

Article

# Implied Tail Risk and ESG Ratings

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**Abstract:** This paper explores whether the high or low ESG rating of a company is related to the level of its implied tail risk, measured on the basis of derivative data by implied skewness and implied kurtosis. Previous research suggests that the ESG rating of a company is indeed connected to some financial risk; however, often, only volatility is used as a risk measure. We examined the relation between ESG ratings and implied volatility, and explore the relation between ESG ratings and financial risk in more depth by looking into higher implied moments accessing financial tail risk. First, we found that higher ESG rated companies have a lower implied volatility connected with them, and exhibit more negative implied skewness and higher implied kurtosis. In other words, we observed a higher negative tail risk for higher ESG rated companies. However, on a mid-sized company data set, we found that higher ESG rated companies both have lower implied volatility, and exhibit less negative implied skewness and lower implied kurtosis. Hence, negative tail risk is typically lower for high ESG rated companies. Our study further investigated similar effects on individual environmental (E), social (S) and governance (G) scores of the involved companies. Second, we examined whether such a kind of trend exists for different sectors. Our results indicate that the influence of ESG ratings on implied volatility exhibits a similar trend, except for the industrial, information services, and real estate sectors, while for the materials, healthcare, and communication services sectors, the influence of ESG ratings on implied skewness and implied kurtosis is less pronounced. Moreover, the results show that the ESG ratings are correlated with implied moments for companies in consumer discretionary sectors.

**Keywords:** ESG ratings; implied tail risk; implied moments



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## 1. Introduction

The practice of socially responsible investing (SRI) has a long history that began with a series of social and environmental legislation in the U.S. in the 1960s. The legislation focused on the behavior of corporations under social ethical views and attracted the attention of decision makers to link corporate performance to public policy. In the following decades, with the availability of several ethical mutual funds, responsible investing came into public attention and globally expanded from the 1980s. With the development of analytic tools and SRI databases, environmental, social, and governance (ESG) aspects were taken into account in the investment decision process, and its risk management has been on an increasing trend. Nowadays, companies are rated by several rating agencies on these ESG factors, making it, to some extent, clearer for investors to assess how a company is performing on these aspects. There is still, however, some criticism of ESG scoring. One question is whether a company is actually taking care of true environmental issues, or whether it is taking cosmetic actions without actual true impact. The term “green washing” is used in such a setting. In this regard, Hong and Kacperczyk [1] provided evidence that “sin” stocks have higher expected returns than otherwise comparable stocks because of fewer restrictions in social norms. In addition, some studies indicate that there is no significant link between ESG ratings and expected portfolio returns [2,3]. However, despite those negative and neutral opinions about the effect of ESG behavior on firms’ expected

returns, there are many studies that claim that a high ESG rating could improve corporate financial performance [4–6]. Hence, there is currently no clear consensus on whether good ESG behaviors are connected with, or could enhance, companies' financial performance.

Regarding studies that indicate a negative effect of ESG behavior on a firm's stock performance, the main argument of why it has a negative impact is that there is high financial cost for good ESG behavior. For instance, investors pay for their discriminatory taste [7]; as compensation for the costs, they receive non-financial utilities [8]. Hence, instead of finding direct relations between ESG behavior and financial performance, some researchers have discussed the motivation of ESG investors. Different presumed preferences of investors and utility models are also used to construct a better framework for ESG investments [9–11].

Among those studies, a common argument is that ESG investment is a kind of risk-defense investment. The effects of ESG behavior and socially responsible investing on financial risk were studied and discussed by numerous researchers to explore the support for this hypothesis. Ashwin Kumar et al. [12] and De and Clayman [4] focused on the correlation between ESG levels and the volatility of stock returns, and indicated a significantly strong negative correlation between ESG ratings and stock volatility. Moreover, Boubaker et al. [13] argued that better corporate social responsibility helps in reducing financial default risk. Seeing the increasing evidence of strong relations between ESG behaviors and financial risk, many researchers questioned the reason behind this kind of correlation. From a legal perspective, excellent corporate ESG practice could reduce a firm's litigation risk [14]. Chan and Walter [15] argued that good ESG behavior could serve as a form of insurance during financial crisis, and that the "green premium" exists. Furthermore, from a financial perspective, many studies that are consistent with the positive effects of ESG behaviors on financial performance regard ESG behavior as risk compensation for equity during a crisis period. They indicate that such ESG behaviors could decrease a firm's risk and thus help companies gain excess expected returns during the crisis period and in the long term [16]. Consistent with this viewpoint, many studies explored the correlation between ESG performance and tail risk and downside risk [16–19]. As such, it is vital to examine the relationship between ESG behaviors and financial risk, especially tail risk, which plays an important role in the effect of ESG behaviors on financial risk. Here, we take for granted the scoring and investigate its connection with financial risk.

The literature studying the impact of ESG behaviors on tail risk is very limited. Researchers have considered a variety of measures on tail risk, such as VaR [18–20]. In the study of Shafer and Szado [17], they used the slope of implied volatility as a measure of tail risk to explore its relation with ESG behavior. Other research studies have not specifically measured the tail risk, but directly mentioned tail risk through analyzing other types of firm risk. Since there is very little discussion on the relationship between tail risk and ESG behaviors, we add to this literature and explore whether the ESG level is related to financial risk by examining the relations between ESG ratings and implied risk. In contrast with many other studies, we do not use the conventional method of relying on historical time-series data to estimate the return distribution, which is actually looking backward in time, but access it via derivatives data. Option prices attempt to estimate future behavior; hence, we operate in a forward-looking approach. The historical approach is criticized, as it can easily overestimate risk in cases of a sharp temporary price drop [21]. However, the forward-looking method could decrease this kind of risk overestimation. Moreover, option prices are a rich source of information about market sentiments that could give us insight into how the market reacts to major news. Deducing the return distribution from the derivatives data is a forward-looking approach, whereas historical time-series data only reflect past distribution. All this is related to the difference between historical distribution, or P-measure, and pricing distribution, or Q-measure, in quantitative finance. Many studies examined the relations between implied moments and risk measurements [22,23]. Hence, in this paper, we operate within the pricing world and investigate the tail risk of return distributions under the Q-measure. We focus on both its standard deviation, measured by (implied) volatility, which is the most common risk measure, and on tail risk. For the latter,

we look into the higher moments of distribution arising from derivatives' market prices, synthesized as implied skewness and implied kurtosis.

Following the study of Shafer and Szado [17], this paper also explores the relations between implied tail risk and ESG ratings, but the measures of implied tail risk are different. In this study, we use implied skewness instead of calculating the slope of implied volatility. We examine the relations of implied moments and ESG ratings, and then examine this relation in different sectors. The rest of the article is organized as follows. Section 2 is a theoretical introduction to the main techniques used to derive implied moments from option prices. Section 3 describes the data sources and summary statistics of variables, and the methodology. Then, Section 4 discusses the empirical results of the relations between ESG ratings and implied moments. Section 5 presents the conclusions of this paper.

## 2. Implied Moments

Moments deduced from pricing-return distribution via derivatives data are called implied moments. In this section, we introduce implied moments in detail and show how to obtain such implied moments from option data in equity markets.

### 2.1. Concept of Implied Moments

The higher moments of stock-return distribution are important for investors and risk managers to model risk since they contain information on asymmetry, leptokurtosis, and fat tail. One of the methods to estimate these higher moments is that via the pricing probability measure. Moments calculated in this pricing or Q-world probability are called implied moments and are used to infer implied volatility, implied skewness, and implied kurtosis. Implied moments play an important role in the asset-allocation and risk-management fields. For example, many studies use implied moments to proxy the risk [24,25] or tail risk [26] in the energy market; some researchers are interested in predicting future risk, using implied moments [27] or the subsumed information content of historical jumps [28]. In addition, the Chicago Board Options Exchange (CBOE) launched a product called VIX on the basis of the second-order moment of the S&P500 index risk-neutral distribution, which reflects the investors' expected future realized volatility. Then, CBOE also introduced SKEW on the basis of the third-order moment of the S&P500 index risk-neutral distribution, which reflects investors' expected future realized skewness.

The calculation method of the CBOE moment index is based on the study of Bakshi et al. [29]; it has evolved into a model-free method that is widely used by investors and researchers. Hence, we follow the model-free calculation method to calculate the implied moments of stock-return distributions in this study. On the one hand, implied moments could serve as indicators of future higher-order realized moments [30]; hence, many studies deploy these to estimate return distribution [31,32]. On the other hand, implied moments serve as the measures of common risk and tail risk; many scholars are curious about factors that could impact them and they explore whether implied moments could be influenced or predicted. In the next section, we describe the calculation details of implied moments.

### 2.2. Calculation of Implied Moments

Via the Black–Scholes option pricing model, one could estimate the volatility of an underlying asset by identifying the volatility level such that the model's price matches the market's price of vanilla options; the inferred value is then often called the implied volatility (and typically depends on the option's strike and maturity).

One can also estimate the standard deviation of the return by just inferring the risk-neutral distribution on the basis of the given option data at a particular maturity, and then calculate its standard deviation. The advantage is that the estimate is then no longer dependent on a particular choice of strike level; one could also estimate higher moments. We follow this approach.

The theoretical basis of our estimation method is based on the study of Bakshi et al. [29], which is also the reference of the CBOE for calculating the SKEW index. According to the study of Bakshi and Madan [33], any twice-differentiable payoff can be spanned by a portfolio of bonds, the underlying asset, and out-of-the-money vanilla (put and call) options as shown in Equation (1):

$$f(S_T) = f(\kappa) + f'(\kappa)((S_T - \kappa)^+ - (\kappa - S_T)^+) + \int_0^\kappa f''(K)(K - S_T)^+ dK + \int_\kappa^\infty f''(K)(S_T - K)^+ dK, \tag{1}$$

where  $S_T$  is the price of the underlying asset at time  $T$ ,  $f(\cdot)$  is the claim payoff function,  $f'(\kappa)$  is the first-order derivative of the payoff function at a certain strike price  $\kappa$ , and  $f''(K)$  is the second-order derivative of the payoff function at some strike price  $K$ .

Applying the call-put parity to the right-hand side of Equation (1), we have the expectation of a general claim payoff as Equation (2) shows:

$$E_Q[f(S_T)] = f(\kappa) + f'(\kappa)(\exp((r - q)T)S_0 - \kappa) + \exp(rT)\left(\int_0^\kappa f''(K)EP(K, T)dK + \int_\kappa^\infty f''(K)EC(K, T)dK\right), \tag{2}$$

where  $Q$  denotes the Q-measure;  $S_0$  is the current underlying stock price;  $S_T$  is the stock price at time  $T$ ;  $T$  is the option maturity in years;  $r$  is the risk-free interest rate corresponding to maturity  $T$ ;  $EP(K, T)$  and  $EC(K, T)$  represent the payoff of European put and European call options with strike price  $K$  at time  $T$ , respectively.

Accordingly, we can deduce the  $n$ -th moment of log asset return  $X_T = \log(\frac{S_T}{S_0})$  by considering function  $f(S_T) = (\log(\frac{S_T}{S_0}))^N$  as shown in Equation (3), where  $F_0$  is the current forward price at maturity:  $F_0 = S_0 \exp((r - q)T)$ . In the numerical implementation, we derived  $F_0$  from the listed strike price at which the difference between quoted put and call prices is the smallest according to the CBOE methodology.

$$E_Q[(\log(\frac{S_T}{S_0}))^N] = (\log(\frac{\kappa}{S_0}))^N + N(\log(\frac{\kappa}{S_0}))^{N-1}(\frac{F_0}{\kappa} - 1) + \exp(rT)\left(\int_0^\kappa \frac{N}{K^2}((N - 1)((\log(\frac{K}{S_0}))^{N-2} - (\log(\frac{K}{S_0}))^{N-1}))EP(K, T)dK + \int_\kappa^\infty \frac{N}{K^2}((N - 1)((\log(\frac{K}{S_0}))^{N-2} - (\log(\frac{K}{S_0}))^{N-1}))EC(K, T)dK\right) \tag{3}$$

However, the challenge of estimating model-free implied moments is that we cannot observe the option data for a continuum of strikes. In the study of Madan and Schoutens [34], the authors provided a method, using the trapezoidal rule to solve this computation problem. More precisely, Equation (4) [34] is the truncated form of the  $n$ -th order moment of the risk-neutral log return  $X_T = \log(\frac{S_T}{S_0})$ .

$$E_Q[(\log(\frac{S_T}{S_0}))^N] = (\log(\frac{K_0}{S_0}))^N + N(\log(\frac{K_0}{S_0}))^{N-1}(\frac{F_0}{K_0} - 1) + \exp(rT)N \sum_{i=1}^M \frac{\Delta K_i}{K_i^2}((N - 1)(\log(\frac{K_i}{S_0}))^{N-2} - (\log(\frac{K_i}{S_0}))^{N-1})\text{Price}(K_i, T), \tag{4}$$

where  $K_i$  is the strike price of the  $i$ -th out-of-the-money option ( $K_i > F_0$  for call option,  $K_i < F_0$  for put option) and  $\Delta K_i$  is the interval between strike prices, as Equation (5) shows:

$$\begin{cases} \Delta K_1 = K_2 - K_1, \\ \Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}, \quad \forall i \neq 1 \text{ or } N \\ \Delta K_N = K_N - K_{N-1} \end{cases} \tag{5}$$

where  $K_0$  is the first strike price below forward price  $F_0$  and  $Price(K_i, T)$  is the price for option contract with strike price  $K_i$  and maturity  $T$ , given by Equation (6), where  $EC$  and  $EP$  are the midpoint of the corresponding bid and ask price of the European call ( $EC$ ) and the European put ( $EP$ ).

$$\begin{cases} Price(K_i, T) = EP(K_i, T), & \text{if } K_i < K_0 \\ Price(K_i, T) = \frac{EC(K_0, T) + EP(K_0, T)}{2}, & \text{if } K_i = K_0 \\ Price(K_i, T) = EC(K_i, T), & \text{if } K_i > K_0 \end{cases} \tag{6}$$

Then, the implied moments of the distribution of log-asset return  $X_T = \log(\frac{S_T}{S_0})$  (under the pricing measure) are defined in Equation (7).

$$\begin{cases} VAR(X_T) = E_Q[X_T^2] - (E_Q[X_T])^2; \\ Skewness(X_T) = \frac{E_Q[X_T^3] - 3E_Q[X_T]E_Q[X_T^2] + 2(E_Q[X_T])^3}{(Var(X_T))^{3/2}}; \\ Kurtosis(X_T) = \frac{E_Q[X_T^4] - 4E_Q[X_T]E_Q[X_T^3] + 6(E_Q[X_T])^2E_Q[X_T^2] - 3(E_Q[X_T])^4}{(Var(X_T))^2}, \end{cases} \tag{7}$$

where  $n$ -th moments  $E_Q[X_T^n]$  of the risk-neutral distribution of the log-asset return are calculated by Equation (4). Below, the implied volatility is the square root of variance  $VAR$  in Equation (7), and the implied skewness and implied kurtosis are  $Skewness$  and  $Kurtosis$  in Equation (7), respectively.

### 3. Data and Methodology

#### 3.1. Data and Summary Statistics

A firm’s environmental, social, and governance (ESG) behavior can be measured by its ESG ratings. We use the ESG ratings of Sustainalytics, which reports the raw scores of ESG building blocks that include 163 ESG indicators. Sustainalytics also provides the weights of each building block for each company so that we can multiply the raw score and its weight to obtain the ESG composite ratings and ESG pillar ratings for every firm once a month as shown in Equations (8) and (9). It uses a dynamic weighting matrix to reflect the relevance of each ESG aspect to a certain company [35]. The score range is 0–100, where a high score indicates that the company has strong ESG performance and vice versa. The ESG rating data provided by Sustainalytics start from August 2009; we choose a 10 year period as our analysis window, which is from August 2009 to May 2019. In this study, we focus on companies listed on NYSE/NASDAQ/AMEX.

$$ESG = \sum_i raw\ score_i * weight_i \tag{8}$$

$$\begin{aligned} E &= \frac{1}{total\ E - weight} \sum_i raw\ score_i \times weight \\ S &= \frac{1}{total\ S - weight} \sum_i raw\ score_i \times weight \\ G &= \frac{1}{total\ G - weight} \sum_i raw\ score_i \times weight \end{aligned} \tag{9}$$

Implied moments are calculated on the basis of option data from IVolatility following the method described in Section 2. Interest rates are based on U.S. Treasury yield curve

rates. For each day, we use two contracts that are at least longer than 8 days and nearest to 30 days to expiration to obtain the 30-day implied moments by linear interpolation on the two chosen maturities. Referring to the CBOE and the study of Chang et al. [22], we only use out-of-the-money option contracts and option contracts whose bid price equal to 0 are deleted. If there are two consecutive contracts that all have a zero bid price, then we remove the contracts that have strikes that are below those two contracts. The companies that have no remaining contracts after the above operations in a whole month are treated as missing values. Implied moments that are larger than the 0.99 quantile and smaller than the 0.01 quantile are replaced by its median value.

We analyze 1531 companies traded in the three exchanges in the U.S. There are 116,086 observations in total; we ignore the missing value of the ESG ratings, and observe implied moments separately in the following study. Table 1 reports the summary statistics of ESG ratings and implied moments. It describes the mean and standard deviation of the variables, and skewness and kurtosis. Kurtosis in Table 1 is the value of kurtosis minus 3 to compare with normal distribution. This table shows that the mean value and median value of the G pillar rating are obviously higher than those of the E and S pillar ratings, but its skewness is negative, while the skewness of the E and S pillar ratings is positive. Moreover, the standard deviation of the G rating is smaller than that of the E and S pillar ratings. The kurtosis of the E, S, and G pillar ratings and the ESG composite ratings appear to be platykurtic. As for implied moments, the mean and median values of implied skewness are negative and equal to  $-0.9272$  and  $-0.8401$ , while the mean and median values of implied volatility and implied kurtosis are positive.

The company-size variable is represented by the market capitalization of the underlying company. The data of market capitalization are collected from CRSP. After examining the relations between ESG ratings and implied moments using the full data set, we further explore their relations, using a sector-level data set. We follow the Global Industry Classification Standard (GICS) to divide the data set into different sectors. According to GICS, all companies are divided into 11 sectors: energy, materials, industrial, consumer discretionary, consumer staples, healthcare, financial, information technology, communication services, utilities, and real estate sectors.

**Table 1.** Summary statistics of ESG ratings and implied moments.

	Mean	Median	Min.	Max.	Std. dev	Skewness	Kurtosis
E	50.9936	48.6826	20.0000	100.0000	13.1173	0.6838	$-0.1225$
S	54.2422	53.5000	20.8125	92.5014	10.2728	0.3841	$-0.0283$
G	63.2653	63.7500	29.9333	94.7000	9.0186	$-0.0623$	$-0.3762$
ESG	55.2594	53.7781	32.5250	90.7875	8.6126	0.6260	$-0.0654$
Implied volatility	0.3647	0.3297	0.0520	4.0394	0.1629	3.5545	33.8539
Implied skewness	$-0.9272$	$-0.8401$	$-2.9292$	0.1936	0.5208	$-0.9284$	1.0306
Implied kurtosis	4.2228	3.5900	0.0625	16.5412	2.2816	2.0101	5.1280

### 3.2. Methodology

In this study, we first divide the monthly set of companies into high and low ESG rating groups according to their median value, and calculate the average monthly implied moments of the two groups. Then, we compare these implied moments of the two groups over time. In addition, we perform a two sample t-test on the implied-moments series of these two ESG rating groups. Specifically, we investigate whether the averaged implied moments for one group in that month are lower than those for the other group. For example, we examine whether the implied volatility of the high E rating group in a particular month is lower than the implied volatility in the low E rating group. Then, we count such months. In addition, we focus on particular subsets of our database. More precisely, we investigate whether the general findings still hold, for example, for mid-sized companies. A company belongs to this subset of midsized companies if its market capitalization is between the first

and third quantile of market capitalization of the full data set. Lastly, the relation between ESG ratings and implied moments is further examined, using a sector-level dataset.

To arrive to our general conclusions, we use the exponential weighted moving average (EWMA) method to smooth our estimates and identify particular trends when comparing the average implied moments of companies in high and low ESG rating groups. The main idea of EWMA is to give older observations less weight than more recent ones; weights fall exponentially. For a given time series  $Y_t$ , the formula deployed for the calculation of the EWMA is shown in Equation (10).

$$S_t = \begin{cases} Y_1, & t = 1 \\ \alpha S_{t-1} + (1 - \alpha)Y_t, & t > 1, \end{cases} \quad (10)$$

where  $S_t$  is the EWMA series of  $Y_t$ ,  $\alpha \in (0, 1)$ . In this paper,  $\alpha$  is fixed at 0.9.

#### 4. Results and Discussion

In this section, we discuss the obtained estimates and describe the main findings and results.

##### 4.1. ESG Ratings and Implied Moments

Table 2 shows the number of months where the implied moments of companies in either the high or low ESG rating groups are lower. If this number exceeds half of the total number of months, the implied moments of this group are fewer than those of the comparable group. We also provide the results of the related  $t$ -test. In the second, sixth, and tenth columns, the results for implied volatility (IV), implied skewness (IS), and implied kurtosis (IK) are shown, respectively. The total number of months is 118, as shown in the denominator of the provided ratios. The other columns show the mean value, statistics, and  $p$  value of the related  $t$ -test in the same order.

Columns 2, 6, and 10 in Table 2 show the following.

- There are 118 months in which the average value of implied volatility in the high ESG rating group is lower than that in the low ESG rating group, which means that the high ESG rating group has a lower average implied common risk than the low ESG rating group. A similar finding also holds for individual E, S, and G ratings.
- There are only 12 months in which the average value of implied skewness in the high ESG rating group is less negative than that in the low ESG ratings. Since 12 months do not exceed half of the total number of months, this shows that the high ESG rating group has a higher implied tail risk than the low ESG rating group. A similar finding also holds for individual E and G ratings.
- There are 0 months in which the average value of implied kurtosis in the high ESG rating group is lower than that in the low ESG rating group. Hence, we draw the similar results as above, namely, that the high ESG rating group has a higher implied tail risk than the low ESG rating group. A similar finding also holds for individual E, S, and G ratings.

Columns 3–5 show the results of the  $t$ -test, which is tested on equal means. The null hypothesis of equal means is typically rejected with a very small  $p$  value. Hence, these first statistics show that, in terms of implied moments of companies, there are statistically significant differences between the high and low ESG rating groups. Thus, companies with a high ESG, E, S, and G rating tend to have lower implied volatility.

Columns 7–9 and 11–13 provide similar statistics for implied skewness and implied kurtosis, respectively. The  $t$ -test results are not significant for implied skewness and implied kurtosis in the G category, and the  $t$ -test results are significant for implied skewness and implied kurtosis in the E, S, and ESG categories.

Figure 1 provides a time-varying view on these implied moments of companies in the high and low ESG rating groups. We use the exponential weighted moving average smoothing procedure for smoothing the time series. The first column shows that companies

with a high ESG rating tend to always have low implied volatility during the whole period. However, the difference in implied volatility between the high and low G rated groups is much smaller than that in other cases. This could indicate that the influence of the G rating on implied volatility is rather weak. Differences in the G rating tend to be larger after 2016. The last two columns of Figure 1 show that companies with a high E, S, and ESG composite rating always tend to have more negative implied skewness and higher implied kurtosis than those for companies with a low E, S, and ESG composite rating. Although the difference in implied skewness and implied kurtosis of companies between the high and low G rating groups is very small, companies in the high G rating group exhibit less negative average implied skewness after 2015 than companies in the low G rating group.

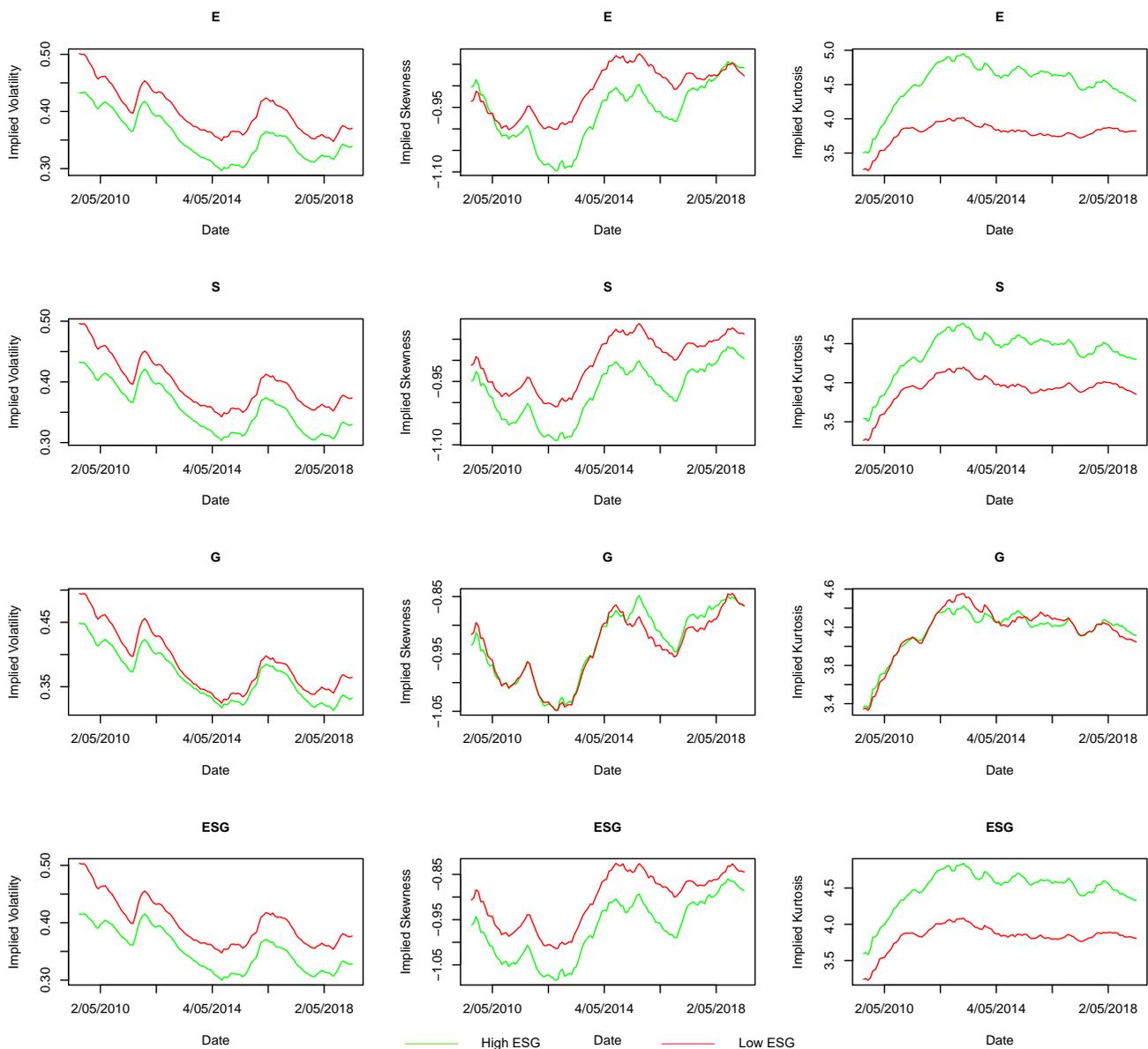


Figure 1. Average implied moments of companies in high and low ESG rating groups.

**Table 2.** Number of months where implied moments of companies in either high or low ESG rating groups is the lower of the two.

	Less IV Months (2)	Mean (3)	<i>t</i> -Test (4)	<i>p</i> -Value (5)	Less IS Months (6)	Mean (7)	<i>t</i> -Test (8)	<i>p</i> -Value (9)	Less IK Months (10)	Mean (11)	<i>t</i> -Test (12)	<i>p</i> -Value (13)
High E	118/118	0.3463	−5.7574	0.0000	25/118	−0.9592	−3.8083	0.0002	0/118	4.5750	17.1110	0.0000
Low E	0/118	0.3894	−5.7574	0.0000	93/118	−0.9067	−3.8083	0.0002	118/118	3.8405	17.1110	0.0000
High S	118/118	0.3474	−5.1830	0.0000	6/118	−0.9690	−5.2600	0.0000	0/118	4.4538	11.6278	0.0000
Low S	0/118	0.3861	−5.1830	0.0000	112/118	−0.8971	−5.2600	0.0000	118/118	3.9713	11.6278	0.0000
High G	111/118	0.3567	−2.5651	0.0110	61/118	−0.9300	0.5448	0.5864	59/118	4.2156	−0.2175	0.8280
Low G	7/118	0.3763	−2.5651	0.0110	57/118	−0.9373	0.5448	0.5864	59/118	4.2247	−0.2175	0.8280
High ESG	118/118	0.3445	−6.1413	0.0000	12/118	−0.9650	−4.7110	0.0000	0/118	4.5425	16.2281	0.0000
Low ESG	0/118	0.3900	−6.1413	0.0000	106/118	−0.9008	−4.7110	0.0000	118/118	3.8736	16.2281	0.0000

Company size is a proven risk factor, and most empirical research sets company size as a control variable when examining the relation between ESG investment and financial risk to exclude its endogenous effect [17,18]. We divide companies into large and small company groups according to quantile to examine whether company size influences the relation between ESG rating and implied moments in our data set. Figure 2 shows the ESG composite rating and implied moments of large and small companies. We categorize a company as large if its market capitalization is larger than the third quantile of the corresponding data set, and categorize it as small if its market capitalization is smaller than the first quantile of the corresponding data set. The figure shows that large companies tend to have a higher ESG rating, but also more negative implied skewness. Hence, to decrease the potential influence of company size, we remove companies that have more market capitalization than the third quantile, or less than the first quantile of the whole data set.

Table 3 shows the comparison of implied moments of companies in the corresponding high ESG rating groups and companies in the low ESG rating groups. Columns 2–5 show that there are 114 months in which the high ESG rating group has lower average implied volatility than the low ESG rating group. This result also holds for E, S, and G pillar ratings. However, the corresponding *t*-test results of the E rating groups are no longer significant, indicating that there is not really a statistical difference in terms of implied volatility between high and low E rated companies. A similar observation holds for the difference between high G and low G rated companies. Columns 6–9 show that, after excluding large and small companies, there are 89 months in which the high ESG rating group has less negative skewness than the low ESG rating group. This result is similar with those of E and G ratings. This is, however, not the case for the S rating; the *t*-test result of the S rating category is no longer statistically significant. No conclusion can, therefore, be made on whether mid-sized companies in a low S rating have less negative skewness or not. The *t*-test results of the E, G, and composite ESG rating, on the other hand, are significant, which means that there are statistical differences in the implied skewness of companies in the two groups. Column 10 shows that there are 56 months in which the high ESG rating group has lower average implied kurtosis than the low ESG rating group; however, the results of the corresponding *t*-test is not significant, as is not the E rating. There are 89 months in which the high G rating group has lower average implied kurtosis than the low G rating group. Moreover, the *t*-test result of the G rating category is statistically significant, which shows that the high G rating group tends to have a lower implied tail risk than the low G rating group.

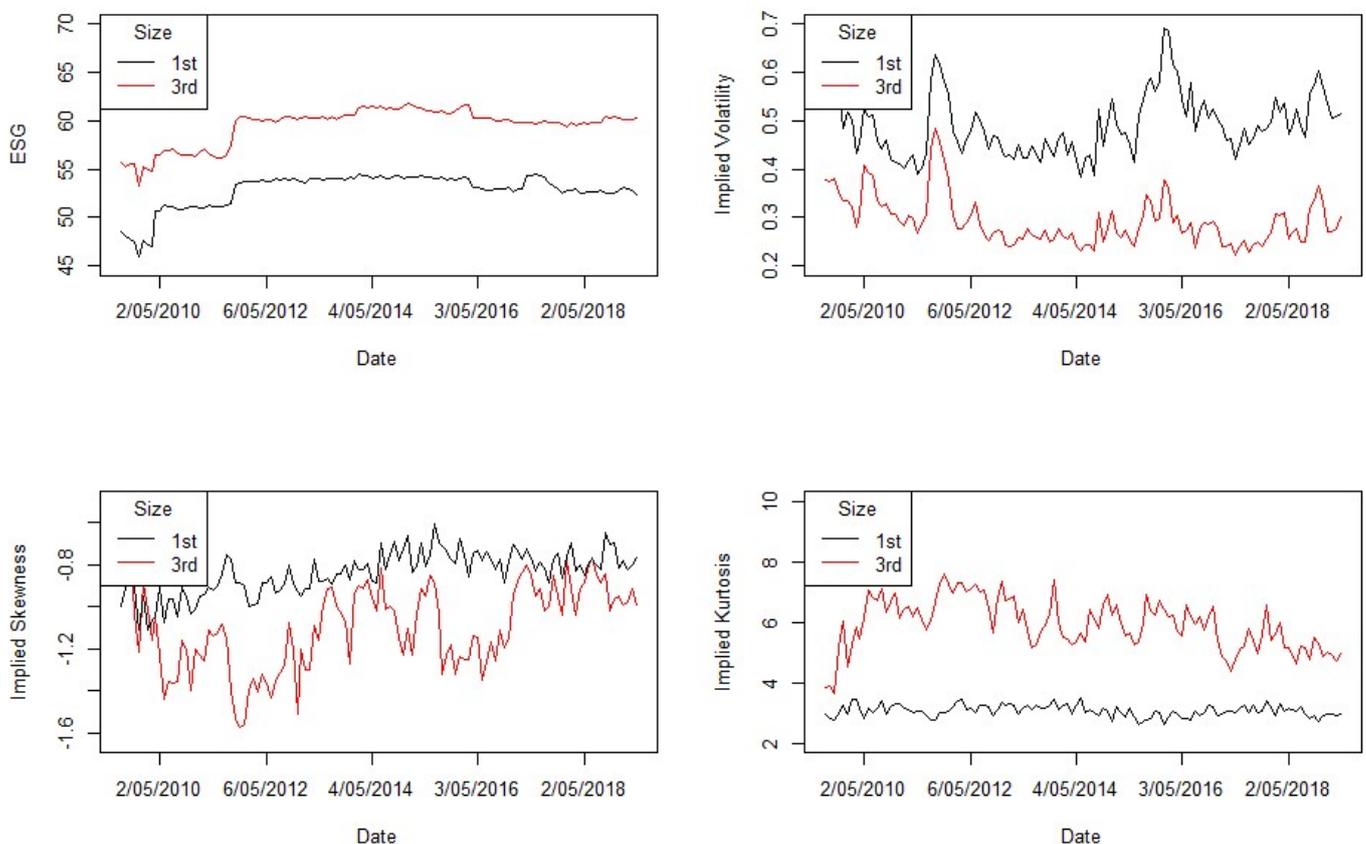
Figure 3 shows the implied moments of mid-sized companies in the high and low ESG rating groups. Although the difference in the implied volatility of mid-sized companies in the high and low ESG rating groups in Figure 3 is not obvious from the first column, companies in the high ESG rating group always appear to have low implied volatility. Moreover, Figure 3 shows that mid-sized companies in the high ESG rating groups tend to have less negative skewness, and this trend is more pronounced after 2016. After 2016, companies with a high E, G, and ESG composite rating tend to have less negative implied skewness and lower implied kurtosis. Moreover, companies with a high G rating always have less implied skewness and lower implied kurtosis after 2010. For the mid-

sized company sample, the difference in implied skewness and implied kurtosis is more pronounced than that for the full sample.

Figure 4 shows the monthly difference in implied moments between mid-sized companies in the high and low ESG rating groups from August 2009 to May 2019. For implied volatility and implied kurtosis, a negative value means that companies in the high ESG rating group have lower implied volatility or lower implied kurtosis than companies in the low ESG rating group. For implied skewness, a positive value means companies in the high ESG rating group have less negative implied skewness than companies in the low ESG rating group. For the ESG composite rating, in most months, the difference in implied volatility is negative, and the difference in implied skewness is positive. This trend is also present for the E and G pillar ratings. However, for the influence of the S rating on implied skewness, in most months, the difference in implied skewness is negative. Moreover, for the E pillar rating, the difference in implied skewness increases, and the difference in implied kurtosis decreases as time goes by. This could indicate that the E rating has played an increasingly important role in decreasing the tail risk in recent years.

**Table 3.** Number of months during which the implied moments of mid-sized companies in either the high or the low ESG rating group was lower.

	Less IV Months (2)	Mean (3)	t-Test (4)	p Value (5)	Less IS Months (6)	Mean (7)	t-Test (8)	p Value (9)	Less IK Months (10)	Mean (11)	t-Test (12)	p Value (13)
High E	77/118	0.3517	−0.5343	0.5936	99/118	−0.8624	4.3130	0.0000	56/118	3.8709	0.2732	0.7850
Low E	41/118	0.3556	−0.5343	0.5936	19/118	−0.9192	4.3130	0.0000	62/118	3.8599	0.2732	0.7850
High S	116/118	0.3440	−2.4495	0.0150	43/118	−0.9015	−1.2258	0.2215	41/118	3.9060	2.1810	0.0302
Low S	2/118	0.3617	−2.4495	0.0150	75/118	−0.8853	−1.2258	0.2215	77/118	3.8185	2.1810	0.0302
High G	94/118	0.3475	−1.4596	0.1458	86/118	−0.8748	2.7567	0.0063	89/118	3.8095	−2.8054	0.0055
Low G	24/118	0.3582	−1.4596	0.1458	32/118	−0.9113	2.7567	0.0063	29/118	3.9207	−2.8054	0.0055
High ESG	114/118	0.3449	−2.1086	0.0361	89/118	−0.8751	2.5409	0.0117	56/118	3.8695	0.3350	0.7379
Low ESG	4/118	0.3600	−2.1086	0.0361	29/118	−0.9091	2.5409	0.0117	62/118	3.8560	0.3350	0.7379



**Figure 2.** ESG composite rating and implied moments of large and small sized company groups.

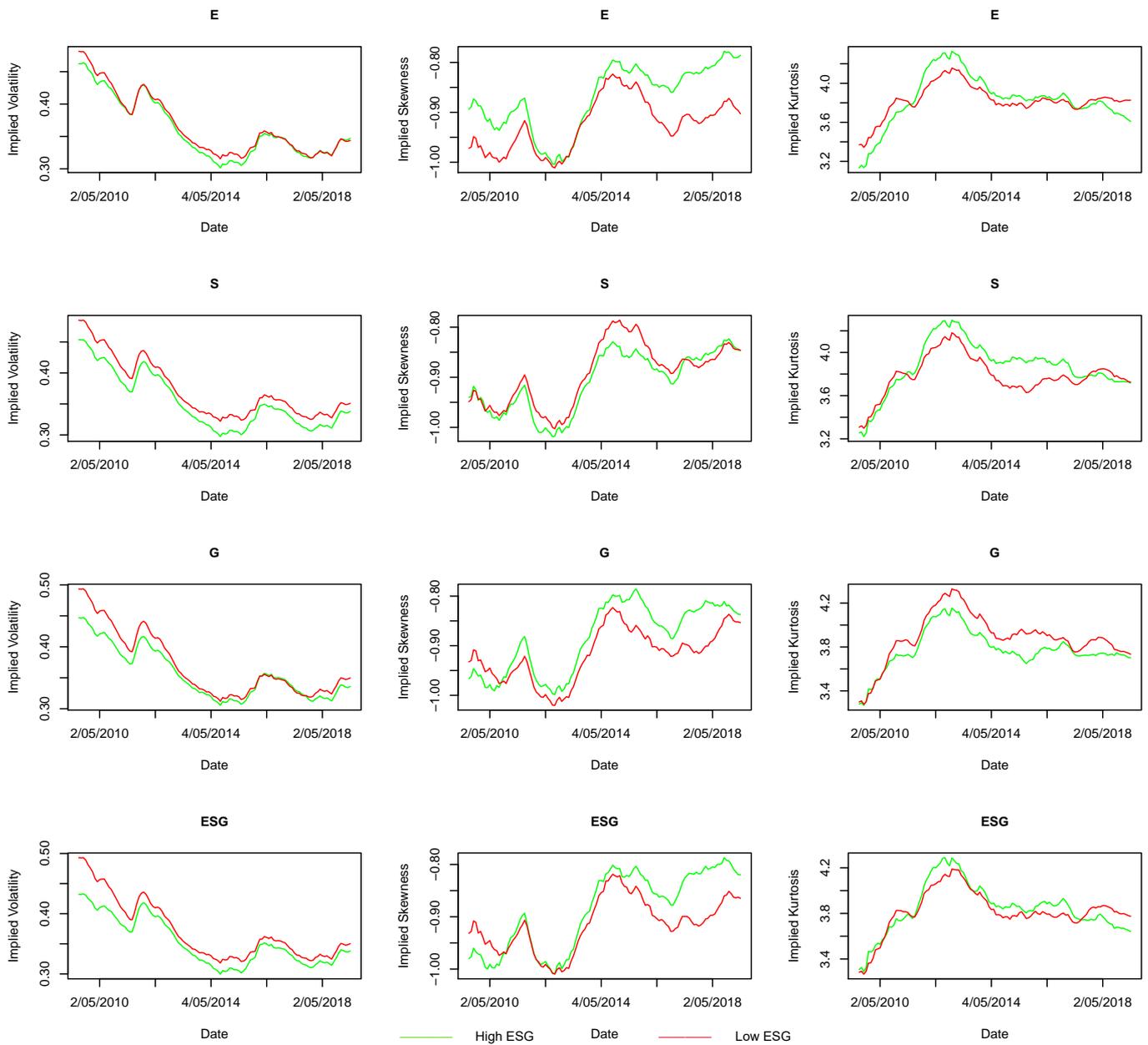
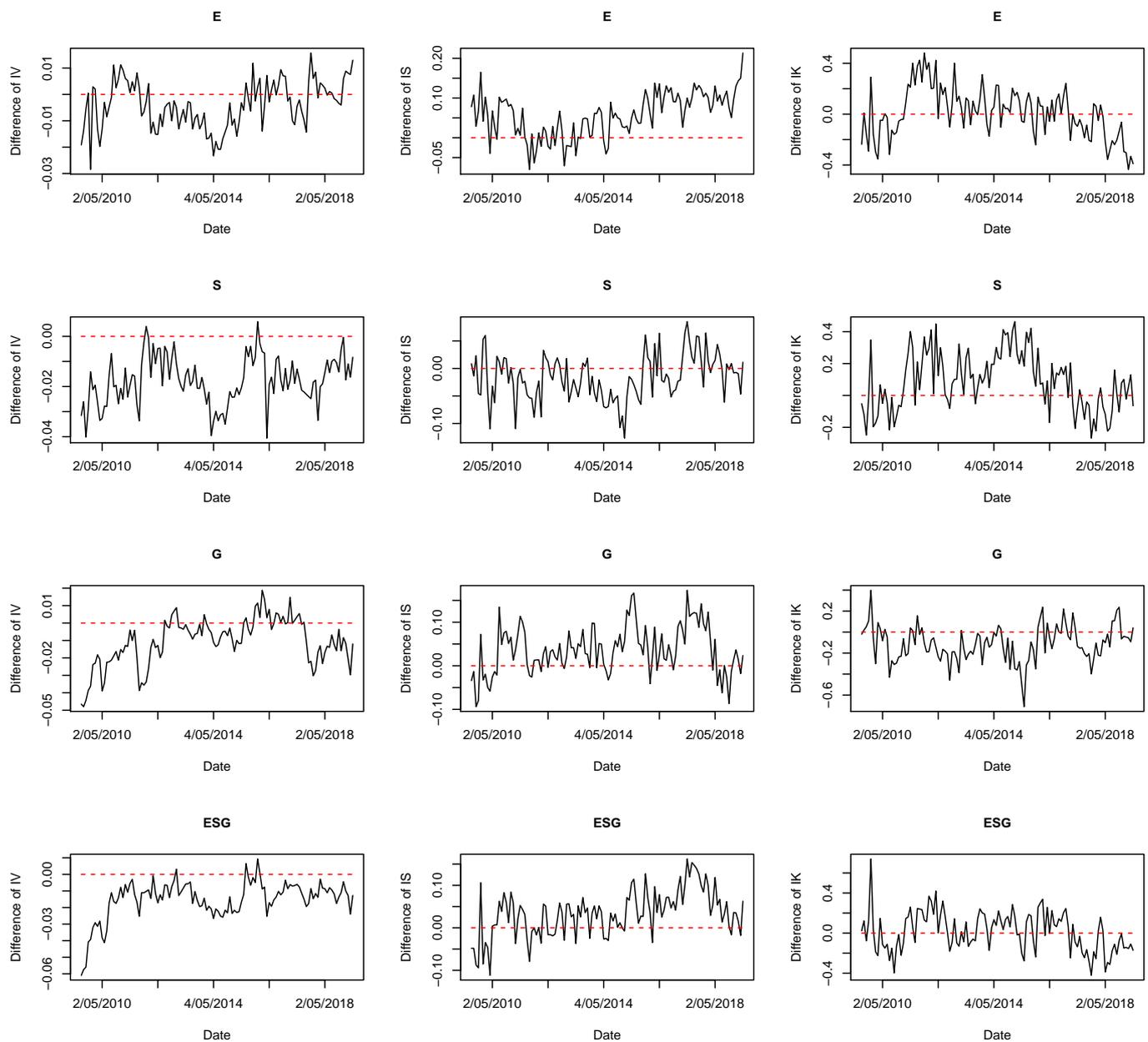


Figure 3. Average implied moments of mid-sized companies in high and low ESG rating groups.



**Figure 4.** Difference in average implied moments between mid-sized companies in high and low ESG rating groups.

#### 4.2. ESG Ratings and Implied Moments Divided by Sector

To further explore the relationship between ESG ratings and implied moments, we divide the data set by sector according to the GICS categorization. To exclude the influence of company size, we only use the mid-sized company data set in the following study.

Table 4 shows the number of months during which companies in the high ESG rating group have fewer implied moments than companies in the low ESG rating group. Column 4 in Table 4 of the ESG composite rating indicates that, in all sectors, the number of months during which companies in the high ESG rating group have lower implied volatility is larger than the number of months during which companies in the low ESG group have lower implied volatility, except for the industrial, information technology, and real estate sectors. A similar trend also holds for the E and S pillar ratings; however, for high G rating, companies in the materials and utilities sectors tend to have fewer months with lower implied volatility.

Compared with implied volatility, the ESG composite rating has a much more pronounced influence on implied skewness in the industrial, information technology, and real estate sectors. Companies with a negative relation between ESG rating and implied skewness are mainly in the materials, healthcare, and communication sectors. The influence of ESG ratings on implied kurtosis is not as obvious as that on implied volatility and implied skewness. However, in the consumer staples, communication services, and real estate sectors, they still play an important role. In addition, for companies in the consumer discretionary sector, E, S, and G pillar ratings are all important for decreasing common risk and tail risk, while for companies in the energy and financial sectors, E and G ratings are both important for decreasing common risk and tail risk.

Table 5 shows the number of months during which companies in the high ESG rating group have fewer moments than companies in the low ESG rating group. The thresholds to divide the high and low ESG rating groups are the 0.4 and 0.6 percentiles of ESG ratings, respectively. Table 5 shows that the trend in Table 4 is still present, and that the number of months during which companies in the high ESG rating group have fewer implied moments than companies in the low ESG rating group increases. Moreover, this phenomenon indicates that the relation between ESG ratings and implied moments is most likely nonlinear.

**Table 4.** Number of months during which companies in the high ESG rating group have fewer implied moments than those in the low ESG rating group. Group-dividing standard is the median value of ESG ratings.

	E			S			G			ESG		
	IV	IS	IK	IV	IS	IK	IV	IS	IK	IV	IS	IK
Energy	91/118	63/118	57/118	88/118	44/118	47/118	87/118	64/118	72/118	101/118	52/118	58/118
Materials	82/118	28/118	28/118	66/118	37/118	58/118	26/118	61/118	49/118	84/118	18/118	39/118
Industrial	41/118	74/118	46/118	53/118	75/118	59/118	26/118	85/118	56/118	45/118	70/118	47/118
Consumer discretionary	89/118	84/118	54/118	78/118	86/118	55/118	76/118	89/118	72/118	87/118	84/118	53/118
Consumer staples	108/118	65/118	86/118	96/118	53/118	69/118	114/118	48/118	74/118	109/118	51/118	87/118
Healthcare	68/118	39/118	28/118	111/118	22/118	25/118	79/118	32/118	32/118	105/118	16/118	18/118
Financial	63/118	67/118	41/118	40/118	61/118	60/118	94/117	69/117	65/117	62/118	67/118	38/118
Information technology	42/118	107/118	51/118	35/118	86/118	60/118	63/118	43/118	63/118	39/118	95/118	56/118
Communication services	96/118	31/118	81/118	68/116	56/116	71/116	89/118	37/118	67/118	101/118	49/118	79/118
Utilities	85/118	53/118	51/118	73/114	57/114	50/114	19/54	41/54	34/54	77/118	58/118	49/118
Real estate	46/118	81/118	85/118	44/118	82/118	81/118	52/118	94/118	94/118	24/118	92/118	91/118

**Table 5.** Number of months during which companies in the high ESG rating group have better performance than those in the low ESG rating group. Group-dividing standards are the 0.4 and 0.6 percentiles of ESG ratings.

	E			S			G			ESG		
	IV	IS	IK	IV	IS	IK	IV	IS	IK	IV	IS	IK
Energy	93/113	61/113	46/113	95/118	45/118	59/118	99/118	66/118	80/118	105/117	60/117	62/117
Materials	88/118	30/118	28/118	79/118	37/118	54/118	32/118	54/118	52/118	94/118	19/118	39/118
Industrial	37/118	75/118	48/118	61/118	76/118	58/118	35/118	78/118	63/118	44/118	86/118	50/118
Consumer discretionary	91/118	90/118	51/118	72/118	88/118	59/118	63/118	92/118	72/118	90/118	97/118	66/118
Consumer staples	101/115	72/115	88/115	97/118	49/118	75/118	116/118	46/118	78/118	109/118	56/118	84/118
Healthcare	70/112	28/112	20/112	110/118	20/118	32/118	77/118	27/118	28/118	102/118	14/118	15/118
Financial	64/118	70/118	34/118	49/118	70/118	73/118	97/117	67/117	72/117	65/117	66/117	38/117
Information technology	38/118	107/118	42/118	28/118	83/118	56/118	55/118	28/118	42/118	37/118	100/118	51/118
Communication services	97/118	41/118	88/118	79/98	46/98	78/98	90/117	33/117	67/117	92/116	50/116	86/116
Utilities	94/118	48/118	50/118	47/56	20/56	8/56	7/34	25/34	19/34	60/89	56/89	44/89
Real estate	33/118	86/118	87/118	33/118	79/118	78/118	45/118	104/118	94/118	31/118	92/118	95/118
All companies	98/118	102/118	49/118	114/118	49/118	48/118	88/118	96/118	94/118	113/118	99/118	58/118

### 4.3. Discussion

In this subsection, we further discuss the results of this study. Companies with a higher ESG rating would typically have a lower implied volatility, as shown in Tables 2 and 3. This holds not only for mid-sized companies, but for the full sample; such effects become weaker for mid-sized companies. Several studies already examined the relationships between ESG rating and company volatility, and found that better ESG rated companies tend to yield a lower volatility [4]. However, the effect that high E and G ratings lead to lower implied common risk becomes statistically insignificant after excluding the effect of company size, which indicates that company size plays an important role in the relation between implied common risk and E and G behaviors.

Companies with a higher ESG rating typically have lower tail risk for mid-sized companies. Since company size is an important risk factor, using the data set that only includes mid-sized companies, companies with a higher ESG rating tend to have lower tail risk, which is measured by implied skewness and implied kurtosis. It is in line with findings that a better ESG rating leads to lower expected tail risk [4,17]. The reason for this empirical result is that ESG behavior would burden small companies, and would not become a decision factor to large companies when decreasing their tail risk. Hence, ESG behaviors play a role in decreasing the volatility and implied tail risk of mid-sized companies. This result also provides some insight to explain the ambiguous and contradictory influence of ESG behavior on companies' performance and risk. In addition, a higher S rating leads to higher tail risk, which is cohesive with the findings of Diemont et al. [19]; nevertheless, they used historical methods, while we use a forward-looking method to measure tail risk. However, Figures 3 and 4 show that the difference in implied tail risk between the two groups became smaller after 2015, and a higher S rating gradually led to a lower tail risk after 2017.

Furthermore, the proposition that a positive ESG standing decreases tail risk appears especially obvious before 2012 and after 2016. Before 2012, the economy was recovering from the 2008 financial crisis; thus, positive ESG behavior was able to decrease the tail risk of companies. In 2016, the Paris Agreement was legally signed, and more companies began to pay attention to their corporate ESG behaviors. Since then, there has been a large difference in tail risk between the high and low ESG rating groups. G rating apparently always plays a significant role in determining the volatility and tail risk of a company. For tail risk, this is even more pronounced for mid-sized companies.

Lastly, we did not find a strong correlation between ESG ratings and implied moments for all sectors. ESG composite rating is, to some extent, correlated to lower implied volatility or lower implied tail risk over all sectors. In other words, if companies with a higher ESG composite rating have, on average, higher implied volatility, they have lower tail risk, and vice versa. Moreover, companies with a higher ESG composite rating in the consumer discretionary and financial sectors (companies with a higher E and G rating in the energy, consumer discretionary, and financial sectors; companies with a higher G rating in the consumer discretionary sector) have on average both lower implied volatility and implied tail risk.

## 5. Conclusions

By exploring the relations between ESG ratings and implied moments, companies with a high ESG rating tended to have lower implied volatility, and this effect was not influenced by company size. Large companies tended to have a higher ESG rating, but also more negative implied skewness, while small companies tend to have a lower ESG rating and less negative implied skewness. Thus, we did not find a strong relationship between ESG ratings, and implied skewness and implied kurtosis using the full sample. However, after excluding large and small companies, companies with a high ESG rating tended to have less negative implied skewness and lower implied kurtosis. Further, the relationship between ESG ratings and implied moments of companies in different sectors was examined. Only companies in the consumer discretionary sector had the same trend as

that in the overall equity market. Although companies in other sectors exhibited different trends, the influence of ESG ratings on implied volatility still appeared for companies in the energy, material, consumer staples, healthcare, communication services, and utilities sectors, while the positive influence of ESG ratings on implied skewness was present in the energy, industrial, financial, information technology, and real estate sectors.

Our study contributes to the existing literature, as we used a forward-looking measure to obtain the firm's risk represented by implied moments in contrast with typically historical measures. Implied tail risk is measured by implied skewness and implied kurtosis, which is different from previous studies. Moreover, company size played an important role when exploring the influence of ESG ratings on implied tail risk.

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## Abbreviations

The following abbreviations are used in this manuscript:

ESG	Environmental, social, and governance
SRI	Socially responsible investment
IV	Implied volatility
IS	Implied skewness
IK	Implied kurtosis

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