Climate Risk Preparedness and the Cross Section

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Abstract

Our paper presents a theoretical model to analyze the relationship between a company's expected returns and its preparation for climate risk. The model is based on a two-date investment framework and considers the impact of a climate change-induced event (CCIE) that may occur on the second date. The extent of damage caused by this event is dependent on the amount spent on climate preparedness on the first date. The company has an initial capital stock, profitability, and readiness. Our analysis demonstrates that the expected return on equity is directly proportional to the company's preparedness for climate change, profitability, and size, but inversely proportional to investment. In addition, we have developed an empirical model based on five factors that can be used to price stocks, ETFs, anomalies, and characteristics sorted portfolios.

JEL Classification: G11, G12, G14

Keywords: asset pricing, climate change, risk factors

1 Introduction

In recent years, the growing body of scientific evidence on climate change, and the large economic and ecological impacts from climate-related events across the globe, has stimulated numerous empirical and theoretical studies on the effects of climate on financial markets. This paper looks at an aspect of the problem that we believe has not been examined before. Given the way that unpredictable climate-related events can affect resource availability (of both raw materials and labor), disrupt supply chains, and raise the cost of capital for doing business, we ask the question of whether spending on climate risk preparedness, with a view to making operations less vulnerable to climate risk, has a positive or negative impact on expected equity returns. As far as we can tell, this question is new to the literature. A naive answer to this question would state that spending on such preparation is an expense that is not likely to be productivity-enhancing, at least in the short run. Therefore, such spending would increase costs and lower profits with a negative impact on expected returns. However, the impact of such spending would pay off in the event of a future climate event. A more resilient or better prepared firm would experience a smaller output disruption and higher profits in the bad state of the world (the one in which a climate event occurs). Thus, to understand the connection between spending on climate preparedness and its impact on expected returns, it is necessary to factor both effects.

To study the link between expected returns and climate risk preparation, we develop an intertemporal general equilibrium investment-based asset pricing model. We assume that the economy is populated by a representative household and a representative firm endowed with initial capital stock and the initial level of preparation/exposure to climate risks. The level of preparation is captured by a score that we call the E score. Later, we point out that the E score supplied by MSCI, the data provider, is an empirical proxy to our theoretical E score. The firm spends on preparation to protect against a possible climate-change-induced event (CCIE) that can occur on the second date. If such an event happens, there is firm-specific damage that decreases in the firm's E-score.

On the next date, a CCIE occurs with probability p. We assume that this event is independent of the stochastic process of profitability at date 1 and that probability p is common knowledge. Therefore, the firm is incentivized to invest in climate preparation because this results in less exposure to downside risk. The representative household maximizes its expected utility over consumption over two dates. The firm invests a fraction of capital to improve physical investment and the rest to improve preparedness (the E score). The firm maximizes the total equity and dividend by taking the stochastic discount factor (SDF) from the household optimization as given.

In equilibrium, we show that the model implies that the firm's expected return depends, ceterius paribus, positively on the E-score. This agrees with empirical evidence in MSCI data suggesting that high E-score stocks have higher returns than low E-score stocks. Our model also implies that the expected return of stocks increases with the profitability, keeping all other things equal.

The theoretical model developed in this paper suggests that a five-factor empirical asset pricing model consisting of the market factor and factors corresponding to the four drivers of asset returns in our theoretical model - the E-score, profitability, size, and investment - can be used to price traded equity-based assets. For this empirical model, we construct the E-factor from MSCI data covering the 2011-2022 time span. We construct those factors through a slope factor method, which is known to satisfy the pure-play property. To illustrate, at the firm level, characteristics are often correlated, which means that when we use double-sorting or ranking methods, we indirectly take long or short positions in other characteristics that are positively or negatively correlated to the one we are interested in. In contrast, the slope factors are the OLS estimates of the slopes in Fama-Macbeth regressions of excess returns on lagged standardized characteristics and these, by the regression property, are automatically purged off the influence of other characteristics in the regression. Chib, Lin, Pukthuanthong, and Zeng (2021) show that the best slope factor model outperforms the best sorted and rank factor models in the pricing of stocks, portfolios, and ETFs.

We call our 5-factor model the CLP5 model. To evaluate the effectiveness of the E factor in pricing the cross section, we consider the CLP4 variant that simply omits the E factor from the CLP5 model. In this way, we can determine the contributing role of the E factor. Then, using the framework of Chib and Zeng (2020) and Chib, Zeng, and Zhao (2020), we evaluate the empirical support for these two models and find that the CLP5 model is better supported by the data. Moreover, the CLP5 model shows promise in pricing the cross section. Using 3,116 stocks as test assets, where each test asset has at least 60 months of data, we find that the CLP5 prices 2566 of those stocks at posterior odds of at least 2:1, more than are priced by the CLP4 model. The outperformance of the CLP5 in pricing cross-section assets still persistent when we use ETFs and anomalies from various sources as testing portfolios.

The remainder of the paper is organized as follows. Section 2 builds an investment-based asset pricing model that incorporates climate change-induced events (CCIE) and the firm's level of climate risk preparedness. In Section 3, we provide evidence that the MSCI E-score differs from the E-score reported by other ESG rating providers and that the MSCI E-score can be interpreted as a measure of climate risk preparedness. We then construct the E factor and report summary statistics of the E factor as well as other prominent factors in the literature. Section 4 checks the cross-sectional pricing ability of the CLP5 factor model. Section 5 concludes the paper.

2 Theoretical Model

In this section, we develop a new two-date stochastic general equilibrium model, inspired by the literature on production-based asset pricing (Cochrane (1991) and Cochrane (1996)), in which the firm mitigates exposure to climate change by proactive spending on climate preparedness. In a production-based asset model, asset returns are linked to marginal transformation rates obtained from the optimal intertemporal investment decision. We measure this preparedness generically in terms of what we call the E-score. The firm invests in this preparedness because of a possible climate change-induced event (CCIE) on the second date that causes damage that is inversely related to the level of preparation. Therefore, the firm is incentivized to spend on climate preparedness because this results in lower risk exposure to such an event.

A representative household and a representative firm populate the economy. We label the two dates as date 0 and date 1. The firm's profitability in date 1 is subject to a random process. Furthermore, the production is subject to a CCIE shock, similar to that documented in studies Barro (2006) and Barro (2009). The probability is the known amount $0 < p \leq 1$, where p is a constant. In the CCIE at date 1, a portion of production will be destroyed. The damage function depends on climate preparedness and E scores. A well-prepared firm is less exposed to CCIE. The distribution of the CCIE shock is given by

$$\text{probability } 1-p : Y_1 \tag{1}$$

$$\text{probability } p : [1-\delta(e_1)]Y_1 \tag{2}$$

where Y_1 represents the firm's production at date 1, $\delta(e_1)$ is the damage function, with e_1 as the E-score of the firm at date 1, and $\delta' < 0$. Let $f(e_1) \equiv 1-\delta(e_1)$. A high $f(e_1)$ implies that preparation limits the damage caused by CCIE. For tractability, we suppose that the climate preparation function takes $f(e_1) = \kappa e_1$, increasing linearly in e_1, where $\kappa > 0$ is a constant parameter. To keep $0 < f(e_1) < 1$, we will set the upper bound of κ.

2.1 Technology

The firm produces a single commodity consumed by the representative household or invested. The firm starts with an initial productive asset, K_0, profitability Π_0, and an E score, e_0. The operating cash flow of the firm at date 0 is $Y_0 = \Pi_0 K_0$. The operating cash flow D_1 at date 1 depends on the occurrence of the CCIE shock, taking the form.

$$D_1 = \begin{cases} \Pi_1 f(e_1) K_1 & \text{CCIE} = 1 \\ \Pi_1 K_1 & \text{CCIE} = 0 \end{cases} \tag{3}$$

Given the initial e_0, we suppose that the E scores evolve according to the specification

$$e_1 = e_0 + \frac{E_0}{c(I_0 + K_0)} \tag{4}$$

where I_0 denotes physical investment, E_0 denotes investment to improve the E score, and $c > 0$ is a constant parameter. The latter investment is not capital-enhancing, but reduces vulnerability to a CCIE. $K_1 = I_0 + K_0$ denotes the capital at date 1. Eq.(4) shows that the E score increases with the E investment per capital unit.

2.2 Assets and asset prices

All decisions are made at date 0. The date-1 profitability is described by a random variable Π_1. Uncertainty of profitability comes from a state variable s, which can take one of N values in $\mathbb{S} = \{s_1, \ldots, s_N\}$. The firm's profitability has support $\{\Pi(s_1), \ldots, \Pi(s_N)\}$ at date 1. Let define the asset and asset prices extending over all N states prior to the CCIE shock.

Definition 1: An *asset* is a contingent claim that pays one unit of the consumption good (the numeraire) in the state of the world s.

Definition 2: An *asset price* at date 0 is the price of the asset that pays one unit of consumption if the state s is realized.

Before the occurrence of the CCIE shock, we can characterize the existence of N Arrow-Debreu assets along with their corresponding prices. In equilibrium, despite having only one representative household and firm, these Arrow-Debreu assets are not actively traded; however, we can still determine their prices. These prices serve as a basis for deriving the stochastic discount factor (SDF). Specifically, the SDF can be expressed as the ratio of the price of an Arrow-Debreu asset in a given state to the price of the same asset in a reference or numéraire state. The firm generates $\pi_1(s)K_1$ units of consumption in state s on date 1. Based on Definition 1 and Definition 2, the output price is $q^0(s)\pi_1(s)K_1$ at state s. The firm takes the price of asset $q^0(s)$ as given when deciding the aggregate investment and the amount of dividend distributed to the household.

However, a shock that says that a CCIE will occur at the probability of p at date 1, arrives after the firm's decision on aggregate investment. In particular, the set of N Arrow-Debreu assets that existed before the CCIE shock does not constitute a complete market, which describes the case where Arrow-Debreu assets exist for all states. Specifically, Arrow-Debreu assets do not exist for states in which the CCIE shock occurs. These states with the CCIE shock are unanticipated when contingent claims are traded. One way to interpret this assumption is that it is either prohibitively costly to introduce new assets or, even if the agent possesses all the necessary information, it is too expensive to incorporate every piece of information due to considerations such as rational inattention in the literature. This assumption simplifies our calculation process, allowing us to derive analytical results to determine the optimal allocation of investments between E (environmental) and physical investments. With this simplification, we can compute the explicit optimal ratio of E investment to physical investment in various states. Importantly, this simplification does not alter the core narrative of our analysis, as our primary focus is on elucidating how characteristics of E, along with other firm's characteristics impact returns, rather than quantifying the precise magnitude of these effects.

We assume that the CCIE shock is independent of the stochastic process of profitability Π_1. Consequently, this results in a total of $2 \times N$ discrete states within our model. Let $\mathbb{S}^*$ represent the set of all states, such that $\mathbb{S}^* = \{s_1, \dots, s_N, s_{1^*}, \dots, s_{N^*}\}$. Here, the subset $s_1, \cdots, s_N$ corresponds to the scenarios where CCIE equals 0, while $s_{1^*}, \dots, s_{N^*}$ pertains to the scenarios where CCIE equals 1. In this market, there are N distinct Arrow-Debreu assets. Let $q^0(s)$ denote the date-0 asset price that pays 1 unit of consumption if the state s is realized. The determination of $q^0(s)$ is made in the absence of information on CCIE shocks, which implies that these prices are fixed before the realization of such shocks and remain unchanged thereafter. In response to this information, the representative firm then makes decisions on investments in E and physical capital.

We assume that the firm is entirely owned by the representative household, which acts as the sole producer and consumer within this model. Firm production yields a single commodity that can be consumed by the representative household or invested. The representative household seeks to optimize a two-date, time-additive utility function. This utility function captures the household's preferences over consumption across two dates, reflecting the trade-offs the household makes between immediate consumption, future consumption, and investment decisions.

$$U = u(C_0) + \beta \sum_{s \in \mathbb{S}} \pi(s) u(C_1(s)) \tag{5}$$

in which β is the subjective discount factor of the representative household, C_0 and C_1 are consumption in dates 0 and 1, respectively, and $\pi(s)$ is the probability of profitability in state s at date 1 with $\sum_{s \in \mathbb{S}} \pi(s) = 1$. Asset prices and the rate of return are determined by the first-order condition for consumption, which is written as

$$u'(C_0) = \beta \sum_{s \in \mathbb{S}} \pi(s) u'(C_1(s)) \tag{6}$$

The stochastic discount factor, before the information related to the CCIE shock, takes the form $m(s) \equiv \frac{\beta u'(C_1(s))}{u'(C_0)}$. The usual first-order conditions give the asset prices

$$q^0(s) = \beta \pi(s) \frac{u'(C_1(s))}{u'(C_0)} = \pi(s) m(s) \tag{7}$$

From Eq.(7), $q^0(s)/\pi(s)$ is equal to the SDF, which is the price of one unit of consumption in the state s per unit of probability. It is also called a state price density or a price kernel.

2.3 The firm's optimization problem

This section presents steps and derivations of the optimization problem of the firm. Initially, agents in the market have information about the stochastic process Π_1. Before the CCIE shock, we characterize the existence of N Arrow-Debreu assets and their corresponding prices. The firm determines the aggregate investment and dividend distributed to the household (say, consumption). Subsequently, as the second step in this sequence, the CCIE shock comes into play. The firm makes decisions regarding the allocation of aggregate investment, which has been determined in the first step to environmental and physical investment.

First-order conditions. The firm chooses a production plan for sales C_0, physical investment I_0, and E investment E_0 to maximize its date-0 contingent claim value, given initial capital stock K_0 and initial E-score, e_0 and a sequence of contingent claims prices $q^0(s)$

$$\left[\Pi_0 K_0 - G_0 - \frac{a}{2}\left(\frac{G_0}{K_0}\right)^2 K_0\right] + \max \sum_{s\in\mathbb{S}} q^0(s)[(1-p)K_1\Pi_1(s) + pf(e_1)K_1\Pi_1(s)] \tag{8}$$

subject to

$$\text{Production:} \quad Y_1 = \Pi_1 K_1 | \text{CCIE} = 0 \quad Y_1 = f(e_1)\Pi_1 K_1 | \text{CCIE}=1 \tag{9}$$

$$\text{Resources:} \quad Y_0 = C_0 + G_0 - \frac{a}{2}\left(\frac{G_0}{K_0}\right)^2 K_0 \quad Y_1 = C_1 \tag{10}$$

$$\text{E-score accumulation:} \quad e_1 = e_0 + \frac{E_0}{c(I_0 + K_0)} \tag{11}$$

$$\text{Capital accumulation:} \quad K_1 = I_0 + K_0 \tag{12}$$

$$\text{Total investment:} \quad G_0 = I_0 + E_0 \tag{13}$$

Based on the timing, we solve the firm's maximization problem backwardly. Given the aggregate G0, the firm chooses I_0 and E_0 in the second stage by comparing marginal costs and benefits. Let $\tau \equiv E_0/I_0$, and then we can write

$$E_0 = \frac{\tau}{1+\tau} G_0 \quad \text{and} \quad I_0 = \frac{1}{1+\tau} G_0 \tag{14}$$

The marginal costs of I_0 and E_0 are

$$\left(1+a\frac{G_0}{K_0}\right)\frac{\tau}{1+\tau} \quad \text{and} \quad \left(1+a\frac{G_0}{K_0}\right)\frac{1}{1+\tau} \tag{15}$$

, respectively. The marginal benefits of I_0 and E_0 are

$$(1-p)\sum_{s\in\mathbb{S}} q^0(s)\Pi_1(s) + p\left[\kappa e_1 - \tau\frac{\kappa}{c}\right]\sum_{s\in\mathbb{S}} q^0(s)\Pi_1(s) \quad \text{and} \quad p\frac{\kappa}{c}\sum_{s\in\mathbb{S}} q^0(s)\Pi_1(s) \tag{16}$$

In equilibrium, marginal benefits equal marginal costs. From Eq. (15) and Eq. (16), we have $p\kappa/c = \tau[p\kappa e_0 + (1-p)]$. Then, we can rewrite it as

$$\tau = \frac{\kappa}{c(\kappa e_0 + (1-p)/p)} \tag{17}$$

τ depends on initial E-score e_0, c, κ and p. In particular, τ increases with p. When p is larger, the firm is willing to invest more in E-score improvement. When $p=1$, $\tau = 1/ce_0$.

We make three additional economically reasonable assumptions.

Assumption 1. Suppose a positive initial e-score, i.e. $e_0 > 0$.

According to Eq. (17), $e_0 < 0$ generates negative τ when $p=1$. In such cases, the firm is less likely to enhance its E-score.

Assumption 2. $\frac{\partial e_1}{\partial e_0} > 0$.

This assumption indicates that the firm with a high initial e-score will have a high e-score at date 1.

Assumption 3. $\kappa < 1/(e_0 + 1/c)$

Assumption 2 implies that $\frac{\partial e_1}{\partial e_0} = 1 - \frac{\kappa}{c^2}\frac{\kappa}{(\kappa e_0+(1-p)/p)^2} = 1-\tau^2 > 0$. To make economic sense, $\tau > 0$. Therefore, we have $\tau < 1$. Combined with the above assumptions, $e_1 = e_0 + \tau/c < e_0 + 1/c$ from Eq. (4). $\kappa < 1/(e_0+1/c)$ guarantees that $\kappa e_1 < 1$.

Lemma 1 τ is decreasing with initial e_0.

Lemma 1 is directly obtained from Eq. (17). A high initial e_0 will indicate a low ratio of E investment.

With τ, in the first stage, the optimality condition for investment is

$$\begin{aligned} 1+a\frac{G_0}{K_0} &= \frac{1}{1+\tau}\sum_{s\in\mathbb{S}} q^0(s)[p\Pi_1(s)f(e_1)+(1-p)\Pi_1(s)] \\ &= \frac{1}{1+\tau}[(pf(e_1)+(1-p))]\sum_{s\in\mathbb{S}} q^0(s)\Pi_1(s) \end{aligned} \tag{18}$$

The return on aggregate investment, therefore is

$$R = \begin{cases} \Pi_1 f(e_1)/(1+\tau)[1+a(G_0/K_0)] & \text{CCIE} = 1 \\ \Pi_1(1+\tau)/[1+a(G_0/K_0)] & \text{CCIE} = 0 \end{cases} \tag{19}$$

The expected return on aggregate investment is

$$\mathbb{E}_0 R = \frac{pf(e_1)\mathbb{E}_0\Pi_1 + (1-p)\mathbb{E}_0\Pi_1}{(1+\tau)[1+a(G_0/K_0)]} \tag{20}$$

Proposition 1: The expected return of investment positively links to the initial E-score, e_0, ceteris paribus, where e_0 depends on p, c and κ.

Assumption 2 implies that high e_0 generates high e_1. e_1 appears positively on the right side of Eq. (20). Eq. (17) shows that high e_0 produces low τ. The term $1/\tau$ on the right side positively links to e_0. In summary, given expected profitability, initial capital, and investment levels, the firm would earn a high expected return with high E-score.

Proposition 2: The expected return on the firm's stock increases with the profitability Π_1, given initial capital, investment level, and e-score.

Proposition 2 says that with other factors kept constant, the expected returns increase with profitability. Intuition is exactly analogous to the intuition underlying the E score-expected return relation.

Proposition 3: If a CCIE has $p = 0$ probability of occurring on date 1, the firm will not invest in improving the e-score, that is, $E_0 = 0$.

Eq. (16) implies that the marginal product of the E investment is 0, while a positive marginal product of physical investment. Therefore, the firm will not invest in improving e-scores. We have a corner solution when $p = 0$ with $E_0 = 0$. Proposition 3 shows that when the economy has no climate risk, our model reduces to an ordinary investment-based asset pricing model.

3 Data and methodology

3.1 MSCI E-score as a proxy of climate preparedness

In this study, we focus on the effects of the firm's climate preparedness. MSCI E score can work as a proxy for climate preparedness. The MSCI E-score measures a firm's preparedness to handle climate risks and exposure. It assesses firm-level vulnerability to climate effects and the preparedness of management to tackle those exposures. MSCI's Environmental pillar covers four themes, including climate change, natural capital, pollution & waste, and environmental opportunities across thirteen environmental issues, and its aggregated E-score measures the firm's exposure to risks or opportunities and its ability to manage those exposures.

A large and growing literature in finance has begun to examine the importance of climate risks on asset prices and returns using environmental, social, and governance (ESG) criteria. There is a divergence between different raters due to unique methodologies and different ways of measuring and aggregating ESG attributes (see, for example, Berg, Koelbel, Pavlova, and Rigobon (2022a) and Berg, Koelbel, and Rigobon (2022b)). The leading ESG raters include Kinder, Lydenberg, and Domini (KLD), Sustainalytics, Moody's ESG, S&P Global, Refinitiv, and MSCI. Among these, MSCI is the largest ESG provider globally, covering a wider range of companies.

Our study focuses on the environmental component of ESG. However, the meaning and measurement of the E score varies by provider. Some providers interpret "E" as a measure of a firm's "greenness" and the impact of its activities on the environment, including aspects such as the use of natural resources and waste generation. For instance, the "E" in Thomson Reuters' Refinitiv data set pertains to resource use, emissions, and innovation. The MSCI E-score, on the other hand, is a measure primarily of a firm's preparedness to handle climate risks and exposure. It assesses firm-level vulnerability to climate effects and the preparedness of management to tackle those exposures. Specifically, MSCI's Environmental pillar covers four themes, including climate change, natural capital, pollution & waste, and environmental opportunities across thirteen environmental issues, and its aggregated E-score measures the firm exposure to risks or opportunities and its ability to manage those exposures. Certain providers, such as S&P Global, adopt a more comprehensive approach and consider both dimensions. S&P Global's CSA criteria use a weighted system across multiple dimensions such as climate strategy, environmental policy & management systems, environmental reporting, operational eco-efficiency, and product stewardship.

As an illustration of how different ESG ratings prioritize different aspects within the same category, Table III of Berg et al. (2022b) offers a comparison of indicators that rating agencies assign to the water category. Refinitiv's water category assigns indicators including Emission Reduction/Discharge into the Water System, Resource Reduction/Water Recycling, and Resource Reduction/Water Use. On the contrary, the MSCI water category score is linked to the firm's water stress management capacity.

According to Eccles and Stroehle (2018), MSCI is the world's largest provider of ESG ratings, covering more firms than other ESG rating providers. Therefore, in line with many other academic studies, we obtain MSCI firm-level environmental scores. As in Pástor, Stambaugh, and Taylor (2022), our sample date starts from November 2012, the month after MSCI began covering small

US stocks, leading to a large increase in coverage of the firm. Our sample date ends in June 2022. The E score is the MSCI variable "environmental pillar score", which measures the weighted average score in 13 environmental issues. Because we are interested in the level of climate risk preparedness, the E score is not adjusted by the "Environmental pillar score". We merge the E score data with the firms from CRSP that have share code 10 or 11. Financial firms with SIC 6000-6999 are excluded.

3.2 The E factor

The most common way to construct characteristics-based factors is to form long-short portfolios sorted by underlying characteristics. We apply the slope factor methodology (see Chib et al. (2021) for the details). The slope factor method involves constructing factors by performing Fama and Macbeth cross-sectional regressions of firm-level returns on firm-level lagged characteristics. In these regressions, the OLS estimates of the slopes represent long-short portfolios that give unit-weighted exposure to each standardized lagged characteristic and zero-weighted exposure to all other standardized lagged characteristics. This means that these OLS estimates of the slopes are portfolios specific to a particular characteristic and remove the influence of other characteristics included in the regression.

Slope factors, sorted factors, and rank factors have significant differences. The reason we use slope factors to construct factors is that they are better at pricing assets. The key property of slope factors is pure play. It is noteworthy that firm characteristics are correlated. Therefore, when we use rank or double-sort, we take long positions in firms with high characteristic values, which indirectly means we also take long positions in any positively correlated characteristic. Similarly, when we take short positions on firms with low characteristic values, we indirectly take short positions in any negatively correlated characteristic. Thus, double-sort and rank methods include returns to positions that are correlated with the characteristic of interest. In contrast, the slope factor method is based on the regression of returns on lagged standardized characteristics, which elegantly overcomes this problem.

3.3 Summary statistics of factors

This section presents summary statistics of our constructed E factor and other relevant factor portfolios. Panel (A) in Table 1 reports the mean, standard deviation, t statistic, and Sharpe ratio of the constructed slope factors from January 2011 to November 2022. The market factor exhibits the highest Sharpe ratio. Our constructed E factor has a low Sharpe Ratio. When examining risk premiums, a similar pattern emerges. The market factor possesses the highest risk premium. However, when we exclude the effect of the Pandemic, the Sharpe ratio of the E slope factor is high, as shown in Panel (B) in Table 1. In terms of correlation, E is most correlated with sf.agr at 52.5% and least correlated with sf.mve at 1.6% in absolute. sf.agr has the highest correlation with sf.operprof at 53.3% in absolute.

Table 1 Factor premiums: mean, standard deviation, t-statistic, and Sharpe Ratio

	Mean	SD	t-statistic	SR
	Panel (A): January 2011 - December 2022			
MktRf	0.96	4.36	2.65	0.21
sf.e	0.04	1.20	0.38	-0.01
sf.mve	-0.03	0.89	-0.34	-0.08
sf.agr	-0.10	0.99	-1.24	-0.15
sf.operprof	-0.04	0.52	-0.94	-0.17
	Panel (B): January 2011 - December 2020			
MktRf	1.15	4.12	3.05	0.27
sf.e	0.20	1.04	2.07	0.15
sf.mve	-0.05	0.89	-0.57	-0.10
sf.agr	0.03	0.80	0.39	-0.02
sf.operprof	-0.09	0.48	-2.03	-0.28

Table 2 Correlation matrix of a slope factor set

	MktRf	sf.e	sf.mve	sf.agr	sf.operprof
	Panel (A): January 2011 - December 2022				
MktRf	1				
sf.e	-0.17	1			
sf.mve	-0.48	-0.02	1		
sf.agr	0.25	0.53	-0.28	1	
sf.operprof	-0.09	-0.30	0.28	-0.53	1
	Panel (B): January 2011 - December 2020				
MktRf	1				
sf.e	-0.19	1			
sf.mve	-0.59	0.09	1		
sf.agr	0.23	0.41	-0.26	1	
sf.operprof	-0.15	-0.17	0.20	-0.54	1

4 Pricing of the cross-section

Our theoretical model posits that the expected return on investment is influenced by several key firm characteristics, including firm size, investment, profitability, and climate preparedness.

$$Re_{i,t} = \beta_{i,Mkt}\mathrm{Mkt}_t + \beta_{i,s.e}\mathrm{s.e}_t + \beta_{i,s.mve}\mathrm{s.mve}_t + \beta_{i,s.agr}\mathrm{s.agr}_t + \beta_{i,s.operprof}\mathrm{s.operprof}_t + \varepsilon_{i,t} \quad (21)$$

where $Re_{i,t}$ is the excess return on equity of firm i. Mkt denotes the market factor, s.mve is the size factor, s.agr is the investment factor, s.operprof is the profitability factor and s.e is the climate preparedness factor.

4.1 Pricing stocks

In the Bayesian pricing test, every test asset is examined individually by the factor model. Let the excess return of a test asset be r^e. The asset is priced by the factor model $\boldsymbol{x}^*$ if

$$r^e = \beta_0' \boldsymbol{x}^* + \varepsilon_0, \tag{22}$$

and mispriced if

$$r^e = \alpha + \beta_1' \boldsymbol{x}^* + \varepsilon_1. \tag{23}$$

In the frequentist pricing test, one estimates the latter model and tests the null hypothesis of no mispricing, i.e., $\alpha = 0$. If the estimate of α differs significantly from zero, one rejects the null, and the asset is deemed not-priced. In the Bayesian approach, both models are estimated and their log-marginal likelihoods are compared. Let m_0 denote the log-marginal likelihood of the regression model with correct pricing given in (22), and m_1 denote the log-marginal likelihood of the regression model of mispricing given in (23), given the data. Then, the probability that the risk factors price the asset given the data is

$$\Pr(r^e \text{ is priced by } \boldsymbol{x}^* | \text{Data}) = \frac{1}{1 + e^{-d}} \tag{24}$$

where $d = m_0 - m_1$ is the difference in log-marginal likelihoods. An asset is priced at posterior odds of 2:1 (priced:mispriced) if the probability in equation (24) is at least 0.667 ($d \geq 0.693$). It is priced at posterior odds of 3:1 if the probability is at least 0.75 ($d \geq 1.09$) and priced at posterior odds of 4:1 if the probability is at least 0.8 ($d \geq 1.38$).

We consider pricing a sample of 3116 stocks (CRSP share codes 10 and 11) ranging from January 2011 to December 2022, and we ensure that there are at least 60 months of observations within this time frame on any given stock. Financial firms (SIC between 6000-6999) and firms with negative book equity are excluded. Stocks with prices per share lower than $5 are also excluded.

Benchmarking pricing performance on stocks is helpful, given that these assets tend to be more volatile than portfolios, posing a more significant hurdle. Table 3 compares the proposed empirical model with the E slope factor and without the E slope factor. As can be seen from the table, under the 4:1 criteria, 1521 out of 3116 stocks are priced by CLP5, and 1445 out of 3116 stocks are priced by CLP4, respectively. The CLP5 model also performs best compared to other models under the 2:1 and 3:1 criteria when pricing stocks and has lower unpriced stocks in all odds. E factor helps to improve pricing ability.

We also consider the sample of 948 ETFs. We obtain data on all exchange-traded funds from the CRSP stock database identified by their share code 73. As ETFs are securities according to the CRSP stock database and funds according to the CRSP Survivor-Bias-Free Mutual Fund database, we can obtain both the fund's price and holdings information, which we match by Cusip. We confirm that the funds are ETFs by retaining only funds with the " F " ETF flag in the CRSP mutual fund database. We retain only equity ETFs, with Lipper asset code EQ in the CRSP mutual fund database. In addition, we exclude foreign and global ETFs as described by excluding ETFs with a Lipper Class Name containing a country or global region name or the words "global" or "international." Finally, we read through each ETF name and remove levered and any remaining international ETFs. The levered ETFs are usually very small compared to their unlevered counterparts.

ETFs are diversified portfolios that are liquid, transparent, and cheap to trade. As a result, the premium of these assets is likely to be determined by exposure to the common non-diversifiable sources of risk manifested in the risk factors. Table 3 compares the proposed model with the E slope factor and without the E slope factor. Under the 2:1 criteria, CLP5 prices 664 out of 948 ETFs, while CLP4 prices 557 out of 948 ETFs. The CLP5 model also performs better than CLP4 under the 3:1 and 4:1 criteria when pricing 948 ETFs and having higher priced assets.

In addition to the ETFs and stocks, we use anomalies used in Hou, Xue, and Zhang (2020) (HXZ anomalies) and decile portfolios from Chen and Zimmermann (2021) (CZ anomalies), an independent source not associated with any factors. In particular, we construct long-short portfolios using the top minus the bottom for the CZ anomalies and remove anomalies with missing data. The results from these assets remain intact, as shown in Table 3. Notably, CLP5 prices more portfolios and unprices fewer assets than CLP4, suggesting that the E factor improves the pricing ability of the model.

Table 3 Bayesian pricing results on a large collection of test assets: # of assets being priced

Risk factors set	# priced at 2:1	# priced at 3:1	# priced at 4:1
		3116 Stocks	
CLP5	2566	2077	1495
CLP4	2449	1929	1371
		948 ETFs	
CLP5	664	494	315
CLP4	557	412	258
		188 HXZ anomalies	
CLP5	101	61	34
CLP4	68	39	23
		185 CZ anomalies	
CLP5	115	71	43
CLP4	94	57	33

5 Conclusion

In this paper, we have compared various ESG raters and justified that MSCI E represents climate risk preparedness. Precisely, MSCI E score measures climate risk exposure, which assesses the potential exposure of a company to environmental risks, and management, which evaluates how effectively a company is managing its identified environmental risks. Motivated by the fact that MSCI E associates with climate risk preparedness, we built a theoretical two-date investment-based asset pricing model to examine the link between firm-level expected return and its preparedness for climate risk.

Two new features define this model. One is a theoretical counterpart of the MSCI E-score, which measures the firm's preparedness/exposure to climate risks. The other includes a possible climate change-induced event (CCIE) on the second date that causes firm-specific damage. Our model implies that the firm's expected return depends, ceterius paribus, positively on the E-score. This agrees with empirical evidence in MSCI data suggesting that high E-score stocks have higher returns than low E-score stocks.

We constructed the E factor and other factors through the slope factor method. Our CLP5 model shows promise in pricing the cross-section using 3,116 stocks, 948 ETFs, HXZ anomalies, and CZ anomalies as testing assets. E factor helps improve pricing ability. For these test assets, the CLP5 model shows superior pricing performance. E factor helps to improve pricing ability at 2:1, 3:1, and 4:1 criteria.

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