	−0.48
	(−0.77)	(−0.48)	(−0.27)	(−1.14)	(−0.64)	(−0.19)
6-factor alpha	−1.54	−1.59	−0.66	−2.02	−2.15	−0.62
	(−0.87)	(−0.69)	(−0.39)	(−1.11)	(−0.90)	(−0.24)
7-factor alpha	−2.19	−0.97	−1.48	−3.16	−3.07	−0.88
	(−0.83)	(−0.32)	(−0.56)	(−1.12)	(−1.05)	(−0.30)
Panel B: Gamma-positive, vega-neutral (jump risk sensitive) straddle returns						
Average return	−2.40	−2.92	−2.69	0.02	1.27	3.68
	(−1.39)	(−1.67)	(−1.65)	(0.01)	(0.75)	(2.85)
6-factor alpha	−2.09	−2.47	−2.71	0.00	1.20	3.30
	(−1.00)	(−1.14)	(−1.41)	(0.00)	(0.64)	(2.41)
7-factor alpha	−0.60	−2.30	−1.05	2.02	2.65	3.26
	(−0.19)	(−0.77)	(−0.35)	(0.75)	(0.85)	(2.04)

Table 5: Impact of the Google search volume index, Paris Agreement, and aggregate ESG news on the risk premium

This table reports the time-series regression estimates of the H−L spread of the daily rebalanced delta-hedged option return in the following regression.

$$R_{t+1} = \alpha_0 + \alpha_1 D_t + \beta' F_{t+1} + \varepsilon_{t+1}.$$

At the end of each month, all of the available options (calls and puts together) are sorted into quintiles based on ESG performance. The H−L portfolio is constructed by buying options with the highest ESG scores and shorting options with the lowest ESG scores, held until maturity. In Panel A, the whole period is divided into two subperiods based on the innovation of the Google SVI of the topic "ESG. D_t equals one when the innovation of the Google SVI of this topic is higher. In Panel B, D_t equals one during the Paris Agreement period (January 2016 to June 2017) and zero during the 18 months before the Paris Agreement period and 18 months after the Paris Agreement period (July 2014 to December 2015, July 2017 to December 2018). In Panel C, the whole period is divided into two sub-periods based on the total number of ESG news stories obtained from RepRisk scaled by the total number of news stories from Ravenpack. D_t equals one when there are more aggregate ESG news stories, and zero otherwise. F_t is a vector including the Fama and French (2018) 6 factors in the 6-factor model plus the market volatility factor included in 7-factor model. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses.

	α_0	α_1
Panel A: Impact of the Google search volume index		
Average return	0.10	0.18
	(1.73)	(2.19)
6-factor alpha	0.09	0.19
	(1.43)	(2.36)
7-factor alpha	0.06	0.20
	(0.87)	(2.43)
Panel B: Impact of the Paris Agreement		
Average return	−0.03	0.30
	(−0.31)	(2.09)
6-factor alpha	−0.05	0.36
	(−0.51)	(1.99)
7-factor alpha	−0.05	0.34
	(−0.51)	(1.82)
Panel C: Impact of aggregate ESG news		
Average return	0.07	0.19
	(0.94)	(1.96)
6-factor alpha	0.08	0.19
	(0.88)	(1.93)
7-factor alpha	0.06	0.18
	(0.71)	(1.81)

Table 6: Impact of the Google search volume index, Paris Agreement, and aggregate ESG news on volatility risks

We calculate the risk of rising volatility as VOV+ (positive VOV) following Cao, Vasquez, Xiao, and Zhan (2023). We calculate jump intensity as the relative signed jump (RSJ) following Bollerslev, Li, and Zhao (2020). At the end of each month, all available options are sorted into quintiles based on ESG performance. The risk spread is the VOV+ and RSJ difference between the portfolio with the highest ESG score and the portfolio with the lowest ESG score. This table reports the time-series regression of the risk spread similar to that in Table 5:

$$Risk\ spread_{t+1} = \alpha_0 + \alpha_1 D_t + \varepsilon_{t+1}.$$

In Panel A, the whole period is divided into two sub-periods based on the innovation of the Google SVI of the topic "ESG." D_t equals one when the innovation of the Google SVI of this topic is higher. In Panel B, D_t equals one during the Paris Agreement period (January 2016 to June 2017) and zero during 18 months before the Paris Agreement period and 18 months after the Paris Agreement period (July 2014 to December 2015, July 2017 to December 2018). In Panel C, the whole period is divided into two sub-periods based on the total number of ESG news stories obtained from RepRisk scaled by the number of all news stories from Ravenpack. D_t equals one when there is more aggregate ESG news, and zero otherwise. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses.

	α_0	α_1
Panel A: Impact of the Google Search Volume Index		
Relative signed jump (RSJ)	−0.64	0.14
	(−5.22)	(0.99)
VOV+ (Positive VOV)	−4.70	−0.32
	(−7.44)	(−0.45)
Panel B: Impact of the Paris Agreement		
Relative signed jump (RSJ)	−0.72	0.18
	(−2.23)	(0.43)
VOV+ (Positive VOV)	−2.38	−1.10
	(−2.39)	(−0.80)
Panel C: Impact of aggregate ESG news		
Relative signed jump (RSJ)	−0.59	0.19
	(−3.94)	(1.24)
VOV+ (Positive VOV)	−4.85	0.49
	(−8.54)	(0.68)

Table 7: Delta-hedged option return and ESG performance

This table reports the average coefficients from the monthly FM cross-sectional regressions. The dependent variable (in percentage) is the daily rebalanced delta-hedged option gain until maturity scaled by $(\Delta_C \times S - C)$ for calls and $(P - \Delta_P \times S)$ for puts. Columns (1) and (2), columns (3) and (4), and columns (5) and (6) report the results for call options, put options, call and put options together, respectively. The ESG score is the monthly updated ESG performance measure from ASSET4. The definitions of the other control variables are reported in the supplementary appendix. All of the independent variables are winsorized each month at the 0.5% level. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 2004 to December 2018.

	Call options		Put options		Call + Put options	
	(1)	(2)	(3)	(4)	(5)	(6)
ESG score	0.238	0.234	0.103	0.101	0.175	0.171
	(3.05)	(3.27)	(1.72)	(1.73)	(2.75)	(2.89)
Ln(ME)	0.154	0.094	0.044	0.022	0.100	0.059
	(2.70)	(1.90)	(0.98)	(0.56)	(2.04)	(1.40)
Ln(BM)	0.035	0.010	−0.024	−0.030	0.006	−0.011
	(0.80)	(0.23)	(−0.84)	(−1.07)	(0.17)	(−0.32)
RET1	−0.358	−0.612	−0.632	−0.598	−0.447	−0.560
	(−0.99)	(−1.56)	(−1.91)	(−1.80)	(−1.35)	(−1.60)
RET212	−0.188	−0.241	−0.032	−0.036	−0.107	−0.133
	(−1.33)	(−1.74)	(−0.30)	(−0.34)	(−0.89)	(−1.11)
IVOL	−1.774	−1.476	−1.562	−1.571	−1.670	−1.524
	(−6.61)	(−6.57)	(−7.38)	(−8.50)	(−7.25)	(−8.01)
Ln(AMIHUD)	0.198	0.160	0.089	0.070	0.146	0.115
	(4.16)	(3.34)	(2.19)	(1.74)	(3.50)	(2.79)
OPTION OI	−2.177	−2.420	−4.167	−3.980	−2.660	−2.657
	(−4.76)	(−5.38)	(−7.94)	(−8.36)	(−6.11)	(−6.58)
OPTION BA	−0.312	−0.705	−0.352	−0.632	−0.342	−0.618
	(−1.49)	(−2.73)	(−2.22)	(−3.43)	(−2.59)	(−3.51)
BETA		0.035		0.053		0.045
		(0.51)		(0.98)		(0.74)
IMPVAR		−0.092		0.014		−0.035
		(−0.87)		(0.20)		(−0.44)
IMPSKEW		−0.740		0.249		−0.242
		(−4.02)		(3.17)		(−2.20)
IMPKURT		0.184		0.158		0.165
		(2.75)		(3.66)		(3.12)
Avg adj-R^2	0.040	0.051	0.042	0.049	0.054	0.070
# obs	63,727	63,727	63,727	63,727	127,454	127,454

Table 8: Delta-hedged option gains around heightened ESG risks

This table presents the difference-in-differences estimates of delta-hedged option gains around suddenly heightened ESG risks, using panel regression. The treated group (TREATED) is identified with the RepRisk Index Trend (RepRisk Index this month minus RepRisk Index 30 days prior) equal to or larger than 16. The control group is identified via propensity score matching of the firms based on size, book-to-market ratio, stock return in the prior month, momentum, and idiosyncratic volatility. POST is an indicator variable that equals one after the sudden increase in ESG risks. EVENT is an indicator variable representing the event month. PRE1 (PRE2) is an indicator variable that equals one month (two months) before the sudden increase in ESG risks. We define event windows as five months prior to and six months after the event. Observations from three months prior to the event serve as the benchmark. We run panel regressions, controlling for firm fixed effects and time fixed effects. The coefficients on the control variables are omitted. The t-statistics in parentheses are calculated from robust standard errors clustered by firm.

	Call options		Put options		Call + Put options	
	(1)	(2)	(3)	(4)	(5)	(6)
POST×TREATED	−0.298	−0.279	−0.226	−0.212	−0.263	−0.247
	(−2.62)	(−1.91)	(−2.34)	(−1.91)	(−2.76)	(−2.15)
POST	0.034	0.019	0.025	0.023	0.030	0.022
	(0.43)	(0.17)	(0.38)	(0.28)	(0.45)	(0.25)
TREATED	0.048	0.029	0.033	0.020	0.041	0.025
	(0.52)	(0.22)	(0.46)	(0.21)	(0.54)	(0.25)
EVENT×TREATED		0.086		0.156		0.119
		(0.39)		(0.91)		(0.69)
PRE1×TREATED		0.131		0.038		0.084
		(0.60)		(0.21)		(0.47)
PRE2×TREATED		−0.125		−0.153		-0.140
		(−0.59)		(−0.98)		(−0.86)
EVENT		−0.056		−0.128		−0.092
		(−0.36)		(−1.12)		(−0.75)
PRE1		−0.095		0.085		−0.005
		(−0.58)		(0.59)		(−0.03)
PRE2		0.079		0.078		0.080
		(0.48)		(0.69)		(0.65)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg adj-R^2	0.162	0.162	0.234	0.234	0.186	0.186
# obs	26,560	26,560	26,560	26,560	27,216	27,216

Table 9: Delta-hedged option return and alternative ESG scores

This table reports the average coefficients from the monthly FM cross-sectional regressions for the call and put options together. The dependent variable (in percentage) is the daily rebalanced delta-hedged option return until maturity. The ESG scores in columns (1) to (4) are from KLD, MSCI, Sustainalytics and RepRisk, respectively. The ESG score in column (5) is a combined ESG score from ASSET4, KLD, MSCI, Sustainalytics, and RepRisk. For each ESG data provider, we sort the stocks into quintiles and assign the rank to the stocks. The combined ESG score is the ranking average of the available ESG scores, requiring at least three measures available. The ESG score in column (6) is the fitted value from the regression of the ASSET4 ESG score on KLD, MSCI, Sustainalytics, and RepRisk (as shown in Equation (9)). The definitions of the other control variables are presented in the supplementary appendix. All of the independent variables are winsorized each month at the 0.5% level. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses.

	(1) KLD	(2) MSCI	(3) Sustainalytics	(4) Reprisk	(5) Combined	(6) IV
ESG score	0.013	0.025	0.713	0.004	0.102	0.276
	(2.02)	(2.36)	(3.60)	(2.32)	(3.85)	(2.17)
Ln(ME)	0.076	0.065	−0.048	0.134	0.065	−0.044
	(1.71)	(0.95)	(−0.97)	(2.08)	(1.26)	(−0.87)
Ln(BM)	0.095	0.098	−0.035	0.096	0.050	−0.023
	(2.99)	(2.36)	(−1.23)	(2.83)	(1.28)	(−0.78)
RET1	0.012	−0.621	−1.066	−0.209	−0.602	−1.204
	(0.04)	(−2.02)	(−2.48)	(−0.57)	(−1.78)	(−2.79)
RET212	−0.171	−0.441	−0.286	−0.209	−0.270	−0.372
	(−1.57)	(−2.78)	(−2.06)	(−1.74)	(−2.05)	(−2.39)
IVOL	−1.599	−1.882	−1.862	−1.527	−1.692	−1.908
	(−9.33)	(−8.33)	(−7.14)	(−7.98)	(−8.41)	(−7.01)
Ln(AMIHUD)	−0.096	0.053	0.016	0.023	0.091	0.033
	(−2.44)	(0.79)	(0.33)	(0.43)	(1.70)	(0.58)
OPTION OI	−2.520	−3.032	−1.616	−3.100	−2.633	−2.033
	(−6.58)	(−5.48)	(−2.85)	(−5.49)	(−5.97)	(−3.39)
OPTION BA	−0.246	−0.386	−0.793	−0.396	−0.441	−0.977
	(−1.87)	(−2.42)	(−4.31)	(−2.22)	(−2.78)	(−4.37)
BETA	0.144	0.103	−0.029	0.115	0.100	−0.032
	(3.06)	(1.51)	(−0.77)	(2.00)	(1.29)	(−0.83)
IMPVAR	−1.060	−0.285	−0.053	−0.626	−0.220	−0.030
	(−11.98)	(−1.99)	(−0.56)	(−6.34)	(−2.20)	(−0.30)
IMPSKEW	−0.261	−0.303	−0.290	−0.353	−0.366	−0.203
	(−3.24)	(−2.40)	(−4.50)	(−3.40)	(−2.95)	(−2.17)
IMPKURT	0.333	0.187	0.155	0.233	0.171	0.169
	(8.13)	(3.63)	(4.68)	(4.88)	(3.16)	(4.70)
Avg adj-R^2	0.045	0.052	0.066	0.046	0.053	0.060
# obs	284,858	146,116	93,596	172,364	142,922	69,446

Table 10: Product market, ESG attention, firms' hedging activity, and the impact of ESG performance on delta-hedged option returns

The table reports the average coefficients from the monthly FM cross-sectional regressions for the call and put options together. The dependent variable (in percentage) is the daily rebalanced delta-hedged option gain until maturity. Panel A analyzes the impact of the product market. CONSUMER is an indicator variable equal to one if the firm's SIC codes are 0000-0999, 2000-2399, 2500-2599, 2700-2799, 2830-2869, 3000-3219, 3420-3429, 3523, 3600-3669, 3700-3719, 3751, 3850-3879, 3880-3999, 4813, 4830-4899, 5000-5079, 5090-5099, 5130-5159, 5220-5999, 7000-7299, 7400-9999. Fluidity data (Hoberg, Phillips, and Prabhala (2014)) are calculated based on 10-Ks and proxy for product market threats. Panel B analyzes the impact of ESG attention. BLUE is an indicator variable that refers to companies headquartered in states whose voters predominantly choose the Democratic presidential candidate. CONFENV is the share of the transcript of the conference call that focuses on political risk related to the environment (Hassan, Hollander, van Lent, and Tahoun (2019)). Panel C analyzes the impact of firms' hedging activity. HEDGER is an indicator variable equal to one if the firm has a non-zero record of cash flow hedge gains/losses in COMPUSTAT. All regressions include the control variables in Table 7, but their coefficients are not reported. The ESG score is the monthly updated ESG performance measure from ASSET4. The definitions of the other control variables are reported in the supplementary appendix. All independent variables are winsorized each month at the 0.5% level. We report Newey and West (1987) t-statistics in parentheses below the coefficients. The sample period is from 2004 to 2018.

Panel A: Product market		
	(1)	(2)
CONSUMER×ESG score	0.250	
	(2.24)	
CONSUMER	−0.254	
	(−2.71)	
FLUIDITY×ESG score		0.051
		(2.91)
FLUIDITY		−0.046
		(−3.75)
ESG score	0.083	−0.196
	(1.08)	(−1.77)
Controls	Yes	Yes
Avg adj-R^2	0.056	0.057
# obs	127,440	124,610

Panel B: Attention to ESG		
	(1)	(2)
BLUE×ESG score	0.259	
	(2.10)	
BLUE	−0.199	
	(−2.13)	
CONFENV×ESG score		0.019
		(1.95)
CONFENV		−0.018
		(−2.45)
ESG score	−0.020	0.113
	(−0.17)	(1.70)
Controls	Yes	Yes
Avg adj-R^2	0.054	0.055
# obs	127,440	119,486

Panel C: Firms' hedging activity	
	(1)
HEDGER×ESG score	−0.390
	(−3.37)
HEDGER	0.288
	(3.21)
ESG score	0.336
	(4.09)
Controls	Yes
Avg adj-R^2	0.054
# obs	127,440

Table A1: Sample coverage

This table provides details about the stock-month sample for the underlying stocks with qualified option observations of both call and put options. At the end of each month, we extract one call and one put on each optionable stock from the Ivy DB database of Option-Metrics. The selected options are approximately ATM with a common maturity of about one and a half months. We exclude the following option observations: moneyness lower than 0.8 or higher than 1.2; a reported option trading volume in the last month of zero; the underlying stock has announced, at the time of establishing the portfolio, a dividend payment during the remaining life of the option. We keep common stocks with stock prices larger than $5 in the previous month. We also exclude stocks with missing ESG scores from ASSET4 data and only retain stocks with both call and put options available after filtering. Panel A reports the time-series summary statistics and Panel B reports the time-series average of the cross-sectional distributions. Panel C reports the time-series average of the Fama-French 12-industry distribution for the stocks in our sample. The percent coverage of the stock universe (EW) is the number of sample stocks divided by the total number of CRSP stocks. The percent coverage of the stock universe (VW) is the total market capitalization of sample stocks divided by the total market value of all CRSP stocks. The percentage in the S&P500 index is the number of stocks in the S&P500 index divided by the number of stocks in the sample. The size and book-to-market percentiles are defined using the full CRSP sample. INSTOWN is the percentage of common stocks owned by institutions in the previous quarter. ANLST is the number of analysts following the firm in the previous month. The sample period is from 2004 to 2018.

	Mean	Std Dev	10th prctl	Lower qrtl	Median	Upper qrtl	90th prctl
Panel A: Time-series distribution (180 monthly observations)							
Number of stocks in the sample	384	74	271	336	402	439	464
Stock % coverage of stock universe (EW)	5.58	1.12	4.03	4.80	5.77	6.38	6.97
Stock % coverage of stock universe (VW)	34.40	4.72	27.17	30.59	35.49	38.13	39.64
Stock % traded at NYSE/AMEX	72.98	3.20	69.40	70.48	72.17	75.71	77.98
Stock % in S&P500 index	72.68	7.75	64.47	66.32	70.62	80.29	94.47
Panel B: Time-series average of cross-sectional distributions (69,058 stock-month observations)							
Size CRSP percentile	0.90	0.07	0.81	0.87	0.92	0.96	0.98
Book-to-market CRSP percentile	0.36	0.25	0.08	0.16	0.31	0.55	0.74
INSTOWN	0.80	0.16	0.60	0.71	0.82	0.90	0.97
ANLST	16.43	7.43	7.11	11.02	15.87	21.14	26.53

Panel C: Time-series average of industry distribution

FF-12 Industry	This sample	CRSP sample	FF-12 Industry	This sample	CRSP sample
Consumer nondurables	5.20%	4.64%	Telecom	2.65%	2.87%
Consumer durables	2.37%	2.17%	Utilities	5.02%	2.49%
Manufacturing	11.07%	8.26%	Wholesale	11.99%	9.09%
Energy	6.25%	3.91%	Healthcare	7.97%	10.47%
Chemicals	4.08%	2.06%	Finance	12.48%	18.78%
Business Equipment	17.98%	15.52%	Others	12.94%	19.73%

Table A2: Synthetic variance swap rate and variance risk premium

At the end of each month, we rank all of the stocks in our sample into quintiles by the ESG scores. We follow Carr and Wu (2009) and use a portfolio of vanilla options to calculate the synthetic variance swap rate with the same maturity as the corresponding options (approximately 50 days) in Panel A. Then we take the difference between the synthetic variance swap rate and the ex-post realized variance to measure the variance risk premium in Panel B. More details on the construction of these variables are provided in the body of the text. The ESG score is the monthly updated ESG performance measure from ASSET4. The sample period is from January 2004 to December 2018.

Low	2	3	4	High	H−L
Panel A: Synthetic ˜50-day variance swap rate					
15.71	11.55	10.60	9.03	5.77	−9.94
(9.44)	(8.27)	(8.52)	(6.49)	(6.94)	(−10.96)
Panel B: Variance risk premium					
0.82	−0.47	−0.50	−0.77	−0.80	−1.63
(0.77)	(−0.53)	(−0.51)	(−0.75)	(−1.30)	(−3.19)

Table A3: Fama-MacBeth regressions of delta-hedged option returns on ESG performance and carbon intensity

This table reports the average coefficients from the monthly FM cross-sectional regressions. The dependent variable (in percentage) is the daily rebalanced delta-hedged option (calls and puts together) gain until maturity. Carbon intensity is the Scope 1 carbon emissions obtained from Trucost scaled by the market value of the firm. The ESG score is the monthly updated ESG performance measure from ASSET4. The definitions of the other control variables are reported in the supplementary appendix. All of the independent variables are winsorized each month at the 0.5% level. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. The sample period is from January 2004 to December 2018.

	(1)	(2)
Carbon intensity	−0.020	−0.031
	(−1.94)	(−2.87)
ESG score	0.265	0.233
	(4.65)	(4.05)
Ln(ME)		0.021
		(0.50)
Ln(BM)		0.015
		(0.42)
RET1		−0.377
		(−1.03)
RET212		−0.148
		(−1.13)
IVOL		−1.513
		(−7.33)
Ln(AMIHUD)		0.085
		(2.04)
OPTION OI		−2.647
		(−6.39)
OPTION BA		−0.769
		(−4.52)
BETA		0.044
		(0.71)
IMPVAR		−0.058
		(−0.79)
IMPSKEW		−0.207
		(−2.04)
IMPKURT		0.180
		(3.14)
Avg adj-R^2	0.007	0.059
# obs	122,592	116,708

Table A4: Fama-MacBeth regressions of delta-hedged option returns on ESG performance: Different levels of moneyness

This table reports the average coefficients from monthly FM cross-sectional regressions for options with different maturities. We define the OTM, ATM, and ITM option groups based on the absolute value of delta: OTM ($0.2 < |\Delta| \leq 0.4$) ATM ($0.4 < |\Delta| \leq 0.6$), and ITM ($0.6 < |\Delta| \leq 0.8$). The selected options have a common maturity of about one and a half months. Delta-hedged option returns (in percentage) are defined as the daily rebalanced delta-hedged option gain until maturity. The dependent variable is the average value of the delta-hedged option returns for all of the options in these three categories. The ESG score is the monthly updated ESG performance measure from ASSET4. The definitions of the other control variables are reported in the supplementary appendix. All of the independent variables are winsorized each month at the 0.5% level. We report the Newey and West (1987) t-statistics in parentheses below the coefficients. The sample period is from 2004 to 2018.

	OTM	ATM	ITM
ESG score	0.206	0.152	0.081
	(2.13)	(2.30)	(1.73)
Ln(ME)	0.136	0.059	0.046
	(1.96)	(1.32)	(1.47)
Ln(BM)	0.026	0.021	0.017
	(0.47)	(0.56)	(0.73)
RET1	−0.887	−0.694	−0.316
	(−1.76)	(−2.04)	(−1.40)
RET212	−0.178	−0.097	−0.033
	(−1.03)	(−0.76)	(−0.42)
IVOL	−6.333	−5.364	−2.631
	(−5.76)	(−7.60)	(−5.72)
Ln(AMIHUD)	0.170	0.126	0.091
	(2.46)	(2.90)	(2.91)
OPTION OI	−4.839	−3.309	−2.060
	(−5.16)	(−6.31)	(−3.57)
OPTION BA	−0.287	−0.741	−0.613
	(−2.17)	(−3.90)	(−3.17)
BETA	−0.054	0.018	−0.006
	(−0.80)	(0.35)	(−0.16)
IMPVAR	−0.147	−0.059	−0.043
	(−1.32)	(−0.68)	(−0.77)
IMPSKEW	−0.441	−0.335	−0.117
	(−2.74)	(−2.37)	(−1.53)
IMPKURT	0.146	0.129	0.003
	(1.88)	(2.42)	(0.08)
Avg adj-R^2	0.041	0.057	0.044
# obs	126,827	116,628	126,950

Table A5: Fama-MacBeth regressions of different risks on ESG performance

This table reports the average coefficients from the monthly FM cross-sectional regressions for VRP, MFIS, MFIK, and SlopeD. VRP is a measure of the variance risk premium. MFIS is a measure of the model-free implied skewness. MFIK is a measure of the model-free implied kurtosis. SlopeD measures the steepness of the function that relates implied volatility to moneyness (measured by an option's Black-Scholes delta) for OTM put options with 30 days (60 days) of maturity in Panel A (Panel B). ESG score is the monthly updated ESG performance measure from ASSET4. The definitions of the other control variables are reported in the supplementary appendix. All of the independent variables are winsorized each month at the 0.5% level. We report the Newey and West (1987) t-statistics in parentheses below the coefficients. The sample period is from 2004 to 2018.

Panel A: Maturity of 30 days				
	(1) VRP	(2) MFIS	(3) MFIK	(4) SlopeD
ESG score	−1.409	−0.959	−11.482	−4.796
	(−4.08)	(−0.81)	(−6.00)	(−10.28)
Ln(ME)	−0.338	−4.053	−1.678	−0.019
	(−1.41)	(−7.78)	(−1.20)	(−0.05)
Ln(BM)	0.343	0.171	7.908	1.182
	(2.81)	(0.74)	(11.79)	(7.93)
RET1	4.379	−17.985	13.791	6.113
	(3.29)	(−8.02)	(2.10)	(3.87)
RET212	−0.320	−3.731	−2.518	2.208
	(−0.97)	(−5.24)	(−1.07)	(3.59)
IVOL	0.649	68.907	−531.44	−88.451
	(0.19)	(10.13)	(−14.27)	(−7.81)
Ln(AMIHUD)	0.901	−0.127	15.424	5.247
	(3.42)	(−0.30)	(10.00)	(7.43)
BETA	−0.639	0.761	−19.618	−2.197
	(−2.92)	(1.82)	(−12.91)	(−6.45)
Avg adj-R^2	0.097	0.047	0.132	0.161
# obs	114,852	114,852	114,852	114,852

Panel B: Maturity of 60 days				
	(1) VRP	(2) MFIS	(3) MFIK	(4) SlopeD
ESG score	−0.879	0.039	−16.675	−6.467
	(−2.24)	(0.03)	(−6.29)	(−10.75)
Ln(ME)	−0.167	−4.859	−2.927	−0.334
	(−0.76)	(−6.43)	(−1.15)	(−1.01)
Ln(BM)	0.158	−0.563	11.830	1.969
	(0.98)	(−1.78)	(9.37)	(9.82)
RET1	2.507	−55.160	69.027	9.505
	(2.09)	(−16.10)	(5.58)	(5.25)
RET212	−0.275	−13.970	9.142	2.193
	(−0.74)	(−8.99)	(1.54)	(2.89)
IVOL	−3.074	212.058	−1163.6	−69.750
	(−0.74)	(14.60)	(−14.49)	(−5.87)
Ln(AMIHUD)	0.942	−2.960	21.751	4.536
	(4.14)	(−2.83)	(6.76)	(5.81)
BETA	−0.241	4.864	−44.129	−1.883
	(−0.81)	(11.12)	(−11.77)	(−4.34)
Avg adj-R^2	0.110	0.104	0.181	0.113
# obs	115,236	115,634	115,634	115,633