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AN EXPLORATION ON THE RELATIONSHIP BETWEEN ESG PERFORMANCE AND OPTION PRICE

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ABSTRACT

This paper explored the relationship between ESG performance and option price. First, the relationship between ESG performance and option's implied volatility was examined using Panel Regression. It was found that low-ESG options are correlated with higher implied volatility indicating a more expensive option. Afterward, the relationship between ESG performance and option return was examined using Fama-Macbeth Regression (FM-NW). Using daily-rebalanced delta-hedged option return, it was found that low-ESG options are correlated with lower delta-hedged option return, which indicates a more expensive option. These results were then tested against three events – the Global Financial Crisis, the Occupy Wall Street Movement, and the US-China Trade War. These additional results supported the original claims. Furthermore, the ESG premium was quantified using the portfolio sort approach for the daily-rebalanced delta-hedged option return, buy-and-hold option return, and zero-beta straddle portfolio return. All option returns increased monotonically as the ESG quintile increased. The ESG premium was then found to be 2.22% on average per month. Additional results also showed that demand for low-ESG options is higher due to hedging activities and speculative purposes. Likewise, further analysis of other risks found that exposure to jump risk can contribute to the positive relationship between ESG performance and option return. Finally, a proposed option pricing model for call options with ESG score as a feature obtained 23.55% lower mean squared error (MSE) compared to a model based on the Black-Scholes Merton model on the out-of-sample data. Overall, the results of this paper highlighted the predictive power of ESG performance in pricing options.

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CHAPTER 1
INTRODUCTION

1.1. Background of the Study

There has been an increasing interest in firms' environmental, economic, social, and corporate governance (ESG) performance in the last decades. Recent studies have shown an encouraging relationship between the ESG performance of a firm and its financial performance (Whelan et al., 2021). One study provides evidence of the close relationship between ESG performance and stock performance. They found that better ESG performance brings about lower volatility, which leads to a higher risk-adjusted return (Ashwin Kumar et al., 2016). Other studies point to the relationship between ESG performance and the firm's risks, including systematic and downside risks (Albuquerque et al., 2019; Hoepner et al., 2021).

1.2. Statement of the Problem

This paper explores the relationship between the ESG performance of a firm and the price of its options in the market. Many practitioners and researchers alike have studied the pricing of options in the past. However, much work still needs to be done in this relatively new field of Finance. This paper aims to improve the performance of existing option pricing models by studying the pricing impact of ESG-related uncertainties in the options market. Specifically, it wants to determine if investors recognize ESG-related risks and consequently pay a premium, henceforth called ESG premium, to hedge against these risks. Should such a premium exist in the market, then the hypothesis is that including the ESG score of options as a feature will improve the performance of option pricing models.

To begin with the investigation, the impact of ESG performance on option's implied volatility as a measure of normalized option expensiveness is studied. First, the difference in the average implied volatility between low-ESG and high-ESG options is observed across time. This highlights the expensiveness of options with respect to ESG performance. Moreover, the relationship between ESG performance and option's implied volatility is formally studied using Panel Regression. Lastly, this relationship is further examined in three quasi-natural events relating to corporate ESG practices to determine how investors price ESG-related uncertainties after a sudden increase in ESG awareness.

Afterward, the impact of ESG performance on option return is studied. First, a baseline Fama-Macbeth Regression (FM-NW) is performed to study the effect of ESG performance on delta-hedged option return. This identifies how much the delta-hedged option return changes as the ESG score of an option changes. Moreover, Fama-Macbeth Regressions are performed on each sub-periods for the three quasi-natural events to determine the difference in the impact of ESG performance during the different sub-periods. Likewise, the components of ESG are individually studied with another Fama-Macbeth Regression to determine their individual relationship with delta-hedged option return. Lastly, a robustness test is performed on out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM) options following the baseline Fama-Macbeth Regression to determine whether the results hold for options with different moneyness.

Next, the ESG premium is quantified. First, three option returns are considered – the daily-rebalanced delta-hedged option return, buy-and-hold delta-hedged option return, and zero-beta straddle portfolio return. The options are then sorted into quintiles based on their ESG scores. The average option return and the average risk-adjusted return from the Fama-French five-factor model are reported for each quintile. The difference between the fifth and first quintile option returns is then quantified as the ESG premium. Furthermore, the relationship between ESG performance and option demand from users is also explored. Two quantities representing option demand are constructed and compared across quintiles to determine the option demand in relation to the ESG performance.

Additionally, the relationship between ESG performance and volatility and jump risk is also explored. Two additional portfolios are created – the beta-neutral, vega-neutral, and gamma-positive portfolio and the beta-neutral, gamma-neutral, and vega-positive portfolio – to act as tradable portfolios for the two risks. A similar Fama-Macbeth Regression is performed to determine the relationship between ESG performance and the two risk premia. A portfolio sort approach is also done to quantify the corresponding risk premia.

Finally, this paper ends by proposing two neural network models for pricing call options. The first model uses the features of the Black-Scholes Merton model to predict option price. This model acts as a baseline model. The second model utilizes the relationship between ESG performance and option's implied volatility and return by including the ESG score and other control variables as additional features. The performance of the second model is then compared against the baseline model to determine the predictive power of ESG performance in pricing options.

1.3. Significance of the Study

This paper contributes to the growing literature on option pricing. As this paper focuses on real options data, it attempts to capture market dynamics, specifically ESG-related market dynamics, that standard models such as the Black-Scholes Merton model fail to capture. Additionally, the proposed model for option pricing can be potentially beneficial for options market analysis and trading activities.

1.4. Scope and Limitations

While this paper attempts to use ESG scores to price options, Berg et al. (2019) showed a divergence between ESG scores among six prominent ESG rating agencies. Since this paper only uses ESG data from one ESG rating agency (IHS Markit), the data from other ESG rating agencies can potentially show a different result. Moreover, this research primarily focuses on short-term at-the-money (ATM) options since they are traded more frequently and have lower effective transaction costs as compared to long-term options. Hence, the results obtained may not readily apply to options with longer maturity or different moneyness. Finally, the analysis is primarily made for the period from January 2007 to December 2018 using the data from the United States markets. Hence, the results might potentially differ for other markets or other periods.

1.5. Definition of Terms

The following definitions are used throughout the paper:

1. Daily-rebalanced delta-hedged option return - the change over a month in the value of a portfolio consisting of one long option contract hedged by delta shares of the underlying stock rebalanced daily scaled by the initial investment $\Delta_{c,t}S_t - C_t$ or $P_t - \Delta_{p,t}S_t$.

2. Buy-and-hold delta-hedged option return - the return over a month of a portfolio consisting of one long option contract hedged by delta shares of the underlying stock held for one month without rebalancing.

3. Zero-beta straddle portfolio return - the return over a month of a portfolio consisting of θ units of call option and $(1 - \theta)$ units of put option where θ is determined to make the overall portfolio beta-neutral.

4. ImpVol – the average implied volatility of at-the-money (ATM) call and put options with 50 days to maturity for a month.

5. ESG score - ESG score data is from the IHS Markit database. This rating measures a company's financial and extra-financial health based on 23 factors from the four components of ESG - Environmental, Social, Corporate Governance, and Economic. The range of ESG scores is between 0 and 1 after rescaling.

6. Book-to-market ratio (bm) - the ratio of a firm's book value to its market value at the end of the previous year.

7. Reversal (ret1) - the stock return in the prior month.

8. Momentum (ret212) - the cumulative stock return from the prior second through the 12th month.

9. Return on equity (roe) – the ratio of a firm's net income to its shareholder's equity at the end of the previous year.

10. Open interest - the total number of option contracts open at the end of the previous month scaled by the stock trading volume.

11. Bid-ask spread - the ratio of the difference between the bid and ask quotes of the option to the midpoint of the bid and ask quotes of the option at the end of the previous month.

12. Δ_{OI} - the one-month change in open interest, scaled by the average option trading volume for the month.

13. Z_{OI} - the standardized open interest for the month, scaled by the average stock trading volume for the month.

CHAPTER 2
REVIEW OF RELATED LITERATURE

2.1. ESG Performance and Risks

Numerous studies have been conducted in the past to explore the correlation between ESG performance and the financial risk of a firm. Ashwin Kumar et al. (2016) focused on the volatility of stock returns and challenged the conventional notion in Finance of lower risk leading to lower returns. They focused on stocks in the Dow Jones Sustainability Index (DJSI), which represented firms with good ESG performance, and compared their performance against non-DJSI stocks to represent the average market performance. They noted that firms listed in the DJSI are among the top 10% of their respective industry in terms of ESG performance. Short-term indicators such as weekly stock returns and volatilities were used to isolate the ESG factors from other factors affecting long-term stock performance. They reported that in all the 12 industries studied, ESG firms exhibited a lower annualized volatility by 28.67% on average. This result showed that companies with better ESG performance tend to exhibit less risk compared to other non-ESG firms in the same industry. However, the impact differed per industry with a 6.10% difference between ESG and non-ESG firms for the food and beverage industry to a 50.75% difference between ESG and non-ESG firms for the energy industry. They further noted a pronounced difference in volatilities across different industries for non-ESG firms compared to ESG firms. A 47% difference in volatility was observed for non-ESG firms belonging to the Energy industry and Insurance industry and only an 11% difference for the same industries for ESG firms. Finally, the model they employed showed that even with lower risk, investments could achieve a higher return. In the 12 industries studied, a 6.12% average increase in return was observed for ESG firms. For the majority of the industries (8 out of 12), better returns were obtained for ESG firms than their non-ESG peers.

This difference ranges from 2.25% to 31.84%. The paper concluded by showing that lower risk brought about by better ESG performance leads to an increase in risk-adjusted returns, as measured by the Sharpe ratio and Treynor ratio, by an average of 7.67% and 11.81%, respectively, across the majority of the industries.

Meanwhile, Hoepner et al. (2021) studied the effects of investors' engagement on ESG issues on a firm's downside risks. Proprietary data on ESG engagement was used which was provided by a large institutional asset manager in the United Kingdom and considered to be one of the most influential figures in promoting higher ESG standards at portfolio firms. The data contained 1,712 recorded engagements with themes regarding corporate governance, social, environmental, and strategy across 573 firms for more than a decade. It showed that out of all the investor engagement, the target firm took action to address the concern more than 31% of the time. Using this data, the relationship between investor engagement and downside risks, or left-tail risk, is examined. Downside risk was explored since if the return distribution is heavy-tailed, then risk measures, such as volatility, that do not distinguish between positive and negative movement are uninformative. In the paper, downside risk was measured in two ways – the 5% Value-at-Risk (VaR) for daily returns, and the second-order lower partial moment (LPM) of return distribution that fell below the 0%-return threshold which was calculated as

$$\text{LPM} = \sqrt{\frac{1}{N_1 - 1} \sum_{i=1}^{N_1} \left(r_{n,i} - \overline{r_{n,l}}\right)^2},$$

where $r_{n,i}$ is the negative return of firm i, $\overline{r_{n,l}}$ is the average of $r_{n,i}$, and N_1 is the number of negative returns for firm i during the period. The results showed that across all engagements (successful and unsuccessful), downside risks declined after the engagements for both approaches by an average of 5.5% of the variable's standard deviation. Moreover, a sharp increase was also observed for successful engagements, and its economic significance increases by a factor of 3.5 on average. They also found that the effect of the engagements on risk reduction varies across the theme of the engagement, being primarily driven by environmental issues on climate change. Overall the study showed that downside risk significantly declines after successful investor engagement on ESG issues.

2.2. Options and Risks

Furthermore, several studies have also explored the relationship between option return and the risks of the underlying asset. Goyal & Saretto (2009) studied the cross-section of stock option returns and volatility by sorting based on the difference in historical realized volatility and at-the-money implied volatility (HV-IV). The study reported that a trading strategy involving i) a long position in an options portfolio of stocks with a large positive difference between HV and IV, and ii) a short position in an options portfolio of stocks with a large negative difference generates statistically and economically significant returns. Hence, this indicated that large deviations of IV and HV can have a significant effect on option mispricing. Then, this study also examined whether option returns to the long-short strategy are related to aggregate risk using time series regression on the delta-hedged call returns. The risk factors or regressors used included the Fama & French (1993) three factors, the Carhart (1997) momentum factor (MOM), and the Coval & Shumway (2001) excess zero-beta S&P 500 straddle factor. The results showed that all variables had insignificant loadings on the market factor. Additionally, the loadings on Fama and French and momentum factors were also insignificant. This indicated that the portfolios earn abnormal returns with positive alphas even with positive exposure to volatility risk. Hence, the option return is not explained by these sources of risks and other stock or option market factors. The paper suggested that some other types of risks are being priced in option returns.

The previous study used several risk factors pioneered by Fama & French (1993) in their three-factor model which have since then evolved to larger models. Numerous studies on asset pricing use the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) to investigate the relationship between risk and return. The CAPM assumes that the expected asset return co-moves with the expected return on the market portfolio. The differences in beta are sufficient to explain the cross-sectional differences in stock returns. However, this model has received criticisms over time and many alternatives to this model have emerged to improve the CAPM. One alternative was the three-factor model of Fama & French (1993), which added two factors relating to size and book-to-market to the single factor model (CAPM). The three-factor Fama-French model was given by

$$R_{it} - R_{Ft} = \alpha_i + \beta_i \left(R_{Mt} - R_{Ft}\right) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + \epsilon_{it},$$

where R_{it} is the return of the security or portfolio i for the period t, R_{Ft} is the risk-free rate, R_{Mt} is the return on the value-weight market portfolio, and β_i is portfolio i's CAPM beta. The two additional factors are SMB_t, representing the difference in the return of small stocks and big stocks, which is the size factor, and HML_t, representing the difference between the returns of high and low B/M stocks, which is the value factor. Another alternative was the five-factor Fama-French model developed later by Fama & French (2015), which added profitability and investment factors to the three-factor Fama-French model. This was given by

$$R_{it} - R_{Ft} = \alpha_i + \beta_i \left(R_{Mt} - R_{Ft}\right) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + r_i \mathrm{RMW}_t + c_i \mathrm{CMA}_t + \epsilon_{it},$$

where RMW_t, representing the difference in the return of robust and weak stocks, is the profitability factor, and CMA_t, representing the difference in the return of conservative and aggressive stocks, is the investment factor. Moreover, independent of Fama and French, Carhart (1997) developed an additional momentum factor (MOM), representing the difference in the returns of the lowest performing firms and the highest performing firms, lagged by a month. Coval & Shumway (2001) also developed a market volatility factor represented by the zero-beta straddle return on the S&P 500 index, contributing to the growing list of market risk factors initially proposed by Fama and French.

Foye (2018) analyzed the performance of the five-factor Fama-French model to offer a better description of emerging market equity returns as compared to the single-factor model and the three-factor model. The study was conducted across a broad range of emerging markets in 18 countries from Eastern Europe, Latin

America, and Asia. The factors were calculated according to the Fama & French (2015) approach and regression of the left-hand-side (LHS) portfolios on the different factor models were performed. It was found that there is a pronounced value premium for all three regions and the value factor (HML) was the only one out of the five factors that was not redundant in any of the regions. The profitability factor (RMW) was also found to be significant in Eastern Europe and Latin America, which indicated the presence of a profitability premium. Moreover, the five-factor model was shown to consistently outperform the three-factor model across the six sets of LHS sorts in terms of producing reduced intercepts and GRS statistics. With these results, the study concluded that the five-factor model provides a better description of average returns rather than the three-factor model, especially for Eastern Europe and Latin America, although it offered no significant improvements from the three-factor model for data in Asia.

Likewise, Cao & Han (2013) examined the relation between delta-hedged option return and stock idiosyncratic volatility using cross-sectional Fama-Macbeth Regression and the portfolio sort approach. The study evaluated 210,000 delta hedged option returns for six thousand underlying stocks, that are rebalanced daily so that the results are not sensitive to stock price movements. First, using the Fama-Macbeth Regression, the study found that delta-hedged options have negative returns when the underlying stocks have high idiosyncratic volatility. These options attract high demand from investors but are also more difficult to hedge, thus tend to be more expensive and have lower returns. The same pattern was observed for both call and put options. Then, the study also examined the relation of liquidity to option returns, by sorting the stocks' idiosyncratic volatility based on the stock price and the Amihud illiquidity measure. It was shown that the average delta-hedged option return is significantly more negative when the underlying stocks or the options are less liquid and when the option open interests are higher. Hence, the average return of this idiosyncratic volatility-based option strategy is significantly higher for illiquid and low-priced stocks, which was consistent with how options that are more difficult to hedge and have higher arbitrage costs are usually charged a higher premium. Lastly, the study investigated whether the return of options can be explained by systematic volatility risk factors by regressing the time series of equal-weighted monthly returns on proxies of market volatility risks and common idiosyncratic volatility risks. Some of the risk factors observed included market volatility risk using the zero-beta straddle return on the S&P index, and the individual stock variance risk using the value-weighted zero-beta straddle returns on the stocks. The Fama-French three factors and the momentum factor were also included as additional regressors. The estimated coefficients for the volatility risk factors were found to be negative, with only the coefficient for the common individual stock variance risk as significantly negative in all specifications. Nonetheless, the option strategy still had a positive alpha of 1.318% per month, as compared with the raw equal-weighted average return of 1.400%. Therefore, exposure to market volatility risk or common idiosyncratic volatility risk explained only a small portion of the under-performance of delta-hedged options on stocks with high idiosyncratic volatility.

In the previously mentioned study, the regression method developed by Fama & MacBeth (1973) was used. The Fama-Macbeth Regression is widely used for asset pricing to examine various factors and their pricing power in the cross-section of asset returns. The Fama-MacBeth Regression (FM-i) estimates the betas and risk premia for any risk factors in asset pricing and also addresses concerns about cross-sectional correlation. Bai & Zhou (2015) represented the standard Fama-Macbeth Regression model in two stages. First, each of n asset returns are regressed against the time series of the m proposed risk factors to determine each asset's beta exposures by applying ordinary least-squares (OLS) to the equations

$$\begin{aligned}
R_{1,t} &= \alpha_1 + \beta_{1,F_1} F_{1,t} + \beta_{1,F_2} F_{2,t} + \cdots + \beta_{1,F_m} F_{m,t} + \varepsilon_{1,t} \\
R_{2,t} &= \alpha_2 + \beta_{2,F_1} F_{1,t} + \beta_{2,F_2} F_{2,t} + \cdots + \beta_{2,F_m} F_{m,t} + \varepsilon_{2,t} \\
&\vdots \\
R_{n,t} &= \alpha_n + \beta_{n,F_1} F_{1,t} + \beta_{n,F_2} F_{2,t} + \cdots + \beta_{n,F_m} F_{m,t} + \varepsilon_{n,t}
\end{aligned}$$

where $R_{i,t}$ is the return of asset i at time t, β_{i,F_j} is the regression beta of asset i

for the jth risk factor, and $F_{j,t}$ is the realization of the jth risk factors at time t. Then, the second stage runs a cross-sectional regression on all asset returns for each T time periods against the previously estimated betas to determine the risk premium for each factor by applying the ordinary least-squares (OLS) to the equations

$$\begin{aligned}
R_{i,1} &= \gamma_{1,0} + \gamma_{1,1}\widehat{\beta}_{i,F_1} + \gamma_{1,2}\widehat{\beta}_{i,F_2} + \cdots + \gamma_{1,m}\widehat{\beta}_{i,F_m} + \varepsilon_{i,1} \\
R_{i,2} &= \gamma_{2,0} + \gamma_{2,1}\widehat{\beta}_{i,F_1} + \gamma_{2,2}\widehat{\beta}_{i,F_2} + \cdots + \gamma_{2,m}\widehat{\beta}_{i,F_m} + \varepsilon_{i,2} \\
&\vdots \\
R_{i,T} &= \gamma_{T,0} + \gamma_{T,1}\widehat{\beta}_{i,F_1} + \gamma_{T,2}\widehat{\beta}_{i,F_2} + \cdots + \gamma_{T,m}\widehat{\beta}_{i,F_m} + \varepsilon_{i,T}
\end{aligned}$$

where $\gamma_{t,j}$ is the regression gamma of the jth risk factor at time t, and $\widehat{\beta}_{i,F_j}$ are the betas obtained in the first step. Finally, the estimator of risk premia for the jth risk factor $\widehat{\gamma}_j$ is given by its average

$$\widehat{\gamma}_j = \frac{1}{T}\sum_{t=1}^{T}\widehat{\gamma}_{t,j}.$$

The t-statistics to test the hypothesis of whether $\widehat{\gamma}_j = 0$ is given by

$$t\left(\widehat{\gamma}_j\right) = \frac{\widehat{\gamma}_j}{s\left(\widehat{\gamma}_{t,j}\right)/\sqrt{T}},$$

where $s\left(\widehat{\gamma}_{t,j}\right)$ is the standard deviation of the monthly estimates.

In addition, another variant of the Fama-Macbeth Regression (FM-NW) corrects for serial correlation in addition to cross-sectional correlation. As shown in Petersen (2005), T cross-sectional regression are performed on the equations

$$\begin{aligned}
R_{i,1} &= \alpha_1 + \beta_{1,F_1}F_{1,1} + \beta_{1,F_2}F_{2,1} + \cdots + \beta_{1,F_m}F_{m,1} + \varepsilon_{i,1} \\
R_{i,2} &= \alpha_2 + \beta_{2,F_1}F_{1,2} + \beta_{2,F_2}F_{2,2} + \cdots + \beta_{2,F_m}F_{m,2} + \varepsilon_{i,2} \\
&\vdots \\
R_{i,T} &= \alpha_T + \beta_{T,F_1}F_{1,T} + \beta_{T,F_2}F_{2,T} + \cdots + \beta_{T,F_m}F_{m,T} + \varepsilon_{i,T}
\end{aligned}$$

where $R_{i,t}$ is the return of asset i at time t, β_{t,F_j} is the regression beta at time t for the jth risk factor, and $F_{j,t}$ is the realization of the jth risk factors at time t. The average of the T estimates are then the coefficient estimates

$$\widehat{\beta}_j = \frac{1}{T}\sum_{t=1}^{T}\widehat{\beta}_{t,F_j}.$$

To adjust for serial correlation, the robust Newey & West (1987) standard error and t-statistics are used.

2.3. Option Pricing Models

Aside from determining option returns, several option pricing models also exist in the literature to relax assumptions made in the original Black-Scholes Merton formulation. Some of these include the Heston model and using the Fourier-Cosine series for the Heston model (Fang & Oosterlee, 2008). More recently, the new developments in the field of machine learning have prompted the application of this new paradigm to option pricing. du Plooy & Venter (2021) priced vanilla options using neural networks with a great degree of accuracy. Due to the limited quality options data in the South African market, the training data was artificially generated wherein the training inputs, including the strike price (K), the stock price (S_0), time to maturity (τ), risk-free rate (r), and implied volatility (σ), are randomly sampled and transformed into the price of European call options using the Black-Scholes Merton formula. The input ranges also accounted for extreme values to provide uniqueness to the generated data. Afterward, the features were normalized using the homogeneity hint by Merton (1973) which reduces the number of inputs of the neural network. Thus, the inputs are reduced to $x = \left\{\frac{S_0}{K}, \tau, r, \sigma\right\}$ with an output of $y = \left\{\frac{c}{K}\right\}$. The final neural network is composed of two hidden layers with 256 and 128 units, respectively, with a softplus output layer activation function, and compiled using the Adam optimizer with a batch size of 64 and 20 epochs. After training the model on one million artificially generated data, it was validated against real-world data from the top 40 European call options of the Johannesburg Stock Exchange (JSE). The model achieved a mean squared error (MSE) of 4.11×10^{-7} with an R^2 of 0.999988 on the test data. Overall, the results suggested that neural network models can efficiently and accurately price options and approximate asset pricing models that would otherwise require large computations.

2.4. ESG Performance and Options

In an effort to bridge the discussions on ESG performance and option pricing and returns, Cao et al. (2021) explored the effects of a firm's ESG performance on its option price and return. The necessary ESG data was gathered from Asset4 (now Thomson Reuters ESG Scores), OptionMetrics, Center for Research on Security Prices (CRSP), and COMPUSTAT. The paper considered options near at-the-money, near 50 days to maturity, no dividend in the underlying asset during the life of the option, and no violation of arbitrage conditions. The initial result using monthly Fama-Macbeth Regression on daily-rebalanced delta-hedged option return showed a positive correlation between ESG performance and option return both in the case when control variables were added and not. This translated to an increase of 0.32% in the option return from low-ESG firms to high-ESG firms, economically significant given a mean return of -0.57%. An additional result also using Fama-Macbeth Regression showed that each of the environmental (E), social (S), and governance (G) scores contributed to the positive relationship with the option return, albeit the governance score has the least significant impact. A similar result was observed when tested against out-of-the-money and in-the-money options, indicating the robustness of the model. As a final check, control variables for volatility risk (model-free implied variance) and jump risk (model-free implied skewness and kurtosis) were added and a similar result was obtained. To determine the pricing of ESG-related uncertainties, the researchers turned to portfolio sorts to determine the premia investors pay to hedge against these risks. Options were sorted into quintiles based on the ESG score of the underlying asset and three portfolios were created – daily rebalanced delta-hedged portfolio, buy-and-hold delta-hedged portfolio, and zero-beta straddle portfolio. The difference between the equal-weighted portfolio return of the fifth and first quintile indicated an ESG premium of 0.30% per month. Finally, several Fama-Macbeth Regressions were performed for some additional control variables. These additional results suggested that firms closer to end-consumers, experiencing high market competition, having headquarters in Democratic-leaning states, allocating more time for ESG-related topics during conference calls, and having no corporate hedging activities have option prices more influenced by their ESG performance.

This paper primarily adapts the methodology employed by Cao et al. (2021) but extends it by attempting to compare the performance of existing option pricing models to models where ESG score is added as a feature.

CHAPTER 3
DATA

3.1. Data Sources

This paper uses several market data from the Quantbot Technologies database. First, the data on firms' ESG performance is collected from the IHS Markit ESG database. It provides relevant ESG information and scores based on 23 factors from the four components of ESG. It also includes the integrated ESG rating as well as the aggregated environmental score (E), social score (S), corporate governance score (G), and economic score (Ec). The database provides information on more than 1,200 firms in the United States, covering the major indices. Next, options data is gathered from OptionMetrics which includes information about the underlying asset of the option as well as its strike price, expiration, option type, best bid and best ask prices, trading volume, open interest, and contract size among others for each trading day. Likewise, stocks data is gathered from Bloomberg which includes the stock's open, high, low, and close prices, bid and ask prices, trading volume, shares outstanding, dividends, and market capitalization. The data covers more than 18,000 assets for each trading day. Further information regarding the stocks is gathered from various sources in the Quantbot Tech database. These include the yearly net income and book value. Additionally, the daily zero rates are also gathered from Bloomberg, which includes the zero rates from 1 month until 30 years. Lastly, the daily Fama-French factors are obtained from Kenneth French's data library. For all data, the time period considered is from January 2007 to December 2018.

3.2. Data Processing

The raw data from the various sources are cleaned as follows. First, an actual/360 day count convention is used in the entire data. Likewise, the option price is assumed to be the midpoint of the best bid and best ask prices unless stated otherwise. For consistency, option's implied volatility is computed using a root-finding algorithm, the binary search algorithm, following the Black-Scholes Merton model for option pricing. This is done instead of using OptionMetrics' Volatility Surface file due to the large number of missing entries. The binary search algorithm has a straightforward implementation with a reasonable complexity of $\mathcal{O}(\log N)$. Furthermore, the Black-Scholes Merton option pricing formula is monotonic with respect to the implied volatility, *ceteris paribus*, making this algorithm the best candidate for this task. It is worth noting that while other root-finding algorithms, such as the Newton-Raphson method, have a faster convergence rate, their implementation becomes complicated, especially when dealing with the Black-Scholes Merton formula. Lastly, missing zero-rates and stock-related quantities, such as the ESG score, are filled using the `pandas.DataFrame.ffill()` function which forward fills the data, *i.e.*, the function propagates the last valid observation forward.

Additionally, the options considered in this paper are selected as follows. At the end of each month and for each optionable stock, the pair of options (call and put) closest to at-the-money (ATM) and with remaining maturity closest to 50 days is selected. The moneyness is determined based on the ratio of the underlying stock's closing price and the option's strike price $\left(\dfrac{S_0}{K}\right)$. Options with moneyness from 0.9 to 1.1 are classified as at-the-money (ATM). Meanwhile, options expiring on the third Friday or Saturday of the following month have a remaining maturity closest to 50 days. Short-term at-the-money (ATM) options are the primary focus of this paper due to their high liquidity and lower transaction costs.

Finally, the options are further filtered as follows. First, to address arbitrage opportunities, options with clear violations of no-arbitrage conditions are disregarded from the analysis. These no-arbitrage conditions are

$$C_t \leq S_t, \quad P_t \leq Ke^{-r(T-t)}, \quad C_t \geq \left(S_t - Ke^{-r(T-t)}\right)_+, \quad P_t \geq \left(Ke^{-r(T-t)} - S_t\right)_+,$$

where C_t, P_t are the price of the call and put option, respectively, S_t is the price of the underlying asset, r is the risk-free rate, K is the strike price of the option, and $T - t$ is the remaining life of the option. In addition, only options with non-negative trading volume, positive bid quotes, bid prices strictly smaller than the ask price, and the midpoint of bid and ask prices are greater than \$0.1 are retained. Moreover, to restrict the data on ESG-related uncertainties, options whose underlying asset do not have an ESG score available are removed from the analysis. Lastly, only options with both call and put options after filtering are retained.

CHAPTER 4
METHODOLOGY

4.1. ESG Performance and Implied Volatility

This section explores the relationship between ESG performance and option's implied volatility. It is worth noting that option's implied volatility, derived from the Black-Scholes Merton formula, can be viewed as a normalized measure of option expensiveness. As such, all risks investors find important are embedded in this quantity. Furthermore, while option's implied volatility does not directly indicate the economic significance of ESG premium, it is nevertheless an intuitive way to illustrate option expensiveness with respect to ESG performance.

As an initial analysis, the difference in the monthly average implied volatility between low-ESG and high-ESG options is reported for the entire period considered. Options are sorted into quintiles based on their ESG scores to distinguish the low-ESG (P1) and high-ESG (P5) options. The difference in the average implied volatility between the first and last quintile (P1-P5) is then plotted across time to highlight any sudden increase in this difference. A sudden increase in this difference would then suggest an increase in ESG-related uncertainty which is consequently priced into options. This paper focuses on three global events that raised awareness of firms' ESG performance – the Global Financial Crisis (GFC), the Occupy Wall Street Movement (OWS), and the US-China Trade War (TW). A sudden jump in the difference of average implied volatility is expected near these events as they increase ESG-related uncertainties.

The Global Financial Crisis (GFC) of 2008 was an economic crisis resulting from the downturn in the US housing market that spread to the rest of the world through the linkages in the global financial system. Many banks incurred large losses and millions of people lost their jobs which also led to a subsequent international banking crisis. The Global Financial Crisis of 2008 was considered a severe economic crisis which increased firms' attention to ESG principles and issues. Key ESG-related policies were created in response to the crisis, such as the UK's Stewardship Code and Kay Review, and Sustainable Development Goals. Therefore, the relationship between ESG and option's implied volatility for the period of January 2008 to June 2010 is studied to determine the impact of GFC.

The second global event that provoked attention to ESG-related issues was the Occupy Wall Street Movement (OWS) in 2011. On September 17, 2011, hundreds of activists gathered in Zuccotti Park in New York City's Financial District, which marked the first day of the Occupy Wall Street Movement. This was a protest movement against corporate greed and corruption, calling out companies to address ESG-related issues specifically on corporate governance practices. Hence, the relationship between ESG and option's implied volatility during the period from January 2011 to June 2012 is studied to determine the effect of OWS.

Finally, the US-China Trade War (TW) began in January 2018 when US President Donald Trump began setting additional tariffs and other trade barriers on Chinese imports. On July 2018, American tariffs came into effect on Chinese goods. In retaliation, China started imposing extra tariffs as well on US products. The trade war negatively affected both economies, leading to a dramatic decline in employment and consumption and a disruption in the global supply chain. This raised attention for firms to address ESG-related issues in response to the trade war. Hence, the relationship between ESG and option's implied volatility during the period from January 2017 to December 2018 is studied to determine the impact of the Trade War. While the Trade War continued after 2018, the analysis is made only until December 2018 since the time period considered ended here.

4.1.1. Baseline Panel Regression

In order to properly quantify the relationship between ESG performance and option's implied volatility, a baseline Panel Regression is performed on the entire dataset. A Panel Regression is chosen to control for fixed time and stock effects. For each optionable stock at the end of each month, ImpVol is defined as the monthly average of the daily Black-Scholes Merton implied volatility (in percentage) of at-the-money (ATM) call and put options. Additionally, only options with remaining maturity of 50 days are included in the analysis due to their high liquidity. It must be noted that ImpVol does not only represent the future expectation of the market, it also embeds various risk premium.

For the Panel Regression, ImpVol is the dependent variable while ESG score as well as other control variables such as reversal, momentum, book-to-market ratio, and return on equity are the independent variables. The Panel Regression can be modelled as

$$\text{ImpVol}_{it} = \alpha + \beta_1 \text{ESG}_{it} + \boldsymbol{\beta' X_{it}} + \gamma_t + \theta_i + \varepsilon_{it},$$

where ImpVol_{it} is the average implied volatility of ATM call and put option of asset i for the month t, ESG_{it} is the ESG score of asset i at the end of month t, $\boldsymbol{X_{it}}$ are the control variables, γ_t is the time fixed effect, and θ_i is the stock fixed effects.

4.1.2. Global Financial Crisis

For the Global Financial Crisis (GFC), the period from September 2008 to August 2009 is considered as the In-GFC sub-period, while the period from September 2009 to June 2010 is considered as the After-GFC sub-period. The additional variables $\mathbb{1}_{\text{In}}$ and $\mathbb{1}_{\text{After}}$ would serve as dummy variables indicating the In and After sub-periods in relation to the Global Financial Crisis. A similar Panel Regression is performed on the data with ImpVol as the dependent variable and ESG score and the other control variables as the independent variables. This can be modelled as

$$\text{ImpVol}_{it} = \alpha + \beta_1 \mathbb{1}_{\text{In}} \text{ESG}_{it} + \beta_2 \mathbb{1}_{\text{After}} \text{ESG}_{it} + \beta_3 \text{ESG}_{it} + \boldsymbol{\beta' X_{it}} + \gamma_t + \theta_i + \varepsilon_{it},$$

where $\mathbb{1}_{\text{In}}$ and $\mathbb{1}_{\text{After}}$ are time indicator variables that equal to 1 during the sub-period they indicate. The coefficients on the interaction term β_1 and β_2 are the estimates of the incremental effect of ESG on option's implied volatility during and after the GFC period, respectively.

4.1.3. Occupy Wall Street Movement

For the Occupy Wall Street Movement (OWS), the period from September 2011 to December 2011 is considered as the In-OWS sub-period, while the period from January 2012 to June 2012 is considered as the After-OWS sub-period. The Panel Regression can be modelled similarly as

$$\text{ImpVol}_{it} = \alpha + \beta_1 \mathbb{1}_{\text{In}}\text{ESG}_{it} + \beta_2 \mathbb{1}_{\text{After}}\text{ESG}_{it} + \beta_3 \text{ESG}_{it} + \boldsymbol{\beta' X_{it}} + \gamma_t + \theta_i + \varepsilon_{it}.$$

4.1.4. US-China Trade War

For the US-China Trade War (TW), the period from January 2018 to December 2018 is considered as the In-TW sub-period. A similar Panel Regression is performed on the data with ImpVol as the dependent variable and the same independent variables. This can be modelled as

$$\text{ImpVol}_{it} = \alpha + \beta_1 \mathbb{1}_{\text{In}}\text{ESG}_{it} + \beta_2 \text{ESG}_{it} + \boldsymbol{\beta' X_{it}} + \gamma_t + \theta_i + \varepsilon_{it},$$

where $\mathbb{1}_{\text{In}}$ is the time indicator variable that equals to 1 during the In-TW sub-period.

4.2. ESG Performance and Option Return

The relationship between ESG performance and option's implied volatility only suggests the existence of ESG premium in the options market since the latter embeds various risk premia. Hence, this section studies the relationship between ESG performance and option return to formally quantify the pricing effect of ESG performance. Specifically, this section analyzes the effect of ESG performance on the cross-section of delta-hedged option return.

Following Bakshi & Kapadia (2003) along with some modifications, the daily-rebalanced delta-hedged call option gain is defined by considering a portfolio of one long call option hedged by delta shares of short position in the underlying asset with the net investment earning the risk-free rate. Moreover the portfolio is hedged discretely N times over a period $[t, t+\tau]$ with rebalancing times $t_1, t_2, \ldots, t_{N-1}$. The portfolio is rebalanced daily so it would not be sensitive to stock price movements. Thus, the delta-hedged call option gain can be represented as

$$\Pi_{t,t+\tau} = (C_{t+\tau} - C_t) - \sum_{n=0}^{N-1} \Delta_{c,t_n} \left([S_{t_{n+1}} + d_{t_{n+1}}] - S_{t_n} \right) - \sum_{n=0}^{N-1} \frac{(t_{n+1} - t_n) r_{t_n}}{360} (C_{t_n} - \Delta_{c,t_n} S_{t_n}),$$

where C_{t_n} is the price of the call option at time t_n, Δ_{c,t_n} is the delta of the call option at time t_n, S_{t_n} is the price of the underlying stock at time t_n, $d_{t_{n+1}}$ is the dividend paid at time t_{n+1}, and r_{t_n} is the annualized risk-free rate at time t_n. The delta-hedged put option gain is defined similarly. Moreover, instead of using the midpoint of best bid and best ask price, the price of the option used in the delta-hedging is the best bid price except at time $t = t_0$ where the best offer price is used. This is done to simulate the actual transactions involved in the delta-hedging, *i.e.*, buying the option at time $t = t_0$ and selling the option at time $t_1, t_2, \ldots, t_{N-1}$. With a zero-net investment initial position, the delta-hedged option gain $\Pi_{t,t+\tau}$ is the excess dollar return of the delta-hedged option. Finally, the dollar return is scaled by $\Delta_{c,t} S_t - C_t$ for call options or by $P_t - \Delta_{p,t} S_t$ for put options to be comparable across stocks and is denoted as the daily-rebalanced delta-hedged option return.

4.2.1. Baseline Fama-Macbeth Regression

To analyze the relationship between ESG performance and option return, the following portfolio is considered. At the end of each month and for each optionable stock, the one-month return of a daily-rebalanced delta-hedged portfolio is calculated for both call and put options. Afterward, the Fama-Macbeth Regression (FM-NW) is performed on the daily-rebalanced delta-hedged option return against the ESG score. The other independent variables used are reversal, momentum, book-to-market ratio, return on equity, option open interest, and option bid-ask spread. The average coefficients and the Newey-West t-statistics are also reported. The Fama-Macbeth Regression is done to describe the average relationship between ESG score and the daily-rebalanced delta-hedged option return across time.

4.2.2. Global Financial Crisis

An additional test for the Global Financial Crisis (GFC) is done to investigate how the relationship between ESG performance and option return changes across the sub-periods. The period from January 2008 to June 2010 is divided into three sub-periods – January 2008 to August 2008 as the Before-GFC sub-period, September 2008 to August 2009 as the In-GFC sub-period, and September 2009 to June 2010 as the After-GFC sub-period. A similar Fama-Macbeth Regression is done for each of the sub-periods using the same dependent and independent variables. The coefficients and t-statistics are reported and compared across the three sub-periods to determine the impact of the event. The focus is on the difference in the ESG coefficients across the three sub-periods.

4.2.3. Occupy Wall Street Movement

An additional test is also done for the Occupy Wall Street Movement (OWS) to determine the change in the relationship between ESG performance and option return across the different sub-periods. The period from January 2011 to June 2012 is divided into three sub-periods – January 2011 to August 2011 as the Before-OWS sub-period, September 2011 to December 2011 as the In-OWS sub-period, and January 2012 to June 2012 as the After-OWS sub-period. Similarly, the Fama-Macbeth Regression is performed for each sub-period and the results are compared across the three sub-periods to determine the impact of OWS. Again, the difference in the ESG coefficients across the three sub-periods is the main focus.

4.2.4. US-China Trade War

Lastly, an additional test for the US-China Trade War (TW) is done to determine its impact on the relationship between ESG performance and option return across the sub-periods. The two sub-periods considered are January 2017 to December 2017 as the Before-TW sub-period and January 2018 to December 2018 as the In-TW sub-period. For each sub-period, the Fama Macbeth Regression is performed using the same dependent and independent variables. The coefficients and t-statistics are reported and compared between the two sub-periods to determine the impact of TW. The focus is again on the difference in the ESG coefficients.

4.2.5. Separating the Effects of E, S, G, and Ec Score

Since the three events considered are more relevant for corporate governance and economic issues, this subsection addresses the concern of whether the results obtained earlier are driven only by the G-score and Ec-score. In order to determine the individual impact of the four components of ESG on option return, a similar Fama-Macbeth Regression is performed on the daily-rebalanced delta-hedged option return with the E-score, S-score, G-score, and Ec-score as independent variables. The regression is done both individually with only one ESG component and aggregated with all four components. The coefficients of each component of ESG are reported and analyzed to determine how each component contributes to the option return.

4.2.6. Robustness Test

Finally, since the main results are based solely on at-the-money (ATM) options, a robustness test is performed to examine the effect of ESG performance on option return for options with different moneyness. Options are classified as out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM) options, based on their moneyness $\left(\frac{S_0}{K}\right)$. Options with moneyness ranging from 0.6 to 0.8, 0.9 to 1.1, and 1.2 to 1.4 are classified as OTM, ATM, and ITM depending on the type of option considered. Similarly, only options with a remaining maturity of 50 days are considered. For call and put options, three Fama-Macbeth Regressions are performed, one for each moneyness. The coefficients and the Newey-West t-statistics are reported and compared across the three moneyness groups.

4.3. ESG Premium

The previous sections investigate the option pricing effect of ESG performance in terms of option's implied volatility and option return. This section formally quantifies the effect of ESG performance on option price and demand using the portfolio sort approach.

4.3.1. Portfolio Sort Result

This section quantifies the ESG premium using the portfolio sort approach. Three types of option returns are considered – the daily-rebalanced delta-hedged option return, the buy-and-hold delta-hedged option return, and the zero-beta straddle portfolio return. The spread of the low-ESG and high-ESG option return is then quantified as the ESG premium.

First, the daily-rebalanced delta-hedged option return is constructed according to the formula presented earlier. This portfolio is rebalanced daily to obtain returns not sensitive to stock price movements.

The second type of option return considered is the buy-and-hold delta-hedged option return, which is constructed by buying one contract of the option hedged by delta shares of short position the underlying asset at the end of each month where delta is the hedge ratio under the Black-Scholes Merton model. This position is held for one month without rebalancing to reduce transaction costs. Then, the buy-and-hold return is computed following Goyal & Saretto (2009) as

$$HPR_{t+1} = \left(\frac{H_{t+1}}{H_t} - 1\right) \cdot \gamma,$$

where the cost H_t is $\left(\Delta_{c,t}S_t - C_t\right)$ for call options and $\left(P_t - \Delta_{p,t}S_t\right)$ for put options. The value of γ is set at -1 when the option is a call and 1 when the option is a put. This is done to obtain the return of a portfolio containing one long option contract hedged by delta units of short position in the underlying asset.

The final option return considered is the zero-beta straddle portfolio return which is constructed by selecting θ units of call option and $(1-\theta)$ units of put option, both with maturity of 50 days and are near at-the-money (ATM). The values are determined such that the overall portfolio is beta-neutral, that is

$$\theta\beta_c + (1-\theta)\beta_p = 0,$$

where β_c and β_p are the market betas of the call and put options respectively, where β_c is given as

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

where β_s is the rolling beta of stock. The value for β_p is computed similarly. Then, the straddle return (r_v) is then calculated as

$$r_v = \theta r_c + (1-\theta)r_p.$$

To quantify the ESG premium, the options are first sorted into quintiles based on their ESG score at the end of each month. Then, the equal-weighted portfolio return for each quintile is calculated for the three types of option return constructed. A Fama & French (2015) five-factor model regression is also performed on the three types of option return using the market factor, size factor, value factor, profitability factor, and investment factor as independent variables. The average return and the risk-adjusted return from the five-factor model are then reported. Lastly, the ESG premium is then quantified as the H-L spread of the return.

4.3.2. Option Demand from Users

To investigate the relationship between ESG-related uncertainties and option demand from users, the relationship between ESG performance and demand for call and put options is analyzed. At the end of each month, options are ranked into quintiles based on their ESG score and the equal-weighted demand for each portfolio is then calculated. Two quantities are defined as a proxy for option demand. First, Δ_{OI} is defined as

$$\Delta_{\mathrm{OI}} = \frac{\mathrm{OI}_T - \mathrm{OI}_0}{\text{Option Volume}},$$

where OI_T is the open interest at the end of the month, OI_0 is the open interest at the start of the month, and Option Volume is the average option trading volume for the month. Next, Z_{OI} is defined as

$$Z_{\mathrm{OI}} = \frac{Z'_{\mathrm{OI}}}{\text{Stock Volume}},$$

where Stock Volume is the average stock trading volume for the month, and

$$Z'_{\mathrm{OI}} = \frac{\mathrm{OI}_T - \overline{\mathrm{OI}}}{\sigma\left(\mathrm{OI}\right)},$$

where $\overline{\mathrm{OI}}$ is the average open interest for the month and $\sigma\left(\mathrm{OI}\right)$ is the standard deviation of the open interest for the month. Z'_{OI} can be interpreted as the standardized open interest for the month. Only at-the-money (ATM) call and put options with a remaining maturity of 50 days are considered in calculating both quantities.

4.4. Other Sources of Risk

The relationship between ESG performance and option return is explored in the previous sections using delta-hedged returns and straddle returns. However, these option returns still embed various risk premia. Existing studies document a non-zero volatility risk premium and jump risk premium. Bakshi & Kapadia (2003) demonstrated that volatility risk premium is a significant source of underperformance in delta-hedged returns. They also document the existence of a jump risk premium due to potential unforeseen tail events. This section examines the relationship between ESG performance and exposure to other sources of risk. Specifically, it wants to determine if the relationship between ESG performance and option return is driven by exposure to volatility and jump risks. The main tools used are the Fama-Macbeth Regression and the portfolio sort approach.

First, to directly test whether the volatility risk premium and jump risk premium are related to ESG performance, the volatility risk portfolio and the jump risk portfolio are constructed using two beta-neutral straddles with different maturities. On the one hand, the volatility risk portfolio is constructed by considering i) one long position in a beta-neutral at-the-money straddle with a maturity of 80 days, and ii) a short position in y beta-neutral at-the-money straddle with a maturity of 50 days, where y is chosen to make the overall portfolio gamma-neutral. This is considered a beta-neutral, gamma-neutral, and vega-positive strategy. On the other hand, the jump risk portfolio is formed by considering i) one long position in a beta-neutral at-the-money straddle with a maturity of 50 days and ii) a short position in y beta-neutral at-the-money straddle with a maturity of 80 days, where y is chosen to make make the overall portfolio vega-neutral. This is considered a beta-neutral, vega-neutral, and gamma-positive strategy.

A similar Fama-Macbeth Regression is then performed on the two straddle returns using the same set of independent variables. This examines the relationship between ESG performance and the two straddle returns. Afterward, the volatility risk premium and jump risk premium are quantified using portfolio sort on the two straddle returns. Similar to the previous section, options are first sorted into quintiles based on their ESG score, and the equal-weighted portfolio return for the two straddle returns is calculated. A five-factor model regression is also performed to obtain the risk-adjusted returns.

4.5. Option Pricing Models

Finally, this section explores two neural network option pricing models to evaluate the predictive power of ESG performance in pricing options. As an initial analysis, only call options are considered. Following du Plooy & Venter (2021), the first model uses a neural network with two hidden layers trained on 1,000,000 artificial options data based on the Black-Scholes Merton model. This model acts as a baseline model for option pricing. The model specification are presented in

Table 4.1. Moreover, the features used in this model are $x = \left\{\frac{S_t}{K}, \tau_t, r_t, \sigma_t\right\}$ with an output of $y = \left\{\frac{c_t}{K}\right\}$. This model is then evaluated against out-of-sample data from January 2019 to December 2021 using the mean squared error (MSE) as the error measure.

Table 4.1: Model 1 Specification

Parameter	Configuration
Number of hidden layers	2
Number of neurons	(256, 128)
Hidden layer activation function	ReLU
Output layer activation function	Softmax
Loss function	MSE
Optimizer	Adam
Batch Size	64
Epochs	20

As an improvement, the second model is a deep neural network with five hidden layers that use real options data for training. The in-sample training data is from January 2007 to December 2018. The model specification are presented in Table 4.2. Moreover, the features used in this model are $x = \left\{\frac{S_t}{K}, \tau_t, r_t, \sigma_{t-1}, \mathrm{ESG}_t, \boldsymbol{X_t}\right\}$ with an output of $y = \left\{\frac{c_t}{K}\right\}$. It is important to note that, unlike the first model, the implied volatility used in the second model is the lagged implied volatility to avoid look-ahead bias. Moreover, the ESG score and other control variables used previously are added as features. The second model aims to price the option without the option's current implied volatility as a feature. Finally, the model is evaluated against the same out-of-sample data from January 2019 to December 2021 using the mean squared error (MSE) as the error measure.

Table 4.2: Model 2 Specification

Parameter	Configuration
Number of hidden layers	5
Number of neurons	(256, 128, 64, 32, 16)
Hidden layer activation function	ReLU
Output layer activation function	Softmax
Loss function	MSE
Optimizer	Adam
Batch Size	64
Epochs	20

The performance of the two models in the out-of-sample data is then reported and compared to determine the predictive power of ESG performance in option pricing.

CHAPTER 5
RESULTS AND DISCUSSION

This paper considers the sample period from January 2007 to December 2018. After processing the raw data, the final data consists of 282,008 observations of call and put options or 141,004 pairs of call and put options. For each month, the average number of options considered is 1,972 representing an average of 986 unique stocks. The final sample consisted of options with days to maturity between 44 to 53 days, with an average of 49.5 days. Moreover, the average moneyness is 1.00, representing at-the-money (ATM) options with a small standard deviation of 0.04. These short-term close to at-the-money options have a relatively small bid-ask spread with a mean of 0.20 for both call and put options, which indicates that option prices adjust quickly to new information and changes to investors' perceived risks and uncertainties.

Furthermore, the average daily-rebalanced delta-hedged option return obtained is -2.33% and -2.04% for call and put options, respectively. Additionally, the average delta-hedged option gain is also negative with an average of -0.43 for both call and put options. Consistent with the findings of Cao et al. (2021) and Cao & Han (2013), the average daily-rebalanced delta-hedged option return for both call and put options is negative.

Table 5.1: Summary of Data

	Mean	SD	Min	25%	75%	Max
			Call Options			
Moneyness	1.00	0.04	0.10	0.99	1.02	1.95
Days to Maturity	49.5	2.12	44.0	49.0	51.0	53.0
Bid-Ask Spread	0.20	0.28	0.00	0.06	0.22	1.98
Delta-Hedged Return	-2.33	6.94	-1370	-3.53	-0.29	130
Delta-Hedged Gain	-0.43	1.26	-28.4	-0.67	-0.05	60.1
			Put Options			
Moneyness	1.00	0.04	0.10	0.99	1.02	1.95
Days to Maturity	49.5	2.12	44.0	49.0	51.0	53.0
Bid-Ask Spread	0.20	0.28	0.00	0.06	0.22	1.99
Delta-Hedged Return	-2.04	4.30	-128	-3.29	-0.39	96.4
Delta-Hedged Gain	-0.43	1.32	-173	-0.65	-0.07	61.8

5.1. ESG Performance and Implied Volatility

This section presents the empirical results of the relationship between ESG performance and option's implied volatility. It is important to emphasize that this section only presents an intuitive illustration of option expensiveness since option's implied volatility does not directly present the economic magnitude of the ESG premium.

Figure 5.1 presents the difference in the average implied volatility between low-ESG (P1) and high-ESG (P5) options across the period from January 2007 to December 2018. This figure highlights a higher difference in the average implied volatility when there is a higher uncertainty related to ESG. This is consequently reflected in a higher option premium to hedge against these risks. Therefore, sudden increases in this difference during this period indicate heightened awareness of ESG-related issues. Conversely, a sudden decline in this difference during this period indicates a lowered awareness of ESG-related issues.

From Figure 5.1, a sudden jump in the difference can be seen around September 2008. From a level of approximately 5% in June 2008, the difference increased to 11% by the next month and reached more than 20% by September and October 2008. This peak can be linked to the bankruptcy of Lehman Brothers on September 15, 2008, which was characterized as the climax of the US' subprime mortgage crisis and the beginning of the GFC. The crisis stressed the importance for companies and financial markets to revise their capital allocation policies on solving social and environmental issues more effectively and having better governance to oversee their activities. Furthermore, investors also became more interested in firms with higher ESG as they were linked to having lower volatility and higher returns.

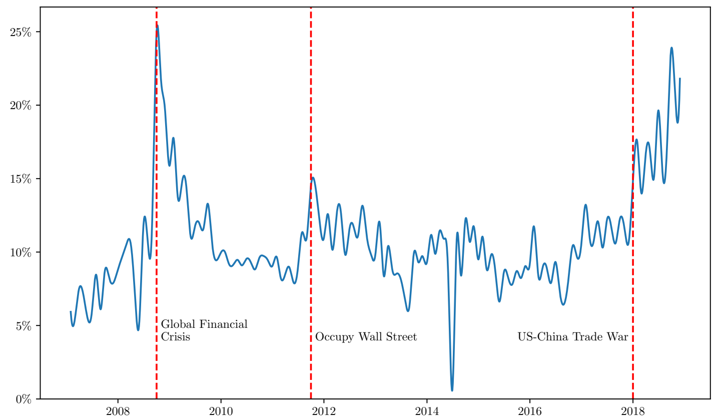

Figure 5.1: Difference in Average Implied Volatility

The next sudden jump in the difference in average implied volatility is observed around September 2011. The difference increased from 8% in June 2011 to 14% by October and November 2011. This can be associated with the Occupy Wall Street movement. It was considered a shock to ESG awareness, particularly towards better corporate governance.

Additionally, a steep decline in the difference can be observed around July 2014. However, upon closer examination, it is determined to be an outlier as no significant ESG-related event occurred during this period that would explain this sudden decline.

Lastly, there is a sudden jump in the difference observed in the period near January 2018. From a level of 10% in November 2017, the difference increased to almost 18% within the next two months. The increase in the difference persisted until the end of the year rising up to almost 24% by October 2018. This jump can be attributed to the US-China Trade War that began in January 2018. There was much uncertainty during this period due to the disruption in the global supply chain. It is then not a surprise for this difference to increase drastically since high-ESG companies have a more resilient supply chain compared to low-ESG companies.

5.1.1. Baseline Panel Regression

As an initial result, a baseline Panel Regression is performed to formally determine the relationship between ESG performance and option's implied volatility. The regression is done to verify the observation that low-ESG options are exposed to greater ESG-related uncertainty and hence higher implied volatility. Thus, the results of the Panel Regressions are expected to show an inverse relationship between ESG performance and option's implied volatility.

Table 5.2 presents two cases of the Panel Regression when control variables are added and not added. The z-statistics are also presented in parenthesis. The variable ret1 (reversal) is the stock return in the prior month, ret212 (momentum) is the cumulative stock return from the prior second through the 12th month, bm is the book-to-market ratio at month-end, and roe is the return on equity at month-end. The results show a statistically significant coefficient of -1.776 and -1.585 for ESG indicating a negative correlation between the ESG performance and option's implied volatility. This supports the earlier observation that low-ESG options have higher implied volatility than high-ESG options.

Table 5.2: Baseline Panel Regression Results

	(1)	(2)
ESG	-1.776	-1.585
	(-8.095)	(-7.407)
ret1		-0.137
		(-36.81)
ret212		-0.060
		(-54.10)
bm		-28.22
		(-60.68)
roe		-0.023
		(-6.686)

Additional Panel Regressions are performed for each of the three events considered. Similarly, negative ESG coefficients are expected to indicate that lower ESG scores are correlated with higher implied volatility on average. Moreover, a negative coefficient is also expected for $\mathbb{1}_{\text{In}}$ESG to indicate a heightened ESG-related uncertainty during the In sub-period. This would indicate a stronger inverse correlation between ESG and implied volatility during this period wherein options with lower ESG scores lead to higher implied volatility.

5.1.2. Global Financial Crisis

A Panel Regression is performed for the period of January 2008 to June 2010 to analyze the impact of the Global Financial Crisis. From Table 5.3, the coefficient estimates of ESG are observed to be -3.744 and -3.208, both statistically significant. This indicates that there is indeed a negative correlation between ESG performance and option's implied volatility. Moreover, the effect of ESG performance on option's implied volatility is heightened during the In-GFC sub-period with incremental coefficient estimates of -5.235 and -5.627, both statistically significant. This indicates that the effect of ESG performance on option's implied volatility is indeed stronger during this sub-period from September 2008 to August 2009. It is worth noting that this was the time when many banks and firms suffered drastic losses and started filing for bankruptcy. This shows that the financial crisis increased ESG-related uncertainties. Finally, the coefficient estimates of the After-GFC sub-period show a positive incremental relationship of 2.091

and 0.874 between ESG and option's implied volatility. This indicates an easing of ESG-related uncertainties after the crisis ended. However, the latter is not statistically significant. Overall, the Global Financial Crisis indeed increased ESG-related uncertainties which translated to a stronger inverse relationship between ESG performance and options' implied volatility.

Table 5.3: Global Financial Crisis Panel Regression Results

	(1)	(2)
ESG	-3.744	-3.208
	(-4.391)	(-3.845)
$\mathbb{1}_{\text{In}}$ESG	-5.235	-5.627
	(-6.905)	(-7.587)
$\mathbb{1}_{\text{After}}$ESG	2.091	0.874
	(2.625)	(1.119)
ret1		-0.139
		(-16.35)
ret212		-0.072
		(-26.49)
bm		-8.251
		(-9.568)
roe		0.014
		(0.995)

5.1.3. Occupy Wall Street Movement

The next Panel Regression is for the Occupy Wall Street Movement, which considers the period from January 2011 to June 2012. The results in Table 5.4 show that there is a statistically significant negative incremental relationship between ESG performance and option's implied volatility during the In-OWS with values -5.674 and -5.356, both statistically significant. This indicates that the effect of ESG performance on option's implied volatility is indeed stronger during this sub-period. Moreover, there is also a negative incremental relationship between ESG performance and option's implied volatility with values -4.261 and -3.924, both statistically significant. This indicates that even after the movement, its impact on ESG-related uncertainties persisted. Additionally, although there is a positive correlation between ESG performance and option's implied volatility with coefficients 1.241 and 0.561, the latter is statistically insignificant. Overall, there is a stronger relationship between ESG performance and option's implied volatility during the In-OWS sub-period.

Table 5.4: Occupy Wall Street Movement Panel Regression Results

	(1)	(2)
ESG	1.241	0.561
	(1.746)	(0.800)
$\mathbb{1}_{\text{In}}$ESG	-5.674	-5.356
	(-11.85)	(-11.27)
$\mathbb{1}_{\text{After}}$ESG	-4.261	-3.924
	(-9.955)	(-9.208)
ret1		-0.125
		(-15.94)
ret212		-0.035
		(-11.66)
bm		-14.35
		(-6.810)
roe		-0.000
		(-0.002)

5.1.4. US-China Trade War

The final Panel Regression analyzes the time of the US-China Trade War. The period considered is from January 2017 until the end of 2018. The results in Table 5.5 show a similar negative correlation between ESG performance and option's implied volatility with statistically significant estimates of -5.643 and -5.795. However, the results also show a slightly positive incremental relationship between ESG performance and option's implied volatility during the In-TW sub-period. However, the coefficient estimates 0.058 and 0.040 are both statistically insignificant. Thus, there is insufficient data to conclude that the US-China Trade War strengthened or weakened the relationship between ESG performance and option's implied volatility. Extending the time period beyond 2018 could potentially produce more conclusive results.

Table 5.5: US-China Trade War Panel Regression Results

	(1)	(2)
ESG	-5.643	-5.795
	(-9.152)	(-9.545)
$\mathbb{1}_{\text{In}}$ESG	0.058	0.040
	(0.193)	(0.134)
ret1		-0.118
		(-20.66)
ret212		-0.029
		(-15.28)
bm		-19.66
		(-12.79)
roe		-0.007
		(-1.199)

5.2. ESG Performance and Option Return

The results from the previous section indicate an overwhelming evidence of the inverse relationship between ESG performance and option's implied volatility. It suggests that investors indeed pay a premium to hedge against ESG-related uncertainties. However, it does not directly suggest the magnitude of the ESG premium. This section presents the empirical results of the relationship between ESG performance and option return to quantify the option pricing effect of ESG performance.

5.2.1. Baseline Fama-Macbeth Regression

To inspect the relationship between ESG performance and the daily-rebalanced delta-hedged option return, a baseline Fama-Macbeth Regression is performed for each type of option. The Fama-Macbeth Regression is performed to verify that low-ESG options are linked with lower (more negative) option return and thus more expensive option price (Ibañez, 2007). Hence, a positive ESG coefficient is expected to indicate a positive relationship between ESG performance and daily-rebalanced delta-hedged option return.

The baseline results are summarized in Table 5.6. The Newey-West t-statistics are also reported in parenthesis. The variable open interest is the total number of option contracts that are open at the end of previous month and scaled by the stock trading volume of last month, and bid-ask spread is the ratio of the difference between the bid and ask quotes of option to the midpoint of the bid and ask quotes at the end of previous month. The results show a positive correlation between the ESG performance and daily-rebalanced delta-hedged option return, with an ESG coefficient of 2.737 for call options and 2.238 for put options. It is worth noting that the magnitude decreases as the number of control variables added increases with ESG coefficients decreasing to 2.559 then 0.936 for call options and to 2.100 then 0.804 for put options. Despite the decline in value, all coefficients remain statistically significant. Moreover, given the mean daily-rebalanced delta-hedged option returns of -2.33% and -2.04% as shown in Table 5.1, the results show that the economic significance of ESG performance on option return is substantial. Therefore, lower ESG scores are indeed correlated with lower option return. This complements the results in the previous section.

Table 5.6: Baseline Fama-Macbeth Regression Results

	Call Options			Put Options		
	(1)	(2)	(3)	(4)	(5)	(6)
ESG	2.737	2.559	0.936	2.238	2.100	0.804
	(5.549)	(5.422)	(6.829)	(5.789)	(5.735)	(6.794)
ret1		0.012	0.008		0.000	0.001
		(2.656)	(2.226)		(0.021)	(0.668)
ret212		0.010	0.007		0.006	0.005
		(6.306)	(5.466)		(5.853)	(5.006)
bm		6.203	6.098		4.844	4.626
		(4.190)	(4.668)		(4.177)	(4.425)
roe		0.001	0.014		-0.001	0.011
		(0.079)	(2.760)		(-0.126)	(5.158)
open interest			52.92			-12.51
			(3.056)			(-0.758)
bid-ask spread			-10.15			-8.709
			(-26.94)			(-38.24)

Similarly, additional Fama-Macbeth Regressions are performed for each of the three events considered to investigate the change in the relationship between ESG performance and option return across the sub-periods. Positive ESG coefficients are expected, indicating that higher ESG scores are correlated with higher daily-rebalanced delta-hedged option return on average. Moreover, a higher (more positive) coefficient is also expected for the In sub-period to indicate a stronger relationship between ESG performance and daily-rebalanced delta-hedged option return.

5.2.2. Global Financial Crisis

The results of the Fama-Macbeth Regression for each sub-period of the Global Financial Crisis are reported in Table 5.7. For both call and put options, there is an increase in the ESG coefficient from the Before-GFC sub-period to the In-GFC sub-period from 0.347 to 0.651 and from 0.441 to 0.464, respectively. Moreover, the effect of ESG on the daily-rebalanced delta-hedged option return is the strongest during the After-GFC sub-period in both cases. The ESG coefficients during the After-GFC sub-period are 0.693 and 0.685, respectively. Additionally, all ESG coefficients are statistically significant. Overall, the results indicate that the Global Financial Crisis strengthened the relationship between ESG performance and daily-rebalanced delta-hedged option return. However, the change is only significant during the After-GFC sub-period for put options.

Table 5.7: Global Financial Crisis Fama-Macbeth Regression Results

	Call Options			Put Options		
	Before	In	After	Before	In	After
ESG	0.347	0.651	0.693	0.441	0.464	0.685
	(2.647)	(2.340)	(6.557)	(2.952)	(2.363)	(8.687)
ret1	-0.013	-0.027	0.012	-0.012	-0.016	0.009
	(-1.026)	(-1.268)	(1.676)	(-1.167)	(-0.964)	(1.251)
ret212	0.002	0.008	0.001	0.006	-0.001	-0.001
	(0.847)	(1.580)	(0.326)	(2.179)	(-0.157)	(-0.645)
bm	5.569	4.247	1.653	3.858	2.710	1.110
	(8.213)	(5.433)	(4.959)	(5.947)	(3.864)	(5.435)
roe	0.039	0.060	0.007	0.022	0.034	0.007
	(15.43)	(3.794)	(3.898)	(14.21)	(3.633)	(3.124)
open interest	-16.77	-25.75	21.80	-58.79	-92.70	14.04
	(-0.943)	(-0.602)	(1.951)	(-1.955)	(-3.556)	(0.375)
bid-ask spread	-7.097	-12.49	-10.35	-9.734	-11.11	-8.963
	(-14.91)	(-13.22)	(-11.80)	(-19.16)	(-18.01)	(-32.36)

5.2.3. Occupy Wall Street Movement

The results of the Fama-Macbeth Regression for the Occupy Wall Street Movement are summarized in Table 5.8. For both call and put options, there is an increase in the ESG coefficient from the Before-OWS sub-period to the In-OWS sub-period from 0.891 to 0.932 and from 1.057 to 1.082, respectively. In both cases, the ESG coefficient also declined from the In-OWS sub-period to the After-OWS sub-period with coefficients 0.928 and 0.605. It is important to note that the decline is insignificant for call options but significant for put options. Moreover, all coefficients are statistically significant. Thus, the results show that the Occupy Wall Street Movement had an impact on strengthening the effects of ESG performance on the daily-rebalanced delta-hedged option return, albeit the change is not that significant.

Table 5.8: Occupy Wall Street Fama-Macbeth Regression Results

	Call Options			Put Options		
	Before	In	After	Before	In	After
ESG	0.891	0.932	0.928	1.057	1.082	0.605
	(4.098)	(5.713)	(5.649)	(5.844)	(16.75)	(4.289)
ret1	-0.000	0.038	0.016	0.012	0.027	-0.015
	(-0.000)	(2.543)	(1.185)	(5.352)	(2.122)	(2.884)
ret212	0.005	0.012	0.015	0.006	0.007	0.006
	(3.113)	(2.424)	(8.825)	(6.815)	(1.826)	(2.561)
bm	3.058	5.009	-0.102	2.296	3.106	0.305
	(1.613)	(9.526)	(-0.081)	(1.660)	(10.43)	(0.418)
roe	0.009	0.009	-0.003	0.011	0.009	0.008
	(2.551)	(1.982)	(-0.435)	(5.018)	(0.003)	(3.450)
open interest	105.6	-11.78	137.8	44.00	-80.23	-19.68
	(8.759)	(-0.229)	(4.081)	(1.481)	(-3.602)	(-1.335)
bid-ask spread	-10.55	-16.52	-12.97	-9.354	-9.047	-11.21
	(-20.04)	(-10.24)	(-17.09)	(-16.88)	(-7.142)	(-42.49)

5.2.4. US-China Trade War

Lastly, the results of the Fama-Macbeth Regression for the US-China Trade War are shown in Table 5.9. For both call and put options, there is a significant increase in the ESG coefficient from the Before-TW sub-period to the In-TW sub-period from 1.255 to 2.039 and from 0.907 to 1.964, respectively. Furthermore, all coefficient estimates are statistically significant. Hence, in both call and put options, the US-China Trade War magnified the relationship between ESG performance and the daily-rebalanced delta-hedged option return. However, it is worth noting that the Panel Regression results in the previous section suggest an inconclusive relationship between ESG performance and option's implied volatility. Thus, extending the analysis beyond 2018 can test the robustness of the results.

Table 5.9: US-China Trade War Fama-Macbeth Regression Results

	Call Options		Put Options	
	Before	In	Before	In
ESG	1.255	2.039	0.907	1.964
	(7.670)	(7.529)	(8.592)	(16.68)
ret1	0.010	0.019	-0.006	0.023
	(1.967)	(1.968)	(-2.210)	(4.022)
ret212	0.005	0.014	0.002	0.010
	(2.349)	(10.39)	(2.245)	(15.27)
bm	9.968	13.19	8.282	10.54
	(13.85)	(18.91)	(22.64)	(20.76)
roe	0.002	0.027	0.003	0.017
	(0.839)	(3.564)	(4.618)	(7.161)
open interest	39.29	170.3	-2.358	76.46
	(1.102)	(4.879)	(-0.056)	(1.567)
bid-ask spread	-8.332	-10.53	-7.825	-7.542
	(-38.50)	(-10.36)	(-38.87)	(-18.94)

5.2.5. Separating the Effects of E, S, G, and Ec Score

The results earlier in this section suggest a strong and robust relationship between ESG performance and daily-rebalanced delta-hedged option return. However, this relationship might be primarily driven by only some components of ESG. Hence, an additional test is done to determine the individual and separate impact of the four components of ESG on the daily-rebalanced delta-hedged option return. Similar to the baseline Fama-Macbeth Regression, the hypothesis is that all components of ESG will have a positive correlation with the daily-rebalanced delta-hedged option return, *i.e.*, higher E-score, S-score, G-score, or Ec-score is correlated with higher option return.

The results for the Fama-Macbeth Regression with separated E-score, S-score, G-score, and Ec-score are shown in Table 5.10. For brevity, only the relevant ESG coefficients are shown while the coefficients for the control variables are suppressed. It can be observed that the coefficients for both call and put options across all five cases are positive and statistically significant. This is consistent with the baseline results which indicate that the daily-rebalanced delta-hedged option return is higher for firms with higher E-score, S-score, G-score, or Ec-score. This also shows that all four components of ESG have an almost equal contribution to the positive relationship with daily-rebalanced delta-hedged option return. Nevertheless, for both call and put options, the Ec-score and S-score have the highest two coefficient estimates. This indicates that the economic and social components have a marginally stronger effect than the environment and corporate governance components of ESG. Overall, the results show that options with higher scores in either component of ESG have a higher daily-rebalanced delta-hedged option return.

Table 5.10: Separating E, S, G, Ec Results

	Call Options				
	(1)	(2)	(3)	(4)	(5)
E	0.680				0.204
	(5.051)				(1.955)
S		0.802			0.200
		(7.234)			(3.369)
G			0.607		0.118
			(5.186)		(2.855)
Ec				0.851	0.583
				(7.672)	(7.041)
Control	Yes	Yes	Yes	Yes	Yes
	Put Options				
	(1)	(2)	(3)	(4)	(5)
E	0.564				0.161
	(4.463)				(1.538)
S		0.666			0.116
		(6.880)			(1.478)
G			0.511		0.090
			(4.925)		(2.537)
Ec				0.786	0.604
				(7.033)	(6.440)
Control	Yes	Yes	Yes	Yes	Yes

5.2.6. Robustness Test

Similarly, the strong and robust relationship between ESG performance and daily-rebalanced delta-hedged option return might not apply for options with different moneyness. Hence, additional tests are performed to determine the robustness of the results. This is done to compare the relationship between ESG performance and the daily-rebalanced delta-hedged option return for options with different moneyness. Similar to the baseline Fama-Macbeth Regression, the hypothesis is that regardless of option's moneyness, ESG will have a positive correlation with the daily-rebalanced delta-hedged option return.

The results for the Fama-Macbeth Regression for out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM) options are shown in Table 5.11. For brevity, only the relevant ESG coefficients are shown while the coefficients for the control variables are suppressed. Call (put) options with moneyness 1.3 (0.7) are classified as in-the-money while call (put) options with moneyness 0.7 (1.3) are classified as out-of-the-money. For both call and put options, the ESG coefficients across the three moneyness groups are positive and statistically significant. This is consistent with the baseline Fama-Macbeth Regression result in Table 5.6. However, the magnitude of the coefficient varies significantly across the moneyness groups with the strongest correlation for both call and put options observed for out-of-the-money options with ESG coefficient estimates of 2.265 and 1.409, respectively. Overall, the results obtained are robust across options with different moneyness since ESG performance is still positively correlated with the daily-rebalanced delta-hedged option return.

Table 5.11: Robustness Test Results

	Call Options			Put Options		
	OTM	ATM	ITM	OTM	ATM	ITM
ESG	2.265	0.936	1.059	1.409	0.804	0.534
	(8.028)	(6.829)	(4.903)	(4.021)	(6.794)	(11.94)
Control	Yes	Yes	Yes	Yes	Yes	Yes

5.3. ESG Premium

The results of the previous two sections strongly indicate the existence of ESG premium in the market. This section attempts to quantify the ESG premium using the portfolio sort approach. Furthermore, the option demand from users is also studied in relation to ESG performance using the portfolio sort approach.

5.3.1. Portfolio Sort Result

Using the portfolio sort approach, the ESG premium is quantified as the difference in the equal-weighted option return between the lowest quintile (P1) and highest quintile (P5). Moreover, classifying options based on their ESG scores also reveals a trend in the relationship between average option return and ESG score. The hypothesis is that the average option return increase as the ESG quintile increases, supporting the claim that high-ESG options have a higher option return.

Three option returns are used for this result – daily-rebalanced delta-hedged option return, buy-and-hold delta-hedged option return, and zero-beta straddle portfolio return. Table 5.12 shows the summary of the results. For both call and put options, the average daily-rebalanced delta-hedged option return increases monotonically from the lowest ESG quintile (P1) to the highest ESG quintile (P5). This implies that there is a higher premium paid for options with lower ESG scores. Additionally, the standard deviation is also observed to decline monotonically as the quintile increases indicating a more predictable option return for high-ESG options. Similarly, the buy-and-hold delta-hedged option return and the zero-beta straddle portfolio return for both call and put options also exhibit a similar monotonic trend from P1 to P5. The corresponding 5-factor alphas of each option return also exhibit a similar increasing trend. Consistent with Cao et al. (2021), the results support the hypothesis that low-ESG options are more expensive compared to high-ESG options. Overall, the portfolio sort results show an ESG premium of approximately 2.22% (2.44% and 1.99%) per month, economically significant given a mean option return of -2.33% and -2.04%.

Table 5.12: ESG Premium Results

Quintile	P1	P2	P3	P4	P5	P5-P1
Daily-Rebalanced Delta-Hedged Option Return						
	Call Options					
Average Return	-3.540	-3.003	-2.314	-1.631	-1.096	2.444
5-Factor Alpha	-3.192	-2.777	-2.168	-1.569	-1.097	2.095
	Put Options					
Average Return	-2.997	-2.620	-2.056	-1.485	-1.008	1.988
5-Factor Alpha	-2.734	-2.424	-1.926	-1.424	-1.009	1.725
Buy-and-Hold Delta-Hedged Option Return						
	Call Options					
Average Return	-3.664	-3.263	-2.561	-1.878	-1.309	2.355
5-Factor Alpha	-3.457	-3.132	-2.500	-1.890	-1.382	2.074
	Put Options					
Average Return	-3.093	-2.759	-2.189	-1.604	-1.072	2.021
5-Factor Alpha	-2.897	-2.652	-2.138	-1.616	-1.140	1.757
Zero-Beta Straddle Portfolio Return						
Average Return	-25.39	-24.74	-21.45	-17.22	-13.53	11.86
5-Factor Alpha	-24.34	-24.04	-20.98	-17.17	-14.31	10.03

5.3.2. Option Demand from Users

To investigate how option users perceive risk related to ESG, the demand for options, as measured by option open interest, for each quintile is studied. The hypothesis is that low-ESG options have a higher demand since option users perceive stocks with lower ESG scores as riskier. Hence, they are willing to pay a higher premium to hedge against these risks.

The results are shown in Table 5.13. For both call and put options, the Z_{OI} of low-ESG options (P1 and P2) are significantly higher than that of the high-ESG options (P4 and P5). Similarly, the Δ_{OI} also shows an overall decreasing trend as the quintile increases, albeit the trend is not as strong. These results highlight that users perceive options with lower ESG scores as riskier, resulting in higher demand or higher willingness to pay a premium to hedge against risks related to poor ESG performance. From an economic perspective, the higher demand for low-ESG options also explains why these options are more expensive than high-ESG options. Overall, low-ESG options are expected to have higher demand due to hedging purposes. However, the demand due to speculation brought by the higher uncertainties can also contribute to this higher demand.

Table 5.13: Option Demand Results

Quintile	P1	P2	P3	P4	P5
	Call Options				
Δ_{OI}	7.406	7.665	7.565	6.488	6.536
Z_{OI}	4.363	4.361	3.670	2.471	1.812
	Put Options				
Δ_{OI}	8.287	8.152	7.443	8.105	7.951
Z_{OI}	4.615	4.652	3.996	2.836	2.189

5.4. Other Sources of Risk

The previous section quantifies the ESG premium based on delta-hedged option returns and straddle return. However, these option returns also embed various risk premia. Hence, this section examines which risk premia contribute to the relationship between ESG performance and option return. Specifically, the focus is on volatility risk and jump risk premia. The hypothesis is that high-ESG options are less exposed to volatility risk and jump risk.

To investigate the relationship between ESG performance and volatility risk and jump risk, two Fama-Macbeth Regressions are performed on the two straddle portfolios returns – volatility risk portfolio return and jump risk portfolio return. The results are shown in Table 5.14. The results show that for the volatility risk portfolio, higher ESG leads to lower straddle return with a statistically insignificant ESG coefficient of -0.682. However, for the jump risk portfolio, higher ESG leads to higher straddle return with a statistically significant ESG coefficient of 5.015. These results suggest that ESG plays an important role in jump risk premium; however, its effect on volatility risk premium is not very significant. Thus, exposure to jump risk can potentially contribute to the positive relationship between ESG performance and option return, but not for volatility risk.

Table 5.14: Volatility Risk and Jump Risk Fama-Macbeth Regression Results

	Volatility Risk Portfolio Return	Jump Risk Portfolio Return
ESG	-0.682	5.015
	(-0.890)	(3.191)
ret1	0.039	-0.070
	(7.215)	(-6.651)
ret212	0.009	-0.028
	(3.258)	(-6.370)
bm	0.902	3.418
	(0.524)	(0.724)
roe	-0.002	-0.005
	(-0.561)	(-0.268)

In addition, the results of the portfolio sort is shown in Table 5.15. On the one hand, for the volatility risk portfolio, the highest average straddle return is observed for the lowest ESG quintile (P1). Additionally, there is general decreasing trend in the average straddle return and the 5-factor alpha. However, the earlier Fama-Macbeth Regression results indicate that the trend is not very strong. On the other hand, for the jump risk portfolio, both the average straddle return and 5-factor alpha is observed to increase monotonically from the lowest ESG quintile (P1) to the highest ESG quintile (P5). This shows that higher ESG scores are correlated with higher straddle return. This result supports the Fama-Macbeth Regression results in Table 5.14. Overall, there is substantial evidence that exposure to jump risk contribute to the relationship between ESG performance and option return, but not for volatility risk. This is consistent with Cao et al. (2021).

Table 5.15: Volatility Risk and Jump Risk Premia Results

Quintile	P1	P2	P3	P4	P5	P5-P1
Volatility Risk Portfolio						
Average Return	1.824	1.644	1.643	1.118	0.999	-0.825
5-Factor Alpha	1.513	1.388	1.592	1.119	0.985	-0.528
Jump Risk Portfolio						
Average Return	-9.654	-9.569	-8.668	-6.499	-5.303	4.351
5-Factor Alpha	-9.400	-9.316	-8.700	-6.619	-5.539	3.861

5.5. Option Pricing Models

Finally, with the results from the previous sections pointing to a strong and robust pricing effect of ESG performance on options, this section explores two neural network option pricing models. The hypothesis is that models with ESG score as a feature will perform better than models without ESG score as a feature. For this initial analysis, only call options are considered.

The performance of the two models is presented in Table 5.16. For both models, the out-of-sample data is the real options data from January 2019 to December 2021. On the one hand, for Model 1, the in-sample data is the artificial data used in training. On the other hand, for Model 2, the in-sample data is the real options data from January 2007 to December 2018 used in training. The results show that using mean squared error (MSE) as the error measure, Model 2 performs 23.55% better than Model 1. Hence, this suggests that adding ESG as a feature can improve the performance of option pricing model in pricing real options data. Overall, the results indicate that ESG performance helps capture some important market dynamics that the Black-Scholes Merton model fails to capture.

Table 5.16: Model Performance Results

Model	In-Sample MSE	Out-of-Sample MSE
1	3.256×10^{-7}	4.976×10^{-4}
2	1.235×10^{-4}	3.804×10^{-4}

CHAPTER 6
CONCLUSION

6.1. Summary and Conclusion

In summary, this paper explores the relationship between ESG performance and option price. As an initial analysis, the relationship between ESG performance and option's implied volatility is studied. A first look at the data shows a negative relationship between the two variables. More formally, using Panel Regression, the relationship is found to be negative indicating that low-ESG options have higher implied volatility. Likewise, additional results for the three events – Global Financial Crisis, Occupy Wall Street Movement, and US-China Trade War – generally support this claim.

To further study the pricing impact of ESG performance, the daily-rebalanced delta-hedged option return is used to determine the relationship between ESG performance and option return. Using Fama-Macbeth Regression, the relationship is found to be positive indicating that high-ESG options have a higher option return. Furthermore, the same procedure is done for the different sub-periods of the three events considered and is found to be consistent with the baseline results. This result is also determined to be robust across different moneyness and for each component of ESG.

Afterward, the ESG premium is quantified using the portfolio sort approach. The option returns considered are the daily-rebalanced delta-hedged option return, the buy-and-hold delta-hedged option return, and the zero-beta straddle portfolio return. The results across the three option returns all exhibit a mononotically increasing trend in option return as ESG quintile increases. With this, the ESG premium is found to be 2.22% on average per month. Additionally, a closer look at option demand from users indicates that low-ESG options have a higher demand due to hedging activities or speculative purposes.

Next, the relationship between ESG performance and exposure to volatility risk and jump risk is explored to address the concern of whether the relationship between ESG performance and option return can be explained by these risk premia. Using Fama-Macbeth Regression and portfolio sort approach, it is determined that exposure to jump risk contribute to the positive relationship between ESG performance and option return. However, the same does not hold for volatility risk.

Finally, two neural network option pricing models are proposed for call options. The second model with ESG as an additional feature is found to perform 23.55% better in terms of mean squared error compared to the first model based on the Black-Scholes Merton model. This suggests the predictive power of ESG in pricing options.

Overall, in line with Cao et al. (2021), there is substantial evidence of the strong and robust relationship between ESG performance and option price.

6.2. Recommendation

While the model proposed does perform better than standard option pricing models, further studies can explore other machine learning and theoretical models to test the robustness of the claim. Moreover, further studies can also explore the robustness of the results presented using data from other ESG rating agencies. These additional results can help solidify the claims presented in this paper.

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