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War Amongst ESG Ratings in China: A Battle of Stock Return Predictability

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Abstract: Existing literature on the stock return predictability of Environmental, Social and Governance (ESG) ratings in the Chinese A-share market presents conflicting conclusions, primarily due to divergent sources of ESG ratings and variations in sample selection. We are the first to conduct comparative analyses on ESG ratings from all mainstream agencies using the largest available sample and the longest time window. After considering the real impact of transaction costs, ESG ratings provided by three vendors demonstrate a significant positive correlation with stock future returns. Heterogeneity analyses based on firm market capitalization indicate that Sino ESG ratings stand out among various ratings, demonstrating robust and significant positive predictive power under various conditions. Furthermore, we reexamine asset return anomalies from the perspective of the first moment of ESG ratings. Mean-variance spanning tests also suggest positive factor premiums. The conclusions offer valuable reference for subsequent research on the role of ESG ratings in the Chinese capital market, providing practical guidance for asset managers implementing ESG investment principles to optimize portfolio construction.

Keywords: ESG ratings, Chinese A-share market, asset return anomalies

1. Introduction

Environmental, Social and Governance (ESG) has gradually become a focal point for investors, managers, and regulatory bodies. Proper allocation of resources necessitates institutions serving as information intermediaries [1]. Emerging to meet this demand, ESG ratings, as important indicators of corporate ESG performance, offer a more intuitive and comprehensive perspective. Identifying a company's ESG practices can be costly, especially for retail investors who often rely on institutional investors to express their own commitment to ESG criteria [2]. Due to constraints on time and resources, one direct way for investors to implement ESG investment principles is to buy stocks with higher ESG ratings.

As asset managers, it is not feasible to solely rely on altruism. Ignoring the performance of investment portfolios in order to adhere to ESG principles is clearly unsustainable. For ESG investors, it would be ideal if supporting ESG could be aligned with maximizing portfolio returns, achieving a win-win situation. With this goal in mind, one question that has garnered significant attention is whether there is a relationship between ESG ratings and stock returns. More specifically, whether ESG ratings can serve as a significant factor affecting expected stock returns in the cross-section has become a topic of great interest [3, 4].

Asset management institutions managing trillions of dollars are seeking to integrate ESG principles into their investment processes. The debate over whether ESG will help improve portfolio performance or act as a drag remains ongoing. Some scholars argue that implementing socially responsible investment can lead to better portfolio performance. Pedersen et al. [5] utilize ESG scores and three sub-components to examine the performance of their ESG frontier portfolios. They find that high scores in corporate governance (G) indicate strong future fundamentals, leading to relatively inexpensive valuations and significantly positive subsequent stock returns. Alessandrini and Jondeau [6] propose an ESG screening strategy capable of generating returns at least equivalent to MSCI index investments. This strategy significantly enhances portfolio ESG quality without compromising financial performance. Pástor et al. [7] also find that in the US stock market over the past decade, green assets have outperformed brown assets in terms of actual returns.

However, Pástor et al. [4] arrive at a starkly opposite conclusion by building theoretical models to study the investment process after integrating ESG criteria. They find that due to investors' preferences for holding green assets and the ability of green assets to hedge climate risks, green assets have lower expected returns compared to brown assets under equilibrium. Bolton and Kacperczyk [3] also conclude that investors facing exposure to carbon risk will demand additional risk compensation. The negative relationship between ESG and future stock returns can also be well explained mechanistically because these stocks' better ESG performance attracts investors with ESG preferences, causing excess demand and subsequently lower returns. Of course, the abnormal returns of stocks with low ESG ratings can also be easily explained by

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risk compensation. Cornell [8] also argues that while investor preference for companies with high ESG ratings may lower capital costs, it could also reduce expected stock returns. Whether ESG can serve as a risk pricing factor remains inconclusive at present. Even in the UK stock market, Luo [9] has found that companies with lower ESG ratings often exhibit higher subsequent returns. Heterogeneity analysis suggests that this ESG premium is more pronounced for low-liquidity stocks.

Besides, Cao et al. [10] find at the institutional investor level that socially responsible investors exhibit weaker responses to quantitative mispricing signals. ESG investments divert investor attention from correcting mispricing, thereby resulting in lower information efficiency. Shanaev and Ghimire [11] study the impact of changes in ESG ratings on subsequent stock returns. Specifically, they find that an increase in ESG ratings is associated with a positive abnormal return of 0.5% per month. Conversely, a downgrade in ESG ratings leads to a risk-adjusted alpha as low as −1.2% per month. Li et al. [12] find that companies with higher ESG ratings often experience lower risks of stock price crash.

As for the potential criticisms and limitations, Edmans [13] highlights that ESG matrices form a crucial foundation for ESG ratings. These matrices typically categorize factors as ESG-related or non-ESG-related. This classification method typically relies on historical facts and the current state of affairs, often neglecting potential future trends. If the purpose of ESG evaluation is to focus on a company's long-term value, then ESG analyses should place greater emphasis on a company's future potential rather than being overly constrained by historical data. Besides, one of the most heated discussions around ESG ratings involves the criticism of their lack of clear standards and unified rules. Berg et al. [14] point out that the divergence among US ESG ratings ranges between 0.38 and 0.70. In comparison, our measurement of the divergence in Chinese ESG ratings ranges between 0.25 and 0.45, indicating a more severe degree of discrepancy in China than in the USA, which is also confirmed by Zhu et al. [15]. Moreover, current asset pricing analyses that incorporate ESG factors often lack proactive adaptation to the prevailing state of ESG rating discrepancies.

A summary observation of existing literature reveals that the majority of studies have focused on the relationship between ESG ratings and stock performance in the US capital markets. However, due to differences in empirical design details such as data sources, indicator selection, and sample periods, there is no consensus among scholars regarding the relationship between ESG ratings and stocks. Inspired by these studies, we conduct a comparative analysis of asset pricing using ESG ratings from various sources and conclude that there is a consistent relationship between ESG ratings and stock returns.

Our objective is to examine whether there is a significant relationship between corporate-level ESG ratings and cross-sectional stock returns in the Chinese A-share market and to identify the best return predictor across all ESG ratings. We primarily focus on ESG ratings provided by mainstream Chinese ESG rating agencies available on the Wind Financial Terminal, as well as ESG ratings released by Bloomberg, which covers a relatively comprehensive range of Chinese A-share companies. Based on the entire sample covered by each agency (with the longest time interval from January 2009 to January 2022), we conduct cross-sectional return anomaly tests on ESG ratings using portfolio sorting. The results indicate that exposure differences in ESG ratings issued by SynTao, Sino, and Bloomberg lead to economically and statistically significant differences in future asset returns at the portfolio level. Even after considering trading costs resulting from portfolio rebalancing, these anomaly trading strategies still generate robust positive returns. Furthermore, we use multifactor models to adjust portfolio returns for risk exposure. The significant alpha confirms that these anomalies cannot be simply attributed to common risk exposures. These portfolios have asset pricing significance as they preliminarily reveal return differences attributable to ESG-factor exposure differences that warrant further research. In contrast, the alpha of portfolios constructed by using CASVI and Wind ESG ratings can be explained by exposure to traditional factors, indicating that they do not provide unique explanatory power for cross-sectional stock returns.

When adjusting portfolio returns for risk factor exposure, we find that all long-short arbitrage portfolios exhibit negative exposure to SMB (Small-Minus-Big, representing the size factor in the Fama-French three-factor model), indicating that large-cap companies are more likely to be assigned higher ESG ratings by institutions. To clarify whether the direction of return predictability of ESG ratings will exhibit a reversal when controlling for market capitalization, we systematically exclude stocks when the size is below a certain threshold to form various sub-samples. We then conduct cross-sectional anomaly retests on each sub-sample. The results show that Sino ESG exhibits significant positive return predictive power across all enterprise size levels. However, the predictive power of SynTao and Bloomberg is limited, particularly for ultra-large companies with size ranking within the top 200 of all A-share stocks.

Furthermore, this paper represents one of the pioneering works to conduct cross-sectional anomaly tests based on the first moment of ESG ratings for the Chinese A-share market. The mean-variance spanning test demonstrates that the mean of ESG ratings indeed contains unique incremental information for explaining cross-sectional stock returns. Fama-MacBeth regressions further confirm that even after controlling for various return predictors, the mean ratings still exhibit significant positive factor premiums both economically and statistically.

The main contributions of our work are as follows: In the research on the relationship between ESG ratings and cross-sectional stock returns, earlier literature typically relies on ESG ratings provided by a single rating agency as the core variable for portfolio sorting. Our research is the first to conduct empirical analyses on Chinese ESG ratings from all five mainstream agencies simultaneously. It not only conducts cross-sectional comparisons of the predictive power of ESG ratings for each individual agency but also takes a holistic perspective by retesting the first moment of ESG ratings. Besides, this paper stands out for its completeness in terms of time span and sample selection. Through detailed and rigorous testing, it confirms the overall positive correlation between ESG ratings and stock cross-sectional returns. It verifies that ESG ratings can contribute unique incremental information to explain expected stock returns in the Chinese A-share market.

The paper proceeds as follows. Section 2 describes the data source and sample selection. Section 3 presents the baseline results and provides additional analyses on the relation between ESG ratings and stock returns. Section 4 concludes. Auxiliary tests and results are provided in the Appendix.

2. Data Source and Sample Selection

The Wind Financial Terminal has become the primary tool for Chinese institutional investors to access financial information. Following the research paradigm of predecessors, we collect alphabetic ESG ratings provided by all rating agencies available on the Wind Financial Terminal. The four ESG rating agencies are significant participants in the Chinese capital market, and their ratings have been adopted in studies on Chinese ESG issues [12]. For the sake of comparability, we refer to the methodology proposed by Xiao et al. [16] to convert the alphabetic ESG ratings into numerical scores.

Table 1
The overview of all mainstream ESG rating agencies in China

Panel A: The coverage of various ESG rating agencies

Agency names	Rating score	Coverage	Frequency
Sino-Securities Index (Sino)	C to AAA	A-share firms (2009–2022)	Quarterly
Wind	CCC to AAA	CSI 800 (2018–2022)	Quarterly
China Alliance of Social Value Investment (CASVI)	C to AA+	HuShen 300 (2016–2022)	Semi-annually
SynTao Green Finance (SynTao)	C to A	HuShen 300 (2015–2022) CSI 500 (2018–2022)	Yearly

Panel B: Descriptive statistics

	Mean	SD	Pearson correlations		
	(1)	(2)	(3)	(4)	(5)
			SynTao	Sino	CASVI
SynTao	4.04	1.38			
Sino	4.33	1.69	0.25		
CASVI	5.76	1.83	0.36	0.35	
Wind	5.84	1.37	0.45	0.30	0.38

The essential details of the prominent Chinese ESG rating agencies pertinent to this research, along with the corresponding descriptive statistics, are presented in Table 1. The average ratings from SynTao and Sino are approximately 4.0 and 4.3, respectively, indicating that they generally do not assign extremely high ESG ratings to companies and employ a stricter ESG analysis framework. In contrast, the average ratings from CASVI and Wind are around 5.7 and 5.8, suggesting that they assign higher ESG ratings to more companies, indicating a more lenient standard for excellent ESG practices. Besides, the standard deviations from SynTao and Wind are about 1.4, which is lower than Sino's 1.7 and CASVI's 1.8. This implies that the ratings from SynTao and Wind are more concentrated in terms of their distribution, whereas the ratings from Sino and CASVI exhibit greater variability among individual ratings.

In terms of the level of consensus among the rating agencies, SynTao and Sino show the greatest degree of disagreement, with a Pearson correlation of only 0.25. The strongest correlation, which is still relatively low, is between SynTao and Wind, with a coefficient of just 0.45. Compared to the correlation coefficients ranging from 0.38 to 0.70 reported by Berg et al. [14] for different ESG rating agencies in the US market, the preliminary descriptive statistics support the existence of significant discrepancies among different ESG rating providers in the Chinese market. Moreover, these discrepancies are more pronounced than those in the US ESG market, highlighting the practical significance of this research.

To enhance the comprehensiveness of our work, in addition to the four mainstream Chinese ESG rating agencies, we also utilize Bloomberg Financial Terminal to collect ESG ratings provided by Bloomberg for Chinese-listed companies. Bloomberg ESG also only covers a portion of Chinese-listed companies, with ratings starting from 2011. We gather three pillar scores provided by Bloomberg, enabling us to conduct a more comprehensive analysis.

Regarding sample selection, we include the maximum available sample of ESG ratings issued by each agency in our empirical analyses. To avoid the impact of the Russia–Ukraine conflict on the capital markets, we set the end of January 2022 as the endpoint. Following Liu et al. [17], we exclude newly listed stocks to mitigate the impact of IPO overpricing. According to Chen et al. [18], we focus solely on stocks listed on the main board and the ChiNext board to avoid the interference of stock illiquidity. Following Yang and Zhang [19], we minorize all variables at the 1% level to mitigate the influence of extreme values on the estimation of relationships between variables. Considering observations with missing fundamental financial data cannot control for multiple stock return forecasting factors in the Fama-MacBeth regression, we exclude these incomplete observations to achieve a purer sample. Stock trading data, quarterly institutional investor holdings, and company financial disclosure data are sourced from the China Stock Market & Accounting Research Database (CSMAR).

3. Empirical Baseline Results and Additional Analyses

3.1. Portfolio construction

We first analyze whether the ESG ratings can significantly affect stock returns in the cross-section. We employ a single-dimensional portfolio sorting. At the initial release date of ESG ratings for each rating agency, we establish positions. We rank the firms in ascending order based on their ESG ratings and divide them into three groups. Within each group, we allocate holdings based on the market capitalization of individual stocks, which means the portfolios are value-weighted. Subsequently, we calculate the monthly average returns of each investment portfolio until the end of the holding period. Upon the next rating update by the agency, we rebalance the portfolios and repeat this process until the end of the final holding period. In addition to the conventional grouping, at each time point, we also construct a zero-cost long-short arbitrage portfolio by longing the highest-rated stocks and shorting the lowest-rated stocks, thereby capturing the return differences attributable to factor exposure disparities. Taking Sino ESG ratings as an example, Sino began providing ESG ratings in January 2009, with updates occurring every January, April, July, and October. Therefore, we set our portfolio inception date at the end of January 2009, with a rebalancing period of three months.

To thoroughly explore the cross-sectional relationship between ESG ratings and stock returns over different horizons, we refer to Jegadeesh and Titman [20] and extensively examine the significance of cross-sectional return anomalies under various formation-holding period combinations. We implement portfolio sorting based on the average ESG ratings over the past few months, with the formation period referring to the number of months included in the backtest. The holding period refers to how long each portfolio is held after construction. For the formation period selection, we start from using only the current period's ESG ratings (formation period = 0), gradually increasing up to a maximum formation period of 12 months. As for the holding period, we adopt short-term, medium-term, and long-term perspectives, selecting 1 month, 3 months, 6 months, and 12 months, respectively. For brevity, we report the portfolio alpha adjusted by the Carhart four-factor model in Appendix A (J denotes the formation period, while K denotes the holding period). We highlight in boldface those portfolio alphas that are statistically significant at the 1% level or better while also demonstrating economically meaningful magnitudes (exceeding 45 bps per month). Preliminary test results indicate that SynTao, Sino, and Bloomberg can significantly trigger stock return anomalies in the cross-section.

3.2. Comprehensive risk exposure adjustment

We use individual stock ESG ratings as indicators of factor exposure and screen out portfolios with economically and statistically significant alpha, especially for those long-short zero-cost arbitrage portfolios. These portfolios preliminarily reveal return differences that warrant further investigation and can be attributed to differences in factor exposure. To provide a more comprehensive risk-adjusted perspective, we refer to Cooper et al. [21] and Filippou et al. [22] and subsequently employ the Fama-French three-factor model, the Fama-French five-factor model, the Fama-French six-factor model augmented with the momentum factor (FF5+UMD), and the Fama-French six-factor model augmented with the illiquidity factor. Taking the Fama-French five-factor model as an example, the specific model form is as follows, with similar formulations applied to other models:

$$r_{it} - r_{ft} = \alpha_t + \beta_t^1 MKT_t + \beta_t^2 SMB_t + \beta_t^3 HML_t + \beta_t^4 RMW_t + \beta_t^5 CMA_t + \varepsilon_{it} \tag{1}$$

For the choice of the holding period, we refer to a series of literature on the relation between ESG and stock returns [2, 12, 23], and therefore, we only analyze the trading strategies that are continuous and non-overlapping in time series. For each agency, we set the holding period of one given portfolio to be equal to this agency's rating update cycle. Regarding the formation period, we uniformly implement conventional empirical designs for portfolio construction based solely on the current value of ESG ratings (we denote the formation period equal to 0). Accordingly, we denote the chosen formation period and holding period in the form "[J, K]." For brevity, we only report the two extreme portfolios, representing the lowest 1/3 and highest 1/3 (labeled as "Low" and "High," respectively), as well as the long-short arbitrage portfolio (labeled as "HML").

For the illiquidity factor IML, as highlighted by Xiao et al. [16], there are endogeneity issues with traditional firm-level liquidity measures. Therefore, they adopt robust "distance" instrument variables (RIV) and the generalized method of moments to

Table 2
Comprehensive risk exposure adjustment for portfolio returns

	FF3	FF5	FF5+UMD	FF5+IML(RIV)
Panel A: SynTao – [0, 12]				
Low	0.089	0.086	0.096	0.107
	(0.57)	(0.50)	(0.56)	(0.75)
High	0.457***	0.443***	0.498***	0.423***
	(3.82)	(3.50)	(4.19)	(3.26)
HML	0.368*	0.357*	0.401**	0.316*
	(1.89)	(1.74)	(2.10)	(1.77)
Panel B: CASVI – [0, 6]				
Low	−0.172	−0.127	−0.025	−0.144
	(−1.11)	(−0.78)	(−0.15)	(−0.84)
High	0.237**	0.200*	0.289***	0.196*
	(2.14)	(1.79)	(2.95)	(1.84)
HML	0.409**	0.328	0.313	0.341
	(1.97)	(1.61)	(1.48)	(1.55)
Panel C: Sino – [0, 3]				
Low	−0.317***	−0.288**	−0.306***	−0.206
	(−2.80)	(−2.56)	(−2.71)	(−1.24)
High	0.202***	0.206***	0.227***	0.201***
	(3.48)	(3.43)	(3.88)	(2.93)
HML	0.520***	0.494***	0.533***	0.407**
	(3.71)	(3.58)	(4.12)	(2.46)
Panel D: Wind – [0, 3]				
Low	0.029	0.284	0.290	0.305
	(0.10)	(1.18)	(1.11)	(1.27)
High	0.439**	0.431***	0.440***	0.418**
	(2.37)	(2.65)	(2.65)	(2.50)
HML	0.410	0.146	0.150	0.113
	(1.42)	(0.58)	(0.56)	(0.55)

(*Continued*)

Table 2
(*Continued***)**

	FF3	FF5	FF5+UMD	FF5+IML(RIV)
Panel E: Bloomberg ESG – [0, 12]				
Low	−0.081	−0.063	−0.057	−0.039
	(−0.65)	(−0.50)	(−0.44)	(−0.32)
High	0.329***	0.318***	0.398***	0.370***
	(4.17)	(3.97)	(6.49)	(4.45)
HML	0.410***	0.382**	0.455***	0.410***
	(2.6)	(2.47)	(3.02)	(2.59)
Panel F: Bloomberg E – [0, 12]				
Low	−0.053	−0.044	0.014	0.011
	(−0.41)	(−0.34)	(0.12)	(0.08)
High	0.315***	0.316***	0.383***	0.356***
	(3.99)	(3.84)	(5.41)	(4.23)
HML	0.368**	0.360**	0.369***	0.345**
	(2.53)	(2.53)	(2.63)	(2.40)
Panel G: Bloomberg S – [0, 12]				
Low	0.107	0.127	0.145	0.169
	(0.84)	(1.00)	(1.13)	(1.35)
High	0.262***	0.257***	0.315***	0.290***
	(3.83)	(3.67)	(5.02)	(3.98)
HML	0.156	0.130	0.171	0.120
	(1.01)	(0.85)	(1.14)	(0.74)
Panel H: Bloomberg G – [0, 12]				
Low	0.000	0.014	0.030	−0.004
	(0.00)	(0.12)	(0.24)	(−0.03)
High	0.293***	0.301***	0.362***	0.366***
	(3.53)	(3.91)	(5.48)	(4.57)
HML	0.293*	0.287*	0.332**	0.370**
	(1.69)	(1.74)	(2.01)	(2.22)

Note: Following Liu et al. [17], we report the Newey–West *t*-statistics in parentheses with three lags, where the number of lags is based on autocorrelations in monthly stock returns. The asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The subsequent tables are handled in the same manner.

address the endogeneity. And they observe a significant improvement in the explanatory power of the adjusted model. We denote the adjusted risk factor model as "FF5+IML(RIV)."

The risk-adjusted returns of ESG portfolios employing multiple risk factor models are systematically presented in Table 2. Panel A reports portfolios constructed using SynTao ESG ratings, and each portfolio is held for 12 months after rebalancing. With an increasing number of factors in the risk factor pricing model, the economic and statistical significance of the "High" portfolio alpha does not significantly diminish. The "HML" portfolio also demonstrates consistently significant positive returns across various risk factor models. Overall, while stocks with higher SynTao ESG ratings are likely to show positive future returns, stocks with lower factor exposure do not exhibit significant negative returns. This may be related to the long holding period chosen, as it is challenging for stocks to maintain a consistently upward trend over a year.

Appendix A suggests that selecting a six-month holding period would likely yield more statistically significant alpha, but this would result in discontinuities in the time series. If our goal is to maximize trading strategy performance, exploring the optimal holding period is justifiable. However, the focus is to study the impact of ESG ratings on expected stock returns, and obtaining continuously uninterrupted time series over time is essential for a comprehensive analysis of the relationship. Similarly, in Panels E, F, and H, the "HML" long-short arbitrage portfolios constructed around Bloomberg ESG ratings and its pillar scores also exhibit positive returns, indicating that these ESG ratings have some robust predictive power for stock returns.

Most notably, Panel C reports that the risk-adjusted returns of portfolios constructed based on Sino ESG exhibit the most distinct return characteristics among all rating agencies. For the "High" portfolio with the highest factor exposure, regardless of the risk factor model used for risk exposure adjustment, its alpha is always significant at the 1% level, with an economic magnitude of around 20 basis points per month. The "Low" portfolio with the lowest ESG exposure also demonstrates quite clear return characteristics. Except for the insignificant alpha obtained by using "FF5+IML(RIV)," the "Low" portfolio alpha under the adjustment of the other models is significant at least at the 5% level. Naturally, the long-short arbitrage portfolio "HML" also exhibits both economically and statistically significant return characteristics, with the alpha being significant at the 1% level (the only *t*-statistic significant at a level of at least 5% is 2.46, very close to the critical value of the *t*-statistic significant at the 1% level). Based on this, we can preliminarily determine that Sino ESG has a clear predictive power for future stock returns, which cannot be simply attributed to traditional risk exposure.

In contrast, Panel B utilizes CASVI ESG ratings as the factor exposure indicator and adopts a holding period of six months. The "High" portfolio alpha achieves statistically significant only at the

10% level under the adjustment of most models, while the "Low" group still maintains unclear return characteristics. Consequently, the long-short arbitrage portfolio "HML" cannot generate stable positive alpha. Similarly, in Panel D and Panel G, although the "High" portfolios constructed based on Wind ESG ratings and Bloomberg S pillar scores exhibit positive alpha, the "HML" long-short arbitrage portfolios fail to generate positive alpha. Therefore, the explanatory power of these three ratings for stock future returns is very weak.

In general, this section analyzes and filters ESG ratings from three providers: Sino, SynTao, and Bloomberg. Among these, the portfolios generated by Sino ESG exhibit the clearest return characteristics and demonstrate the most robust predictive power for stock future returns. Furthermore, while portfolios constructed around Bloomberg E and G pillar scores also yield alpha that passes statistical significance tests, their economic magnitude falls short of Bloomberg ESG ratings. Hence, the latter exhibits stronger predictive power for returns compared to the former.

3.3. Transaction costs

In real financial markets, financial frictions abound. When updating investment portfolios at a low frequency, it may not require additional analyses for the negative impact of transaction costs on portfolio performance. However, when updating portfolios quarterly, if the factors used for sorting and grouping vary significantly at the individual stock level, extensive trading activities are required for the constituent stocks within the portfolios during each rebalancing. At such times, transaction costs such as brokerage fees and stamp duties become significant factors affecting portfolio returns and cannot be ignored. To enhance the robustness of our conclusions and ensure that our empirical analyses better reflect reality, we analyze the impact of transaction costs on the portfolio returns of the aforementioned trading strategies in this section.

We analyze the cross-sectional return anomalies of ESG ratings from the perspectives of portfolio turnover and break-even costs to investigate whether they are entirely offset by high turnover-related trading costs. First, we follow Qiao et al. [24] to calculate the turnover ratio during portfolio rebalancing. This proxy is computed as the sum of the absolute changes in weights of all securities in the investment portfolio at the current rebalancing relative to the previous rebalancing. The specific formula is as follows:

$$T_t = \sum_{i=1}^{N_t} \left| w_{i,t} - \widetilde{w}_{i,t-1} \right| \tag{2}$$

$$\widetilde{w}_{i,t-1} = \frac{w_{i,t-1}\left(1+r_{i,t}\right)}{\sum_i^{N_t} w_{i,t-1}\left(1+r_{i,t}\right)} \tag{3}$$

T_t represents the turnover rate of the long or short portfolio at a given time point. $w_{i,t}$ represents the proportion of each stock in the leg of portfolio after rebalancing. $\widetilde{w}_{i,t-1}$ represents the weights of individual stocks right before the latest portfolio rebalancing. N_t represents the total number of stocks included in the portfolio. $r_{i,t}$ represents the cumulative returns of stock i from time t–1 to time t. As for the turnover rate of long-short arbitrage portfolios, following Qiao et al. [24], it is defined as the average of the turnover ratios between the long-leg and short-leg portions in the portfolio.

From another perspective, we aim to understand at what level of transaction costs the performance of the trading strategy will no longer be significant. We also calculate the corresponding break-even costs for the returns of the long-short arbitrage portfolios. Specifically, we consider two types of break-even transaction costs: zero-alpha costs and 5% significance costs. The former is defined as the percentage cost per dollar paid to make the strategy's alpha exactly zero. The latter is defined as the percentage cost per dollar paid to render the portfolio alpha statistically insignificant at the 5% level.

Table 3
The impact of transaction costs on portfolio performance

	Turnover (in % per month)	Break-even costs (in % per month) Zero-alpha	5%-insignificant
Panel A: SynTao – [0, 12]			
Long leg	46.56		
Short leg	89.06		
High Minus Low	67.81	4.90	1.51
Panel B: Sino – [0, 3]			
Long leg	46.02		
Short leg	23.17		
High Minus Low	34.60	4.38	3.17
Panel C: Bloomberg ESG –[0, 12]			
Long leg	35.51		
Short leg	82.34		
High Minus Low	58.92	9.01	2.83
Panel D: Bloomberg ESG – [12, 12]			
Long leg	31.72		
Short leg	62.99		
High Minus Low	47.36	9.98	3.16
Panel E: Bloomberg E – [12, 12]			
Long leg	35.90		
Short leg	53.12		
High Minus Low	44.51	7.44	0.87
Panel F: Bloomberg G – [12, 12]			
Long leg	38.02		
Short leg	70.56		
High Minus Low	54.29	6.84	3.16

Table 3 reports the turnover ratios and break-even costs, expressed in percentage units. Regarding the break-even costs, we employ the alpha adjusted by the Carhart four-factor model to implement the calculation. In Panel A, we construct portfolios based solely on the current SynTao ESG ratings (formation period = 0) and hold them for 12 months (holding period = 12) until the next rating update. The turnover rate for the long leg of the portfolio is only 46%, while the turnover rate for the short leg reaches 89%, nearly twice that of the long leg. The turnover rate for the long-short arbitrage portfolio is 67%, which is also at a relatively high level among all portfolios. This indicates considerable attention given by SynTao to companies with lower ESG ratings regarding their ESG practices, resulting in significant changes in the composition of companies whose ESG ratings are in the lowest 1/3. Even though the long-short arbitrage portfolio has a turnover rate as high as 67%, it still requires a high-level transaction cost of at least 4.9% to precisely offset its portfolio alpha and approximately 1.5% to render its positive alpha statistically insignificant at the 5% level.

In Panel B, using Sino ESG as the portfolio sorting indicator and adopting a holding period of 3 months, the turnover ratios for extreme portfolios range from 17% to 28%, while the ratio for the long-short arbitrage portfolio is approximately 23%. Despite its higher frequency of portfolio rebalancing (quarterly), the trading strategy returns still exhibit strong resilience to transaction costs, which requires an absurdly high level of cost to offset the strategy's returns. Results from the remaining panels also indicate that portfolios constructed based on Bloomberg ESG ratings and its pillar scores demonstrate resistance to the adverse impact of transaction costs on returns. Similar trends are observed for Bloomberg, where extending the formation period also improves the robustness of the abnormal returns.

3.4. Heterogeneity analyses based on firm size

The analyses in the previous section reveal that the short positions with lower ESG ratings generally exhibit higher turnover ratios, while long positions with higher ESG ratings tend to have lower turnover ratios. This indicates that companies with high ESG ratings demonstrate continuity in their excellent ESG practices, while those with low ESG ratings are eager to improve their poor performance. Furthermore, in the aforementioned multifactor risk adjustments of long-short arbitrage portfolios based on ESG ratings, we find that all portfolios exhibit significant negative exposure to the size factor SMB (factor loadings are omitted in the table for simplicity). This suggests that the long positions in the arbitrage portfolios contain more large-cap stocks, while the short positions contain more small-cap stocks. Based on this observation, we tentatively speculate that companies with larger market capitalization not only find it easier to obtain higher ESG ratings but also contribute significantly to the positive returns of long-short arbitrage portfolios. Therefore, to enhance practical guidance, clarifying the joint impact of market capitalization and ESG ratings on stock returns has significant implications for ESG investors.

We progressively exclude stocks with market capitalization below certain percentiles (setting exclusion threshold levels at 20%, 40%, 60%, and 80%) and then divide the remaining stocks into three groups based on factor exposure for further anomaly testing. As indicated in the previous analyses, Bloomberg E and G pillar scores share similarities with Bloomberg ESG ratings in terms of their predictive power for stock returns. Therefore, we only report the empirical test results for Bloomberg ESG in subsequent analyses. The portfolio construction process adopts the setting based solely on current ESG ratings, with the holding period uniformly set to the period between updates of ESG ratings. With this approach, the predictive power of ESG ratings under specific conditions can further clarify for ESG investors how to select stocks based on market capitalization levels and thereby amplify the relationship between ESG ratings and future stock returns, thereby providing guidance toward optimizing the holding performance of investment portfolios.

The empirical results of the heterogeneity analysis categorized by firm size are presented in Table 4. Panel A shows that as the threshold level increases, meaning more stocks are concentrated in large-cap companies, the predictive power of SynTao ESG declines continuously. Even when considering only the top 1/5 of companies by market capitalization, the alpha of the "HML" portfolio is no longer statistically significant under any risk factor model. However, this does not necessarily imply that SynTao ESG lacks predictive power under conditions of larger market capitalization. If large-cap companies are more likely to obtain higher SynTao ESG ratings, then when the sample is limited to mega-cap companies (those in the top 5% of market capitalization among all A-share companies), the differences in SynTao ESG ratings among stocks may not be very significant. Nevertheless, this empirical analysis provides important insights for strategy construction: concentrating long positions in large-cap companies with high SynTao ESG ratings and short positions in small-cap companies with low SynTao ESG ratings is more likely to achieve robust positive future returns.

Panel B shows that Sino ESG exhibits very robust positive return predictability in all samples, with economic magnitudes ranging from 56 to 90 basis points per month and *t*-statistics

Table 4
Market-cap effect analyses on ESG portfolios

Panel A: SynTao – [0, 12]	FF3	Carhart4	FF5	FF5+UMD
Exclude smallest 20%				
Low	0.086	0.181	0.032	0.110
	(0.57)	(1.19)	(0.22)	(0.80)
High	0.461***	0.524***	0.457***	0.505***
	(3.67)	(4.29)	(3.49)	(4.12)
HML	0.375*	0.343*	0.425**	0.395**
	(1.94)	(1.70)	(2.26)	(2.08)
Exclude smallest 40%				
Low	0.089	0.185	0.012	0.096
	(0.53)	(1.13)	(0.07)	(0.66)
High	0.465***	0.526***	0.458***	0.506***
	(3.60)	(4.19)	(3.44)	(4.04)
HML	0.377*	0.342	0.446**	0.409**
	(1.86)	(1.60)	(2.25)	(2.04)
Exclude smallest 60%				
Low	0.153	0.249	0.052	0.142
	(0.87)	(1.38)	(0.30)	(0.89)
High	0.478***	0.558***	0.471***	0.531***
	(3.46)	(4.31)	(3.32)	(4.14)
HML	0.325	0.309	0.419*	0.389*
	(1.53)	(1.33)	(1.97)	(1.76)
Exclude smallest 80%				
Low	0.273	0.375*	0.110	0.217
	(1.24)	(1.68)	(0.52)	(1.20)
High	0.591***	0.661***	0.567***	0.624***
	(2.69)	(3.14)	(2.77)	(3.21)
HML	0.318	0.286	0.457	0.407
	(1.09)	(0.92)	(1.60)	(1.39)

Panel B: Sino – [0, 3]	FF3	Carhart4	FF5	FF5+UMD
Exclude smallest 20%				
Low	−0.407***	−0.419***	−0.376***	−0.402***
	(−3.32)	(−3.37)	(−3.02)	(−3.24)
High	0.206***	0.226***	0.209***	0.230***
	(3.54)	(3.89)	(3.47)	(3.93)
HML	0.613***	0.645***	0.585***	0.631***
	(4.08)	(4.52)	(3.87)	(4.48)
Exclude smallest 40%				
Low	−0.441***	−0.467***	−0.413***	−0.450***
	(−3.32)	(−3.51)	(−3.01)	(−3.32)
High	0.222***	0.242***	0.223***	0.244***
	(3.75)	(4.08)	(3.63)	(4.10)
HML	0.662***	0.709***	0.636***	0.695***
	(4.12)	(4.66)	(3.87)	(4.53)
Exclude smallest 60%				
Low	−0.461***	−0.513***	−0.411**	−0.473***
	(−2.81)	(−3.23)	(−2.42)	(−2.89)
High	0.383***	0.387***	0.379***	0.385***
	(4.92)	(4.91)	(4.73)	(4.84)
HML	0.844***	0.900***	0.790***	0.858***
	(3.99)	(4.52)	(3.64)	(4.26)
Exclude smallest 80%				
Low	−0.119	−0.240*	−0.168	−0.272**
	(−1.05)	(−1.84)	(−1.39)	(−2.04)
High	0.442***	0.445***	0.426***	0.444***
	(4.59)	(4.28)	(4.45)	(4.35)
HML	0.561***	0.685***	0.593***	0.715***
	(3.20)	(3.64)	(3.23)	(3.71)

(*Continued*)

Table 4
(*Continued*)

Panel C: Bloomberg ESG – [0, 12]	FF3	Carhart4	FF5	FF5+UMD
Exclude smallest 20%				
Low	−0.105	−0.091	−0.086	−0.074
	(−0.88)	(−0.73)	(−0.73)	(−0.61)
High	0.327***	0.417***	0.315***	0.399***
	(3.78)	(6.87)	(3.67)	(6.59)
HML	0.431***	0.508***	0.401***	0.473***
	(2.72)	(3.33)	(2.73)	(3.35)
Exclude smallest 40%				
Low	−0.099	−0.100	−0.081	−0.082
	(−0.79)	(−0.77)	(−0.68)	(−0.67)
High	0.318***	0.412***	0.301***	0.389***
	(3.39)	(6.27)	(3.29)	(6.11)
HML	0.416**	0.512***	0.382**	0.472***
	(2.39)	(3.16)	(2.42)	(3.22)
Exclude smallest 60%				
Low	−0.159	−0.168	−0.144	−0.153
	(−1.28)	(−1.31)	(−1.22)	(−1.25)
High	0.331***	0.431***	0.310***	0.404***
	(3.21)	(5.73)	(3.12)	(5.63)
HML	0.490***	0.599***	0.454***	0.557***
	(2.69)	(3.58)	(2.72)	(3.63)
Exclude smallest 80%				
Low	−0.007	−0.010	−0.033	−0.033
	(−0.05)	(−0.07)	(−0.25)	(−0.24)
High	0.388***	0.470***	0.375***	0.450***
	(3.22)	(4.33)	(3.30)	(4.28)
HML	0.395*	0.479**	0.408*	0.483**
	(1.84)	(2.29)	(1.96)	(2.32)

ranging from 3.6 to 4.6. Similarly, Panel C demonstrates that the economic magnitude of return predictability for Bloomberg ESG does not vary significantly across sub-samples, hovering around 40–50 basis points per month. However, it is worth noting that in the sub-sample where market capitalization is in the top 1/5 of all companies, the positive returns exhibited by Bloomberg ESG are the least significant, with statistical significance only at around the 5% level. Nevertheless, compared to the performance of SynTao ESG, which is not significant under the same conditions, Bloomberg ESG still demonstrates more robust positive return predictability.

Overall, regardless of the sample sets stratified by various market capitalization attributes, Sino ESG exhibits a remarkable capacity for positively forecasting stock returns, with Bloomberg ESG trailing thereafter. This indicates that the significant predictive power demonstrated by both is not solely due to differences in company market capitalization but rather includes unique explanatory power for stock returns. Considering that Sino is far more comprehensive than Bloomberg in terms of stock coverage and time window length, we can conclude that the Sino ESG rating is the best stock return prediction indicator among various ESG ratings in the Chinese market.

3.5. The first moment of ESG ratings

Inspired by Avramov et al. [2], our study conducts a re-examination of cross-sectional anomalies from the perspective of the first moment of ESG ratings. The significance of this empirical design lies in two aspects: first, existing literature on the return predictability of ESG ratings in the Chinese capital market has inconsistent conclusions regarding the direction of the effect. One major reason is the diverse sources of ESG ratings. Thus, our study adopts a more robust approach by focusing on the first moment of widely used mainstream ESG ratings, allowing for a qualitative conclusion on the overall impact of ESG ratings on future asset returns through quantitative analyses. Second, empirical studies based on the first moment of ESG ratings in the context of the Chinese capital market are scarce in existing research, making our research pioneering in this aspect.

In the empirical analyses of the predictive power of mean ESG ratings, our work only relies on ESG ratings provided by the four major Chinese ESG agencies mentioned above. There are two reasons for excluding Bloomberg: First, when collecting Bloomberg ESG ratings, we are unable to ascertain the specific release months of the ratings. Including them in the calculation of the ESG rating mean could potentially interfere with the estimation of factor premiums. Second, Chinese institutional investors and the academics focusing on the Chinese A-share market primarily utilize the Wind financial information terminal. In contrast, Bloomberg ESG ratings are only accessible through the Bloomberg terminal, which has a limited application in China. Moreover, analysts from Chinese ESG rating agencies are more familiar with the Chinese market environment and regulatory policies compared to foreign institutions. They also benefit from convenient advantages in conducting on-site research on corporate ESG practices in terms of temporal and geographical dimensions.

Due to the varying update frequencies of ESG ratings, with SynTao updating annually and Sino and Wind updating quarterly, the ESG rating mean is quarterly updated time-series data. Therefore, in constructing portfolios based on ESG rating mean, our analyses in this subsection follow the empirical settings for Sino and Wind as discussed earlier, with portfolio rebalancing conducted at the end of January, April, July, and October each year. To incorporate ESG rating mean from multiple agencies as much as possible, a sample restriction is imposed: Each observation corresponding to a company should cover ratings from at least three ESG rating agencies. Consequently, the sample for empirical analyses around the ESG rating mean is focused on constituents of the HuShen 300 and CSI 500.

Table 5 presents empirical tests on whether the mean ESG rating contains incremental information content in predicting future stock returns. Panel A conducts a mean-variance spanning test on the return series of long-short arbitrage portfolios representing the factor premiums of ESG rating mean from the perspective of the efficient frontier of modern portfolio theory. The objective is to investigate whether the ESG rating mean, when introduced into traditional risk factors, can span a more optimal and efficient frontier. The test model is given as follows:

$$R_t = \alpha + \beta' F_t + \varepsilon_t \tag{4}$$

R_t represents the vector of returns for N factors under examination. α represents the corresponding vector of pricing errors (alpha). β represents the K×N-dimensional factor exposure vector. F_t represents the K×1-dimensional vector of pricing factors. ε_t represents the random error term. The hypothesis of the mean-variance spanning test is as follows:

$$H0: \ \alpha = 0_N \ and \ \beta' I_K = I_N \tag{5}$$

0_N represents a K×1-dimensional zero vector. I_K represents a K×1 dimensional unit vector, and I_N likewise. We refer to

Table 5
Re-examination on the first moment of ESG ratings

	Panel A: Mean-variance spanning test				
	CAPM	FF3	Carhart4	FF5	FF5+UMD
Wald Homo	394.85***	84.10**	64.27**	18.27*	21.38**
	(0.003)	(0.012)	(0.015)	(0.052)	(0.045)
Wald Hetero	532.10***	52.20**	35.78**	40.06**	50.35**
	(0.002)	(0.019)	(0.027)	(0.024)	(0.019)
LR	175.84***	88.15***	76.00***	31.56***	36.19***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM	30.93***	24.05***	21.43***	11.85***	13.11***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

	Panel B: Fama-MacBeth regression			
	(1)	(2)	(3)	(4)
ESG	0.197**	0.145*	0.177**	0.156**
	(2.22)	(1.72)	(2.58)	(2.34)
Beta		−0.534	−0.417	−0.561*
		(−1.36)	(−1.18)	(−1.73)
Log_ME			0.002	−0.074
			(0.01)	(−0.43)
Log_BM			−0.226	−0.088
			(−0.54)	(−0.22)
Mom				0.007
				(1.25)
EP_Positive				−0.713
				(−0.61)
EP_Negative				−0.022
				(−0.06)
R-Squared	0.010	0.031	0.086	0.112
N	43940	43940	43930	43930

Beaulieu et al. [25] to calculate the statistics for the likelihood ratio test, the Wald test, and the Lagrange multiplier (LM) test. According to the results, almost all test statistics are statistically significant at the 5% level (only the Wald statistic under the homoscedasticity condition is slightly above the 5% level). Thus, even relative to the six-factor model of "FF5+UMD," the first moment of ESG ratings can provide incremental information for cross-sectional stock returns.

Furthermore, in order to control for other stock return forecasting factors simultaneously in regression analyses and more accurately estimate the factor premium of ESG rating mean, we follow Sun [26] to employ the Fama-MacBeth regression. Cross-sectional correlation in the panel of stock returns can lead to bias in standard error estimation, and the Fama-MacBeth regression can cleverly circumvent this negative effect. We match the average ESG ratings for each company in January, April, July, and October with the subsequent monthly returns (in %) in the next three months. Every ESG rating average needs to account for explaining the performance of stock returns over the next three months in regression. Panel B shows that in column (1), when the ESG rating average is solely used as the sole factor exposure to explain individual stock returns, its regression coefficient has an economic magnitude of about 0.2 and is statistically significant at the 5% level. The factor premium estimation in columns (3) and (4), after introducing factors such as SMB and EP, is striking. The statistical significance level of the factor premium exhibits an upward trend rather than a decline, all being significant at least at the 5% level, with the minimum t-statistic being 2.3. Referring to Liu et al. [17], the specific definitions of individual stock exposures to the EP_Positive and EP_Negative factors are as follows:

$$EP\_Positive = \begin{cases} \frac{Earnings}{Price}, & Earnings > 0 \\ 0, & Earnings \le 0 \end{cases} \tag{6}$$

$$EP\_Negative = \begin{cases} 0, & Earnings > 0 \\ 1, & Earnings \le 0 \end{cases} \tag{7}$$

The Fama-MacBeth regression results indicate that at the individual stock level, the ESG rating mean possesses a certain degree of positive predictive power for future returns and exhibit robustness even when other competing factors are introduced for "horse-racing tests." Overall, the first moment of ESG ratings contributes incremental information in explaining cross-sectional stock returns, which positions this paper as one of the pioneering studies to reveal its positive predictive power in the Chinese market. Our work provides qualitative conclusions on the factor premium embedded in ESG ratings from a holistic perspective.

4. Conclusion

Against the backdrop of the current complex international political landscape, the competition for carbon discourse power has become a significant focus of economic competition among major powers. ESG, as one of the concrete manifestations of this process, continuously enhances its influence among institutional investors and asset managers in capital markets by attracting institutions and investors to adhere to responsible investment principles, thereby providing crucial capital support for corporate green transformation and high-quality economic development. As of the end of 2022, assets totaling over $121 trillion have been managed following ESG investment principles. With the rapid growth of ESG asset management, ESG ratings, as important indicators of measuring corporate ESG practices, carry crucial information that significantly influences asset price formation and capital allocation. Therefore, exploring the correlation between ESG ratings and cross-sectional stock returns holds significant importance, whether for guiding quality capital to support corporate ESG development or optimizing the performance of ESG investors' investment portfolios.

This paper examines the cross-sectional return anomalies induced by ESG ratings provided by mainstream ESG rating agencies in China. Preliminary empirical results from single-dimension portfolio sorting reveal that ESG ratings indeed exhibit significant positive predictive power for stock future returns. Moreover, visualized results of trading strategy returns support the notion that using ESG ratings as stock screening criteria can yield significant excess returns that can withstand the adverse effects of transaction costs. Results from risk exposure adjustments also indicate that these asset return anomalies cannot be simply attributed to common risk exposures to traditional risk factors. Additionally, we retest this relation based on samples with different market capitalization levels and identify Sino ESG ratings that exhibit the most robust and strongest positive predictive power in the Chinese capital market. Furthermore, this paper stands as pioneering literature in examining anomalies based on the first moment of ESG ratings. Results from mean-variance spanning tests based on the efficient frontier, as well as Fama-MacBeth regressions of horse-racing tests against various return predictors at the individual stock level, fully illustrate that ESG ratings indeed contain unique incremental information for explaining asset returns.

In the context of studying the relationship between ESG and stock returns within the Chinese market, there is room for improvement in the coverage of ESG rating agencies. Our paper provides the most comprehensive coverage of Chinese ESG rating agencies in the existing literature, while the ESG concept has been rapidly evolving in China in recent years, leading to the emergence of new research firms evaluating the ESG practices of companies. Due to the shorter coverage history of these emerging ESG rating agencies, conducting cross-sectional anomaly tests directly on them may not ensure effectiveness and accuracy. Therefore, we do not include them in our study scope. However, for future research, expanding the coverage to include these new ESG rating agencies could lead to more comprehensive conclusions.

From an academic perspective, this study approaches the analyses from the standpoint of the capital market by separately analyzing and comparing the return predictability of the ratings from all mainstream ESG rating agencies. Our work demonstrates considerable completeness and rigor in investigating the relationship between ESG ratings and cross-sectional stock returns, contributing to the research perspective on the first moment of ESG ratings in the Chinese A-share market. In practice, by incorporating ESG ratings into their investment decision-making framework, investors can conduct more accurate valuation and risk management, thereby optimizing their portfolios and achieving long-term positive investment returns. Enterprise managers can utilize this information to enhance their company's ESG performance, thereby improving market competitiveness and sustainability.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Xu Liu: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Xinrong Xiao:** Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Siyan Shen:** Conceptualization, Methodology, Validation, Resources, Writing – review & editing. **Zhiyu Xu:** Conceptualization, Validation, Formal analysis, Investigation, Resources, Writing – review & editing, Visualization.

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Appendix A. Anomaly examination using different formation-holding periods

		Panel A: SynTao ESG			
J=		K= 1	3	6	12
0	Low	−0.211	−0.073	−0.042	0.076
		(−0.99)	(−0.17)	(−0.21)	(0.52)
0	High	1.249***	0.681***	0.568***	0.496***
		(4.33)	(3.04)	(3.74)	(3.85)
0	HML	**1.460*****	0.753	0.610**	0.420**
		(19.09)	(1.41)	(2.13)	(2.22)
12	Low	−1.420***	−0.468	0.009	0.252
		(−6.42)	(−1.07)	(0.04)	(1.36)
12	High	1.209**	0.727***	0.563***	0.480***
		(2.47)	(2.93)	(3.63)	(3.98)
12	HML	**2.629*****	1.195**	0.554*	0.228
		(3.76)	(2.35)	(1.81)	(0.98)

		Panel B: CASVI ESG			
J=		K= 1	3	6	12
0	Low	0.003	−0.155	−0.060	0.002
		(0.00)	(−0.59)	(−0.35)	(0.01)
0	High	−0.030	0.219	0.282***	0.294***
		(−0.11)	(1.58)	(2.75)	(2.84)
0	HML	−0.032	0.374	0.342	0.292
		(−0.04)	(1.07)	(1.51)	(1.19)
6	Low	1.050**	0.021	0.045	0.065
		(2.22)	(0.09)	(0.25)	(0.33)
6	High	−0.219	0.152	0.222*	0.290***
		(−0.99)	(0.97)	(1.86)	(2.60)
6	HML	−1.269**	0.132	0.177	0.225
		(−2.04)	(0.39)	(0.71)	(0.87)
12	Low	0.023	−0.232	−0.010	0.044
		(0.07)	(−1.01)	(−0.06)	(0.19)
12	High	−0.082	0.234	0.309**	0.341***
		(−0.28)	(1.51)	(2.55)	(3.10)
12	HML	−0.105	0.466	0.319	0.297
		(−0.22)	(1.41)	(1.29)	(1.01)

		Panel C: Sino ESG			
J=		K= 1	3	6	12
0	Low	0.138	−0.321***	−0.178*	−0.264**
		(0.66)	(−2.77)	(−1.74)	(−2.47)
0	High	0.230**	0.223***	0.318***	0.331***
		(2.47)	(3.82)	(5.75)	(5.46)
0	HML	0.092	**0.544*****	**0.495*****	**0.594*****
		(0.50)	**(4.06)**	**(4.24)**	**(4.89)**
3	Low	0.189	−0.266***	−0.195*	−0.240**
		(0.99)	(−2.63)	(−1.90)	(−2.27)
3	High	0.302***	0.235***	0.326***	0.334***
		(3.72)	(4.47)	(6.21)	(5.50)
3	HML	0.114	**0.501*****	**0.521*****	**0.573*****
		(0.56)	**(4.07)**	**(4.58)**	**(4.85)**
6	Low	0.103	−0.242**	−0.274***	−0.194*
		(0.57)	(−2.33)	(−2.74)	(−1.81)
6	High	0.318***	0.246***	0.360***	0.348***
		(4.00)	(4.62)	(6.40)	(5.62)
6	HML	0.215	**0.487*****	**0.633*****	**0.542*****
		(1.11)	**(4.01)**	**(5.36)**	**(4.31)**
12	Low	0.072	−0.281***	−0.208**	−0.222*
		(0.37)	(−2.67)	(−1.98)	(−1.81)
12	High	0.274***	0.318***	0.368***	0.343***
		(3.63)	(5.60)	(6.89)	(6.22)
12	HML	0.202	**0.599*****	**0.576*****	**0.565*****
		(1.04)	**(4.74)**	**(4.96)**	**(4.7)**

(*Continued*)

(*Continued***)**

			Panel A: SynTao ESG			
J=		K=	1	3	6	12
			Panel D: Wind ESG			
J=		K=	1	3	6	12
0	Low		−0.023	0.239	0.272	0.101
			(−0.08)	(0.82)	(1.00)	(0.48)
0	High		0.512	0.453**	0.357	0.057
			(1.37)	(2.03)	(1.35)	(0.24)
0	HML		0.535	0.214	0.086	−0.044
			(1.11)	(0.67)	(0.27)	(−0.16)
3	Low		−0.039	0.026	−0.004	0.069
			(−0.08)	(0.11)	(−0.01)	(0.36)
3	High		0.566	0.413**	0.259	−0.001
			(1.51)	(2.34)	(1.38)	(0.00)
3	HML		0.605	0.387	0.262	−0.070
			(1.13)	(1.50)	(1.00)	(−0.36)
6	Low		0.267	0.020	−0.142	−0.005
			(0.60)	(0.09)	(−0.83)	(−0.03)
6	High		0.458	0.284	0.063	−0.087
			(0.90)	(1.36)	(0.27)	(−0.37)
6	HML		0.191	0.263	0.205	−0.082
			(0.45)	(1.02)	(0.90)	(−0.38)
12	Low		−0.133	−0.321**	−0.171	−0.247
			(−0.36)	(−1.98)	(−0.91)	(−1.62)
12	High		−0.179	−0.234	−0.307*	−0.411**
			(−0.66)	(−1.31)	(−1.69)	(−2.29)
12	HML		−0.046	0.087	−0.136	−0.165
			(−0.09)	(0.43)	(−0.58)	(−0.88)
			Panel E: Bloomberg ESG			
J=		K=	1	3	6	12
0	Low		0.161	−0.281	−0.403**	−0.107
			(0.56)	(−1.02)	(−2.37)	(−0.84)
0	High		0.283***	0.418***	0.508***	0.383***
			(2.65)	(3.05)	(6.20)	(6.00)
0	HML		0.122	0.699*	**0.911*****	**0.490*****
			(0.38)	(1.83)	**(4.11)**	**(3.01)**
12	Low		0.112	−0.197	−0.301*	−0.070
			(0.34)	(−0.82)	(−1.91)	(−0.59)
12	High		0.248*	0.423***	0.514***	0.386***
			(1.85)	(2.87)	(5.95)	(6.06)
12	HML		0.136	0.621*	**0.815*****	**0.456*****
			(0.33)	(1.79)	**(3.79)**	**(2.95)**
			Panel F: Bloomberg E			
J=		K=	1	3	6	12
0	Low		0.093	−0.063	−0.289	−0.028
			(0.47)	(−0.20)	(−1.46)	(−0.20)
0	High		0.341**	0.396***	0.405***	0.358***
			(2.00)	(3.21)	(5.43)	(5.98)
0	HML		0.248	0.459	**0.694*****	0.386**
			(1.37)	(1.19)	**(2.95)**	(2.43)
12	Low		−0.046	−0.105	−0.248	−0.006
			(−0.16)	(−0.34)	(−1.31)	(−0.05)
12	High		0.361**	0.358***	0.360***	0.313***
			(2.24)	(2.66)	(4.65)	(4.80)
12	HML		0.408	0.463	**0.608*****	0.320**
			(1.09)	(1.19)	**(2.64)**	(2.00)

(*Continued*)

(*Continued***)**

			Panel A: SynTao ESG			
J=		K=	1	3	6	12
			Panel G: Bloomberg S			
J=		K=	1	3	6	12
0	Low		0.683	0.181	−0.152	0.082
			(1.10)	(0.63)	(−0.76)	(0.61)
0	High		0.222	0.370***	0.422***	0.295***
			(1.39)	(2.67)	(5.23)	(5.05)
0	HML		−0.461	0.189	0.574**	0.213
			(−0.63)	(0.50)	(2.33)	(1.30)
12	Low		0.642	0.267	−0.114	0.096
			(1.05)	(0.95)	(−0.58)	(0.72)
12	High		0.164	0.372**	0.412***	0.304***
			(0.71)	(2.49)	(4.78)	(5.11)
12	HML		−0.478	0.105	0.527**	0.209
			(−0.59)	(0.27)	(2.03)	(1.24)
			Panel H: Bloomberg G			
J=		K=	1	3	6	12
0	Low		0.250	−0.046	−0.253	0.024
			(0.81)	(−0.20)	(−1.53)	(0.19)
0	High		0.413**	0.476***	0.492***	0.324***
			(2.12)	(2.97)	(4.44)	(4.30)
0	HML		0.163	0.522	**0.745****	0.300
			(0.35)	(1.46)	**(3.01)**	(1.62)
12	Low		0.019	−0.228	−0.283*	−0.047
			(0.08)	(−0.88)	(−1.73)	(−0.40)
12	High		0.320*	0.406***	0.476***	0.326***
			(1.85)	(2.60)	(4.54)	(4.35)
12	HML		0.301	0.634	**0.759****	0.373**
			(0.79)	(1.63)	**(3.09)**	(2.16)