Climate Risk Preparedness and the Cross Section*†

Siddhartha Chib‡ Leifei Lyu§ Kuntara Pukthuanthong¶

August 2024

*We thank Yi Chun Lin, Yi Zhang, Guofu Zhou, Gaetano Antinolfi and participants of the 2024 Hong Kong Conference for Fintech, AI, and Big Data in Business for helpful comments.

†There is no conflict of interest to declare.

‡Olin School of Business, Washington University in St. Louis, 1 Bookings Drive, St. Louis, MO 63130. E-mail: chib@wustl.edu

§Department of Economics, Washington University in St. Louis, 1 Bookings Drive, St. Louis, MO 63130. E-mail: leifei.lyu@wustl.edu

¶Department of Finance, Trulaske College of Business, University of Missouri, Columbia MO 65203. Email: pukthuantthongk@missouri.edu

Climate Risk Preparedness and the Cross Section

Abstract

We develop a theoretical framework to examine the relationship between a firm's climate risk preparedness and its investment returns within a two-date stochastic general equilibrium production-based asset pricing model. Our analysis shows that, in equilibrium with an interior solution, a firm's initial climate preparedness is positively correlated with the expected return on equity. We empirically test this theoretical model using a comprehensive set of assets, including stocks, ETFs, anomalies, and portfolios sorted by characteristics. The empirical findings support our theoretical predictions, highlighting the significant role that the constructed preparedness factor plays in explaining the cross-sectional variation in asset returns.

JEL Classification: G11, G12, G14

Keywords: asset pricing, climate preparation, risk factors

1 Introduction

In recent years, the growing body of scientific evidence on climate change and the large economic and ecological impacts of climate-related events around the world have stimulated numerous empirical and theoretical studies on the effects of climate on financial markets.[1] While there has been much analysis on how demand side portfolio choices can mitigate climate risks for investors, and the impact these portfolio choices have on financial market prices and returns (see, for example, Barnett, Brock, and Hansen (2020), Engle, Giglio, Kelly, Lee, and Stroebel (2020) and Bolton and Kacperczyk (2023)), the impact on the cross-section of returns of actions taken by firms to mitigate or prepare for climate change has been little studied. Specifically, we ask the question whether investment in climate risk preparation, with the aim of making operations less vulnerable to climate risk, has a positive or negative impact on expected equity returns.[2]

We view this paper as the first theoretical attempt to analyze the link between firm climate preparation and investment returns. It is undeniable that firms are exposed to climate risks (see, for example, Engle et al. (2020)), but it is unclear what incentives they have to reduce this exposure. In this paper, we develop a model in which a firm can undertake two types of investments, one in physical capital and the other to enhance preparadeness. Our aim is to use this model to quantify the costs and payoffs to investment in preparation and mitigation. It is clear that investment in preparation is an expense that is not likely to improve productivity, at least in the short term. Therefore, this investment would increase costs and lower profits, with a negative impact on

[1] The economic repercussions of climate change on the corporate world are profound and expansive. Stroebel and Wurgler (2021) show that regulatory risk is the main climate risk for companies and investors over the next five years, and physical risk is identified as the main risk over the next 30 years. The UN Environment Program projects that, globally, the expense required for companies to adapt to climate repercussions will soar to between \$140 and \$300 billion annually by the end of this decade (United Nations Environment Programme 2021).

[2] Projections by S&P Global indicate that, should adaptive measures not be implemented, the financial toll exerted by the physical manifestations of climate change will align with current average expenses by the mid-21st century (S&P Global 2021). Research also shows that economic losses due to climate pollution now eclipse the profits of the most polluting sectors, representing 89% of their total revenue (Energy Policy Institute at the University of Chicago 2021)). Furthermore, an EY survey underscores a strategic pivot toward improving climate action among corporations, with 61% of respondents indicating plans to increase their investment in climate change initiatives in the following year. In particular, a quarter of these entities intend to significantly increase their expenditures (EY 2022). This evidence illustrates the growing financial impact of climate change on businesses and the increasing investments in adaptation, compliance, and mitigation efforts.

expected returns. However, such an investment 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). Therefore, to understand the connection between investment in climate preparedness and its impact on expected returns, we built a model to factor in both effects.

The model we build is an intertemporal general equilibrium production-based asset pricing model. The model extends Cochrane (1991) and Cochrane (1996) by allowing the firm to invest in climate preparation. As in Cochrane (1996), we are able to show that the expected asset returns are proportional to the betas of the returns on investments in physical capital and investments in climate preparation. This result forms the basis for the model that we then apply to the data. To get to the essence of the problem, we model investment decisions in a two-date model, denoted date 0 and date 1. 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, which we call the E-score. In our empirical analysis, we use the E-score provided by MSCI, the data provider, as an empirical proxy for our theoretical E-score.[3] The firm invests in preparation to protect against a possible climate-change-induced event (CE) that can occur on the second date. If such an event occurs, there is firm-level damage that decreases the firm's profitability.[4]

On the next date, a CE occurs with probability p. We assume that this event is independent of the stochastic process of profitability at date 1 and that the probability p is common knowledge. Therefore, the firm is incentivized to invest in climate preparation because this results in less

[3]The MSCI ESG score is a measure of the likely impact that environmental factors have on the company and not a measure of "greenness." According to the MSCI ESG Ratings Methodology, the E pillar score is based on exposure scores and management scores. The first measures the effect of the environment on the firm, while the second gauges the level of preparation for environmental-related risks. Other ESG rating systems, however, measure greenness. This explains why the MSCI E score has the lowest correlations with the E scores assigned by other ESG assessors (Berg, Koelbel, and Rigobon, 2022). In particular, the correlation between the MSCI E score and other ESG E scores is below 0.37. In contrast, the correlation between the Moody and S&P E scores is 0.73.

[4]This assumption is consistent with empirical evidence. For example, Addoum, Ng, and Ortiz-Bobea (2023) show that extreme temperatures affect corporate profitability in more than 40% of the US industries, and Pankratz, Bauer, and Derwall (2023) show that increased exposure to extremely high temperatures reduces firms' revenues and operating income.

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. We assume that the firm can reduce climate-related damage by investing in improving climate preparedness. Furthermore, we require that spending on climate preparation reduces damage, and the marginal effect of this investment is decreasing in its climate preparedness level. These assumptions are consistent with Nordhaus (2007), Hong, Wang, and Yang (2023) and Golosov, Hassler, Krusell, and Tsyvinski (2014).

We are able to get several results from the model. First, when the climate preparedness of a firm is sufficiently low and the probability p is high, we get a corner solution characterized by a positive investment in E and no physical investment. In this case, the expected return on aggregate investment aligns with the return on E investment due to the significantly higher marginal benefits associated with E investment compared to physical investment. Furthermore, the expected return inversely correlates with the firm's initial level of climate preparedness, given that the marginal utility of E investment decreases as climate preparedness improves.

Second, conversely, when a firm's climate preparedness is sufficiently high, there is a second corner solution in which resources are allocated solely towards physical investment, as a consequence of our assumption that the marginal utility of E investment decreases with increased climate preparedness. Then, the expected return on aggregate investment corresponds to the return on physical investment, which leads to a positive correlation between expected return and the firm's initial climate preparedness. Since we assume that the risk-averse representative household has a logarithmic utility function, the optimal level of physical investment is unaffected by the firm's initial climate preparedness, which renders the marginal cost of investment constant with respect to climate preparedness levels. However, the marginal benefits of physical investment are positively correlated with readiness levels. Consequently, there is a direct and positive relationship between initial climate preparation and expected returns.

Third, when there is an interior solution in which the optimal levels of E and physical investment are positive, we can numerically determine that there is a positive link between the expected return on aggregate investment and the firm's initial climate preparation. This positive relationship is robust to changes in model parameters.[5]

The theoretical model developed in this paper suggests that a five-factor empirical asset pricing model consisting of the market factor and the 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. This link between our model and pricing of the cross-section follows from the reasoning highlighted in Cochrane (1991). Basically, investment returns and asset returns can be related to the producer's first-order conditions. Assume that the firm manager has access to fully developed financial markets. In such a scenario, the manager can construct a portfolio of assets that replicates the exact payoffs of the weighted average investment return between physical investment and E investment across two states of the CE at date 1. If the cost of acquiring this replicating portfolio exceeds one dollar, the manager should short the portfolio, invest the proceeds to physical investment and E investment with amounts determined by first-order conditions, and use the investment return to settle the mimicking portfolio, thereby securing a guaranteed profit. In contrast, if the cost is less than one dollar, the opposite strategy would apply. Firms will continually adjust their investment and production strategies until the returns of the investments align with the returns from the replicating portfolio. In other words, firms eliminate any arbitrage opportunities between asset returns and investment returns.

In a complete market, the investment return and the return of the replicating portfolio should be equal ex post, across all possible states of nature. The theoretical model developed in this paper suggests that the weighted average return between the physical investment and E investment

[5]The model of Pástor, Stambaugh, and Taylor (2022) has a different focus and motivation than our production-based model and, therefore, comes to a different conclusion. In the former model, the utility function of investors includes the firm's E score, reflecting a taste for green investments. In equilibrium, investors are willing to accept low expected returns from "green" stocks, since this is compensated by non-pecuniary benefits that accrue from high ESG scores. To confirm this implication, one must use an E score that measures greenness, and not the MSCI E score, which does not. Not surprisingly, using the latter, Pástor et al. (2022) failed to find support for their theoretical conclusion.

depends on four firm's characteristics, including the E score, profitability size, and investment. These characteristics are hypothesized to be determinants of asset returns. Consequently, we introduce a five-factor empirical asset pricing model, which includes four factors derived from these firm characteristics, in addition to the market factor. It is important to note that our objective is not to identify the best asset pricing model but rather to investigate the extent to which climate preparedness contributes to pricing in the cross-section of assets. Accordingly, we have excluded some common factors that are not suggested by our theoretical model, such as HML.[6]

We call our 5-factor model the CLP5 model. This model shows that high E factor stocks have higher expected returns than low E factor stocks, which is consistent with the implications of our theoretical model. To evaluate the effectiveness of the E factor in pricing the cross section, we consider a variant that omits the E factor from the CLP5 model. In this way, we can determine the contributing role of the E factor. Then we evaluate the empirical support for these two models and find that the CLP5 model is better supported by the data. Furthermore, the CLP5 model shows promise in pricing the cross section. Using 2,990 stocks as test assets, where each test asset has at least 60 months of data, we find that the CLP5 model prices 2439 of those stocks at posterior odds of at least 2:1, more than is priced by the model without the E factor. This outperformance persists when we consider ETFs and anomalies as test assets.

Related Literature. This paper is a contribution to two strands of literature. The first strand is climate finance. Giglio, Kelly, and Stroebel (2021) and Hong, Karolyi, and Scheinkman (2020) review the literature on this rapidly growing field, summarizing theoretical and empirical contributions. On the theory side, recent papers include, for example, Barro (2015), Van Binsbergen and Koijen (2017), and Giglio et al. (2021), and on the empirical side, for example, Bolton and Kacperczyk (2021), Hong, Li, and Xu (2019), Engle et al. (2020) and Alekseev, Giglio, Maingi, Selgrad, and Stroebel (2021). These articles focus on the impact of climate change on asset prices and returns in financial markets. Our paper, on the other hand, is a theoretical contribution that

[6]We use the MSCI E score as a proxy for the preparedness. The sample starts in November 2012 and ends in December 2022. We construct the climate preparedness factor, the E factor, using the 3 by 2 sorting method in Fama and French (1993).

is based on incentives to invest in climate risk preparation/mitigation and the impact of such investments on the expected return to equity.

The second strand of literature is production-based asset pricing. Balvers, Cosimano, and McDonald (1990) show that there is a link between aggregate output growth and financial asset returns and that output growth can therefore be used as an asset pricing factor, rather than consumption growth. Subsequently, Cochrane (1991) and Cochrane (1996) developed theoretical models with investment returns and output growth rates, as pricing factors, and provided empirical evidence showing that investment-based CAPM outperformed traditional CAPM and CCAPM models. Investment-based asset pricing models have also been used to link asset returns to business cycles, for example, Cochrane et al. (2005), Balvers and Huang (2007), Boldrin, Christiano, and Fisher (2001) and Croce (2014). Our article is inspired by Cochrane (1991) and Cochrane (1996) that demonstrate that the return on investment is approximately proportional to the growth in the investment/capital ratio. We extend these models to include a broader range of firm characteristics, particularly focusing on a firm's climate preparedness level. This extension aims to provide a more nuanced understanding of how firm-specific factors influence asset pricing in the context of evolving market dynamics and considerations of climate risks.

The remainder of the paper is organized as follows. In Section 2 we build an investment-based asset pricing model that incorporates a random climate event (CE) and the firm's level of climate risk preparation. In Section 3 we provide evidence that the MSCI E score can be interpreted as a measure of climate risk preparedness and construct the E factor from the data on these E scores. In Section 5 we consider the cross-sectional pricing ability of the CLP5 factor model. Section 6 concludes the paper.

2 Theoretical Model

We now present a two-date stochastic general equilibrium model in which the firm mitigates exposure to climate change by spending proactively on climate preparation. In a production-based asset model, asset returns are linked to marginal transformation rates obtained from the optimal intertemporal investment decision. We measure this readiness generically in terms of what we call the E score. The firm invests in this preparation because of a possible climate event (CE) 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.

2.1 Production

Consider a two-date model populated by a representative household and a representative firm in the economy. We label the two dates as date 0 and date 1. The firm produces on both dates and starts with an initial productive asset (K_0), profitability (Π), and an E-score (e_0). On date 0, the operating cash flow of the firm, labeled Y_0, is calculated by multiplying its profitability (Π) by its initial asset (K_0). At date 1, operating cash flow, indicated by Y_1, is subject to a CE shock, which hits the economy with a known probability of p. We suppose that the CE shock is the only uncertainty in the economy. The scalar s describes the CE status on date 1. If a CE shock hits the economy, then $s = s_T$; if the economy is not hit by a CE shock, then $s = s_F$. When $s = s_T$, a portion $\kappa(e_1, s)$ of operational cash flow Y_1 is destroyed, where

$$\kappa(e_1, s) = \begin{cases} 1 - e^{-e_1} & s = s_T \\ 1 & s = s_F \end{cases} \tag{1}$$

and e_1 represents the date-1 E-score. The damage function $\kappa(e_1, s)$ captures two features: the boundary ($1 - e^{-e_1} \in (0, 1]$ if $s = S_T$) and concavity. Due to concavity, there are diminishing returns to climate preparation as e_1 increases. We provide empirical evidence in support of this assumption in the A.

Given the initial e_0, we suppose that the E-scores evolve as

$$e_1 = e_0 + f(E_0) \tag{2}$$

where E_0 denotes the investment in climate risk preparation. We assume that $\frac{\partial f}{\partial E_0} \geq 0$ and $e_0 \geq 0$. Any nonnegative E_0 guarantees that e_1 is positive. Consequently, as defined by Eq. (1), $0 \leq \kappa(e_1, s_T) < 1$. Note that investing in climate preparation does not directly enhance the firm's stock of capital, but it reduces vulnerability to the effects of a CE shock. The date-1 operating cash flow is given by $Y_1 = (1 - \kappa(e_1, s))\Pi K_1$.

2.2 Assets and asset prices

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. The price of this asset at date 0 in state s is $q^0(s)$.

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 $\Pi_0 K_1(1 - \kappa(e_1, s))$ units of consumption. The output price is $q^0(s)\Pi_0 K_1(1 - \kappa(e_1, s))$ in state s. The firm takes the price $q^0(s)$ as given when choosing the investments and the dividend distributed to the household.

We assume that the representative firm is entirely owned by the representative household, which acts as the sole producer and consumer within this model. The firm produces 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.

$$U = u(C_0) + \beta[pu(C_1(s_T)) + (1-p)u(C_1(s_F))] \tag{3}$$

where β denotes the subjective discount factor of the representative household, and C_0 and C_1 are consumption in dates 0 and 1, respectively. The first-order condition for consumption can be written as

$$u'(C_0) = \beta[pu'(C_1(s_T)) + (1-p)u'(C_1(s_F))] \tag{4}$$

The stochastic discount factor (SDF), before the realization of the CE shock, takes the form $m(s) \equiv \frac{\beta u'(C_1(s))}{u'(C_0)}$. Therefore, in equilibrium, asset prices must satisfy the pricing conditions

$$q^0(s_T) = p\beta\frac{u'(C_1(s_T))}{u'(C_0)} = pm(s_T) \quad \text{and} \quad q^0(s_F) = (1-p)\beta\frac{u'(C_1(s_F))}{u'(C_0)} = (1-p)m(s_F) \tag{5}$$

2.3 The firm's optimization problem

First-order conditions. The firm at date 0 chooses physical investment I_0 and E investment E_0 to maximize its date-0 expected cum dividend, given initial capital stock K_0 and initial E-score, e_0 and contingent claim prices $q^0(s)$

$$\max_{I_0,E_0}\left[\Pi K_0 - G_0 - \frac{a}{2}\left(\frac{I_0}{K_0}\right)^2 K_0\right] + [q^0(s_T)\Pi_0 K_1 + q^0(s_F)(1-\kappa(e_1,s_T))\Pi K_1] \tag{6}$$

subject to

$$\text{Resources:} \qquad Y_0 = C_0 + G_0 - \frac{a}{2}\left(\frac{I_0}{K_0}\right)^2 K_0 \tag{7}$$

$$\text{E-score accumulation:} \qquad e_1 = e_0 + f(E_0) \tag{8}$$

$$\text{Capital accumulation:} \qquad K_1 = I_0 + (1-\delta)K_0 \tag{9}$$

$$\text{Total investment:} \qquad G_0 = I_0 + E_0 \tag{10}$$

where K_1 represents date-1 capital. Capital can be expressed as the sum of initial capital adjusted for deprecation at a rate δ, denoted as $(1-\delta)K_0$, and physical investment I_0, that is, $K_1 = I_0 + (1-\delta)K_0$. The quadratic term represents a convex adjustment cost. The first-order optimality conditions for E investment E_0 and physical investment I_0 are, respectively,

$$1 = q^0(s_T) f'(E_0) e^{-e_1} \Pi K_1 \tag{11}$$

$$1 + a\frac{I_0}{K_0} = q^0(s_F)\Pi + q^0(s_T)(1 - e^{-e_1})\Pi \tag{12}$$

where $f'(E_0) = \frac{\partial f(E_0)}{\partial E_0}$. Or, equivalently, we can write

$$1 = \sum_s q^0(s) R^E(s) \quad \text{and} \quad 1 = \sum_s q^0(s) R^I(s) \tag{13}$$

where $R^E(s)$ and $R^I(s)$ represent the investment return on E_0 and I_0 at state s, respectively. Consequently, we can express the expected returns on investments as follows

$$\mathbb{E}[R^E] = p f'(E_0) e^{-e_1} \Pi K_1 \quad \text{and} \quad \mathbb{E}[R^I] = \frac{(1-p)\Pi + p(1-e^{-e_1})\Pi}{1 + a\frac{I_0}{K_0}} \tag{14}$$

where $\mathbb{E}[R^E]$ and $\mathbb{E}[R^I]$ denote the date-0 expected return on E_0 and I_0, respectively.

2.4 Expected return on investment

We now turn to our central questions: the impact on the expected return of physical investments, which encompass traditional capital expenditures, and E investments, which are directed towards enhancing the firm's resilience to climate change. We analyze the different expected returns for these investments, highlighting their varying risk and return profiles.

We also consider the expected return to aggregate investment, represented as $G_0 = I_0 + E_0$. Understanding the dynamics of aggregate investment is important, as it reflects the returns to traditional growth objectives with the imperative of climate adaptation. We define the expected rate of return on aggregate investment as

$$\mathbb{E}[R] = \frac{I_0}{G_0}\mathbb{E}[R^I] + \frac{E_0}{G_0}\mathbb{E}[R^E]. \tag{15}$$

In other words, $\mathbb{E}[R]$ is the weighted average of the expected returns of the components. Of particular interest is the characterization of these expected returns under equilibrium conditions.

Definition 2: An equilibrium is an allocation $\{E_0, I_0\}$ and a price system $\{q^0(s_T), q^0(s_F)\}$ that satisfy the following conditions: (1) Each component of the price system and the allocation is non-negative; (2) $C_0 = \Pi K_0 - I_0 - E_0$ is non-negative; (3) Given the price system and given the initial E-score e_0 and capital K_0, I_0 and E_0 solve the optimization problem of the representative firm; (4) Given the choice of E_0 and I_0, the optimization problem of the representative household determines $q^0(s_T)$ and $q^0(s_F)$.

In our analysis, equilibrium allocations are derived by resolving the optimization problems encountered by the household and the firm. For simplicity, we assume a logarithmic utility function $U(C) = \ln C$ which is commonly used and is rather standard in the literature, and a linear climate preparedness increment $f(E_0) = E_0$. As outlined in Section 2.2 and 2.3, determining the equilibrium values for E_0, I_0, $q^0(s_F)$ and $q^0(s_T)$ requires the solution of the equations in (11), (12) and (5). We substitute the price functions specified in (5) into the first-order conditions delineated in (11) and (12). After this substitution, we are left with a simplified system of equations given by

$$1 = p\beta\left(\frac{\Pi K_0 - I_0 - E_0}{(1-e^{-e_1})\Pi K_1}\right)e^{-e_1}\Pi K_1 \tag{16}$$

$$1 + a\frac{I_0}{K_0} = (1-p)\beta\left(\frac{\Pi K_0 - I_0 - E_0}{\Pi K_1}\right)\Pi + p\beta\left(\frac{\Pi K_0 - I_0 - E_0}{(1-e^{-e_1})\Pi K_1}\right)(1-e^{-e_1})\Pi \tag{17}$$

After further algebra, these equations can be expressed as a single equation that depends only on I_0.

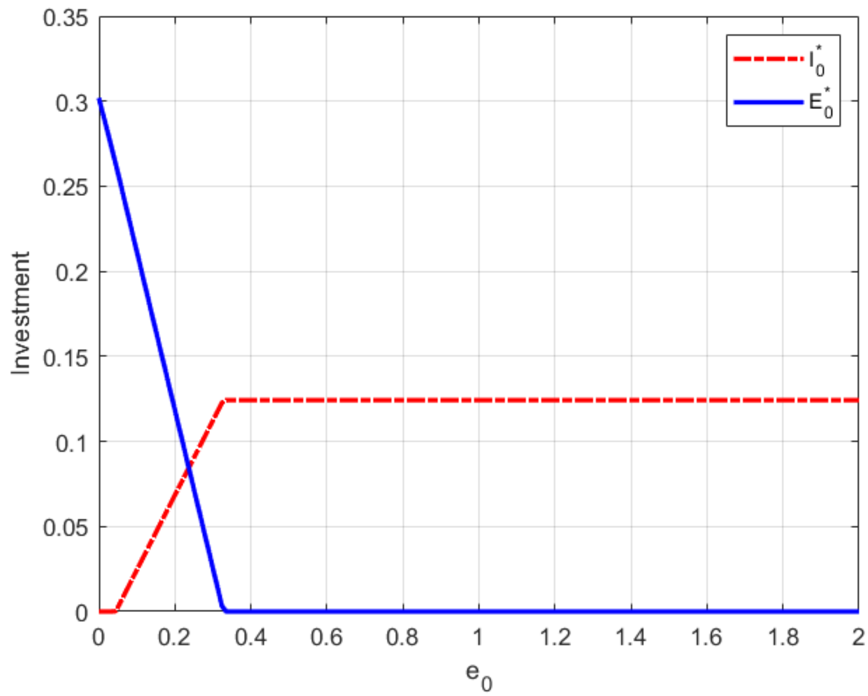

Figure 1 Investments in equilibrium. This figure shows equilibrium values of E_0 (the red dashed line) and I_0 (the blue solid line), denoted as E_0^* and I_0^*, respectively. Results are plotted against $e_0 \in [0,2]$, the initial climate preparedness level. The parameters are set as follows: $K_0 = 2$, $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$, and $p = 0.2$. The figure shows that over the range of e_0 values where both $I_0^* \geq 0$ and $E_0^* \geq 0$ are satisfied, physical investment increases with the initial e_0, while E investment decreases with the initial e_0.

Equilibrium Characterization. Let E_0^* and I_0^* represent the equilibrium values of I_0 and E_0, respectively, as defined in Definition 1. Figure 1 plots the equilibrium value of I_0 and E_0 as a function of e_0. We set the benchmark parameters as follows: $K_0 = 2$, $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$, and $p = 0.2$. We observe that when e_0 is sufficiently low, it is optimal to choose a zero I_0 and a positive E_0. This corner solution arises because the marginal benefits of E_0 are substantially higher than those of an investment in I_0. On the contrary, a corner solution $\{I_0^* > 0, E_0^* = 0\}$ can also occur if e_0 is sufficiently high. Then, in equilibrium, the firm will opt exclusively for positive physical investments. At an interior equilibrium, both Eqs. (16) and (17) hold.

The expected returns on investments can be determined with E_0^* and I_0^*. Figure 2 plots the expected returns for three types of investment: E investment (red dot-dashed line), physical

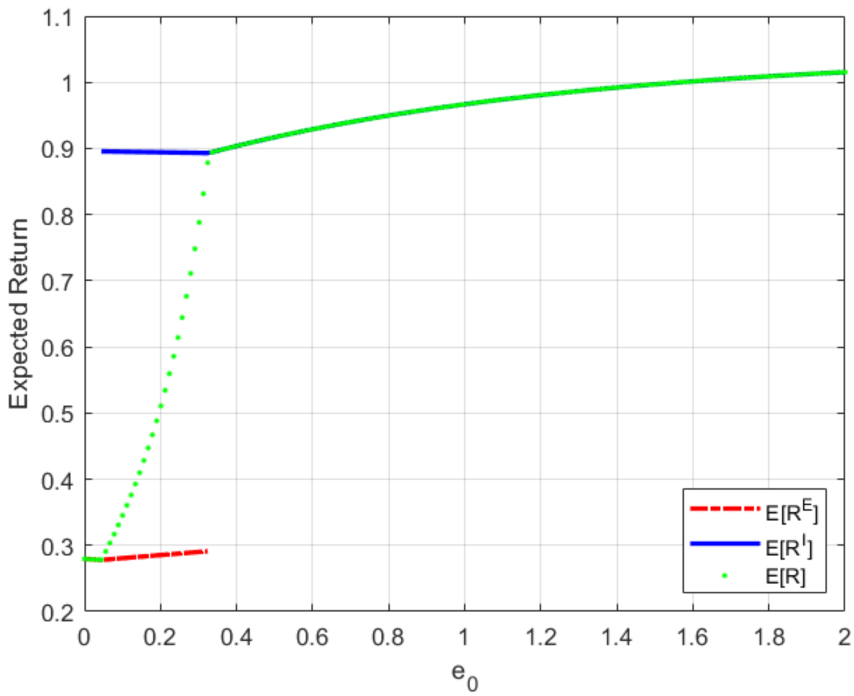

Figure 2 Expected returns on investments. The solid blue line represents the expected return on physical investment I_0. The red dot-dashed line plots the expected return on E investment E_0. The green dotted line plots the weighted average expected return. The results are plotted against $e_0 \in [0,2]$, the initial level of climate preparedness. The parameters are set as follows: $K_0 = 2$, $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$, and $p = 0.2$. The figure shows that over the range of e_0 values where $I_0^* \geq 0$ and $E_0^* \geq 0$, $\mathbb{E}[R]$ calculated as the weighted average of $\mathbb{E}[R^E]$ and $\mathbb{E}[R^I]$, increases with e_0.

investment (blue solid line), and the weighted average investment (green dotted line), under the benchmark calibration. We observe that when e_0 is sufficiently low, the green dotted line overlaps with the red dotted line, indicating $\mathbb{E}[R] = \mathbb{E}[R^E]$. In this scenario, the expected returns on investment in E and the weighted average investment exhibit a decreasing trend with e_0. In contrast, when e_0 is sufficiently high, the green dotted line overlaps with the blue solid line, indicating $\mathbb{E}[R] = \mathbb{E}[R^I]$. The expected returns on physical investment and weighted average investment increase in e_0. For intermediate e_0, where interior solutions emerge, $\mathbb{E}[R]$ is the weighted average of $\mathbb{E}[R^E]$ and $\mathbb{E}[R^I]$, and shows an upward trend with e_0.

We now provide a detailed discussion of the solutions and associated expected returns, starting with the corner solution $\{E_0^* = 0, I_0^* > 0\}$, for which analytical expressions are available. This particular solution emerges when the marginal benefits associated with I_0 are substantially higher than any positive investment in E_0. Under such circumstances, the optimal value of I_0^* can be determined by inserting $E_0^* = 0$ into Eq.(12). This allows I_0^* to be analytically determined independently of e_0. Moreover, $e_1 = e_0$ given that $E_0^* = 0$. Consequently, the expected return on physical investment in (14) shows an increasing trend with e_0. The idea behind this increasing trend is straightforward. for any sufficiently high level of e_0, the marginal benefits associated with E_0 are less than those of I_0, due to the concavity of the function $1 - e^{-e_1}$. As e_0 increases, the incremental benefits of investing in E_0 decrease. In equilibrium, where $E_0^* = 0$, the optimal I^* remains unaffected by E_0, making the marginal costs independent of e_0, while the marginal benefits increase with e_0. As a consequence, the expected return on the weighted average investment $\mathbb{E}[R]$, is equal to $\mathbb{E}[R^I]$, demonstrating a positive correlation with e_0.

We then discuss the other corner solution, $\{E_0^* > 0, I_0^* = 0\}$. The solution arises when the marginal benefits of E_0 are substantially greater than any positive investment in I_0. Similarly to the previous corner solution, we solve E_0^* from (11) by setting $I_0^* = 0$, revealing that E_0^* is a function of e_0. To examine how $\mathbb{E}[R^E]$, which is calculated as $pe^{-e_1}\Pi(1-\delta)K_0$, is affected by e_0, it suffices to explore the relationship between e_1 and e_0, since $\mathbb{E}[R^E]$ is strictly over e_1. When $e_0 > e_0'$, we have $e_1 > e_1'$ (see Figure B.1). Therefore, $\mathbb{E}[R]$, which is equal to $\mathbb{E}[R^E]$, decreases in e_0.

Finally, we turn to the interior solution, where $\{E_0^* > 0, I_0^* > 0\}$. At an interior equilibrium, it must be that both Eqs. (16) and (17) hold. The expected return on physical investment $\mathbb{E}[R^I]$ shows a decreasing trend with respect to e_0. In contrast, the expected return on investment in E $\mathbb{E}[R^E]$ shows an increasing trend as e_0 increases. The aggregate investment return, $\mathbb{E}[R]$, which is the weighted average of $\mathbb{E}[R^E]$ and $\mathbb{E}[R^I]$ reflects the combined effects of these dynamics. As demonstrated in Figure 2, $\mathbb{E}[R]$ increases in e_0, indicating that if the gains of the investment in E outweigh the diminishing returns from physical investment.

2.5 Comparative statics

A change in any parameter might affect the equilibrium values and expected returns. In this section, we consider the comparative statics of our model to examine how variations in specific parameters influence the equilibrium outcomes and expected returns. We begin this exploration by analyzing the possibility of CE in the parameter p, detailed in Section 2.5.1. Subsequently, we examine the implications of different initial capital levels, denoted K_0, presented in Section 2.5.2. Furthermore, the effects of changes in the profitability parameter, Π, are elucidated in Section 2.5.3. Lastly, we address the impacts resulting from adjustment costs, with an in-depth discussion provided in Section 2.5.4.

2.5.1 Changes in p

The CE shock hits the economy at date 1 with a known probability of p. This probability differentially influences the expected marginal benefits of E investments versus physical investments. Specifically, the expected marginal benefits of E investments are positively correlated with p, since such investments primarily aim to mitigate the impacts of CE shocks, thus increasing in value as the probability of the shock intensifies. In contrast, the expected marginal benefits of physical investments are susceptible to reduction upon the occurrence of the CE shock, and a fraction of these benefits potentially being negated due to the adverse effects of the shock on physical assets or operating cash flows.

Figure 3 illustrates the features of the comparative statics of p. In the figure, the parameters K_0, Π, a, β, and δ are constant throughout, taking the value of 2, 1.05, 0.1, 0.98, and 0.1 as a reference, while the probability p increases from left to right and from the top row to the bottom row. Specifically, in the upper row from left to right, p takes the values 0.05, 0.1, and 0.3. In the bottom row, the progression continues with p taking the values 0.5, 0.7, and 1, also from left to right. The higher p, the higher is the incentive to invest in climate preparation, all else equal. So, when we move from left to right and from the top row to the bottom row, we see that the equilibrium starts with interior solutions when p is sufficiently low. This indicates that when p and e_0 are sufficiently low, it is optimal to invest positively in both the E investment and physical investment. When p is sufficiently high and e is sufficiently low, the marginal benefits of the investment in E are significantly higher than the benefits associated with physical investment. It is optimal for the firm to invest exclusively in E. The range of such corner solutions with respect to e_0 is increasing in p. Next, we discuss two extreme cases: $p = 0$ and $p = 1$, which are stated in the following two propositions.

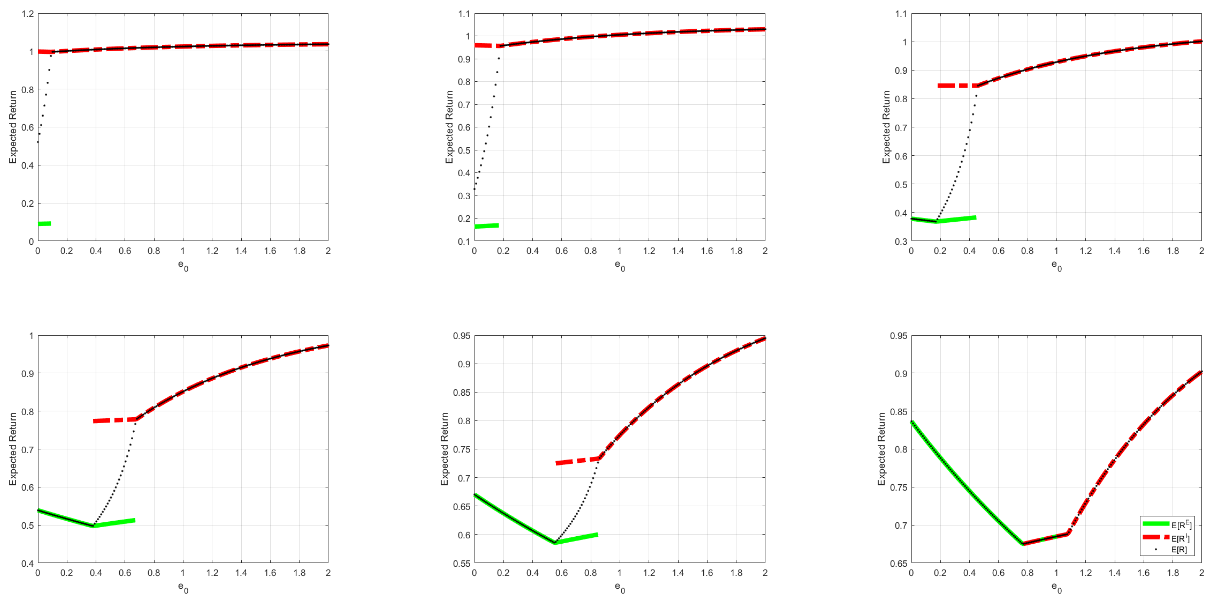

Figure 3 The value of p increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, p takes the values 0.05, 0.1, and 0.3. In the bottom row, the progression continues with p taking the values 0.5, 0.7, and 1, also from left to right. The red dot-dashed line represents the expected return on physical investment I_0. The solid green line plots the expected return on E investment E_0. The black dotted line plots the weighted average expected return. The parameters are set as follows: $K_0 = 2$, $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, and $\delta = 0.1$. This comparison shows that the incentive to invest in climate preparation increases with p, all else equal.

Proposition 1: If a CE has $p = 0$ probability of occurring on date 1, the firm will not invest in improving the E-score, that is, $E_0 = 0$. The expected return $\mathbb{E}[R]$ is uncorrelated with e_0.

Proposition 1 shows that when climate risk is absent, our model reduces to an ordinary production-based asset pricing model and the marginal product of the E investment is 0. In other words, when $p = 0$ we have a corner solution with $E_0^* = 0$.

Proposition 2: If a CE has $p = 1$ probability of occurring on date 1, then $\mathbb{E}[R] = \mathbb{E}[R^E]$ when $I_0^* = 0$. Similarly, $\mathbb{E}[R] = \mathbb{E}[R^I]$ when $E_0^* = 0$. At interior solutions where both I_0^* and E_0^* are positive, $\mathbb{E}[R] = \mathbb{E}[R^E] = \mathbb{E}[R^I]$.

When $p = 1$, uncertainty about climate change vanishes, and the expected returns on E investment and physical investment are identical where there are interior solutions.

2.5.2 Changes in K_0

The initial capital, K_0, has different impacts on the expected returns on E investments and physical investments. Specifically, the expected marginal benefits of E investments are positively correlated with K_0, thereby increasing in value as K_0 increases. In contrast, K_0 affects the marginal costs of physical investments through two distinct channels: (1) increase costs by raising physical investment, I_0 and (2) decrease costs by appearing directly in convex adjustment costs.

Figure 4 illustrates the characteristics of the comparative statics of K_0. In the figure, the parameters K_0, Π, a, β, and δ are constant throughout, while the probability p increases from left to right and from the top row to the bottom row. Specifically, in the upper row from left to right, K_0 takes the values 0.5, 1, and 3. In the bottom row, the progression continues with p taking the values 5, 7, and 10, also from left to right. The figure shows that the range of e_0 values leading to positive E investments widens with an increase in K_0, reflecting a positive correlation between the marginal returns of E investments and K_0.

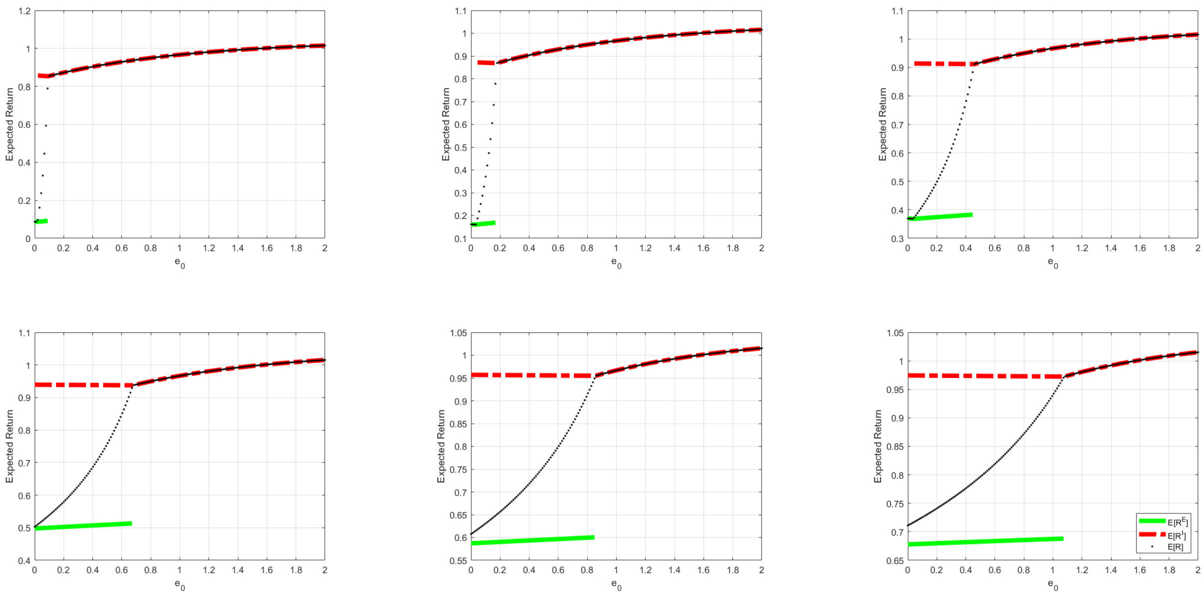

Figure 4 The value of K_0 increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, K_0 takes the values 0.5, 1, and 3. In the bottom row, the progression continues with p taking the values 5, 7, and 10, also from left to right. The red dot-dashed line represents the expected return on physical investment I_0. The green solid line plots the expected return on E investment E_0. The black dotted line plots the weighted average expected return. The parameters are set as follows: $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$ and $p = 0.2$. The figure shows that the range of e_0 values leading to positive E investments widens with an increase in K_0, reflecting a positive correlation between the marginal returns of E investments and K_0.

2.5.3 Changes in Π

The profitability is positively link to both the marginal benefits of E investments and physical investments. Figure 5 illustrates features of the comparative statics of Π. Parameters p, Π, a, β, and δ are constant as the benchmark throughout, whereas the probability Π increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, Π takes the values 0.9, 0.95, and 1. In the bottom row, the progression continues with Π taking the values 1.05, 1.1, and 1.2, also from left to right.

The figure demonstrates that when Π is sufficiently low, the firm will only spend on E investment when e_0 is low. The firm will not invest in either E investment or physical investment when e_0 is above a threshold (the most left subfigure in the top row in Figure 5 when $\Pi = 0.9$). However, when Π is not remarkably low, the firm will exclusively spend on E investment when e_0 is low, and exclusively spend on physical investment when e_0 is sufficiently high. The idea behind this is easy to understand. When e_0 and Π are sufficiently low, the marginal benefits of E investments are significantly higher than those of physical investments, so it is optimal for the firm to choose exclusively positive E investments. When the Π is sufficiently high, we see that the positive correlation between e_0 and the weighted average investment return $\mathbb{E}[R]$ holds for various Π.

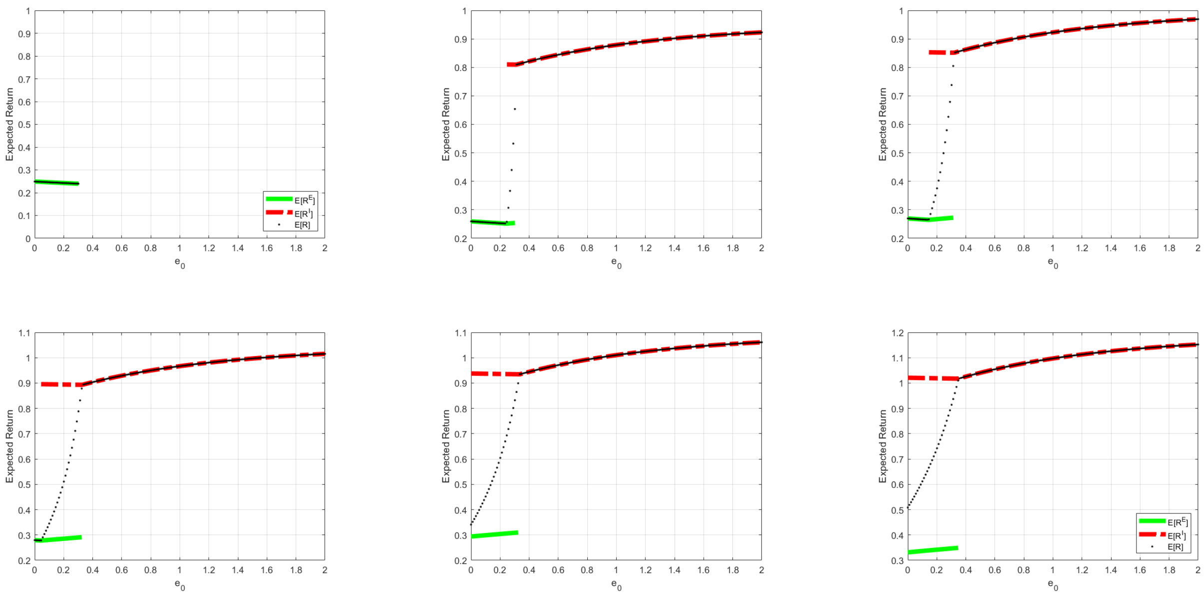

Figure 5 The value of Π increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, Π takes the values 0.9, 0.95, and 1. In the bottom row, the progression continues with Π taking the values 1.05, 1.1, and 1.2, also from left to right. The red dot-dashed line plots the expected return on E investment E_0. The green dotted line plots the weighted average expected return. The parameters are set as follows: $K_0 = 2$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$ and $p = 0.2$. The figure shows that when e_0 and Π are sufficiently low, it is optimal for the firm to choose exclusively positive E investments. When the Π is sufficiently high, we see that the positive correlation between e_0 and the weighted average investment return holds for various Π.

2.5.4 Changes in a

The parameter a is the coefficient of adjustment cost of physical investment. Any positive a suggests a convex adjustment cost that involves physical investment. When $a = 0$, the marginal costs of the physical investment and E investment are equal. The higher is a the higher is the marginal cost of physical investment, all else equal.

Figure 6 illustrates the features of the comparative statics of a. Parameters K_0, Π, p, β, and δ are constant as the benchmark, whereas the adjustment cost coefficient a increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, a takes the values 0, 0.05, and 0.1. In the bottom row, the progression continues with a taking the values 0.5, 1, and 5, also from left to right.

The figure shows that the slope of the relationship between $\mathbb{E}[R^E]$ and e_0 becomes steeper, indicating an intensifying negative correlation. The idea behind this is easy to understand. When a is high, the marginal cost of physical investment is high, the firm spends more on E investment as the increase of a when e_0 is sufficiently low. Given that the marginal benefits of the E investment decrease in e_0, we observe an intensifying decrease in the return of the E investment $\mathbb{E}[R^E]$ as a increases. Note that when a is unreasonable high, $\mathbb{E}[R^E]$ also decreases with e_0. Although the average impact can be mixed depending on adjustment cost parameter a, our comparative statics exhibit a positive correlation between e_0 and weighted average return $\mathbb{E}[R]$.

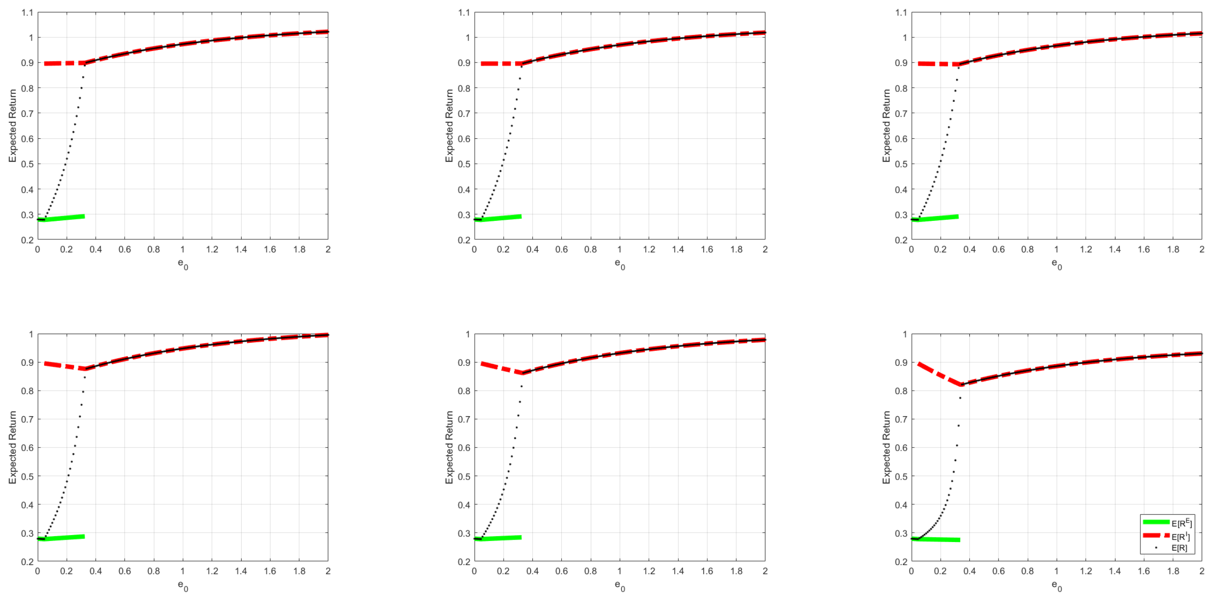

Figure 6 The value of a increases from left to right and from the top row to the bottom row. Specifically, in the top row from left to right, a takes the values 0, 0.05, and 0.1. In the bottom row, the progression continues with a taking the values 0.5, 1, and 5, also from left to right. The red dot-dashed line plots the expected return on E investment E_0. The green dotted line plots the weighted average expected return. The parameters are set as follows: $K_0 = 2$, $\Pi = 1.05$, $\beta = 0.98$, $\delta = 0.1$ and $p = 0.2$. The figure shows that the slope of the relationship between $\mathbb{E}[R^E]$ and e_0 becomes steeper, indicating an intensifying negative correlation.

3 Data

3.1 MSCI E-score as a proxy of climate preparedness

We use the MSCI E-score as a proxy for climate preparedness. Although this score has been used to measure "greenness" in the literature (see, for example, Pástor et al. (2022)), it is more associated with firms' exposure to climate change and preparedness to manage those risks than "greenness". As Simpson, Rathi and Kishan wrote in the Bloomberg article- *The ESG mirage*, "There is virtually no connection between MSCI's 'better world' marketing and its methodology. That is because ratings do not measure a company's impact on the Earth and society. In fact, they gauge the opposite: the potential impact of the world on the company and its shareholders. MSCI does not dispute this characterization".[7] Furthermore, according to the MSCI ESG Ratings Methodology, the E pillar score is based on exposure scores and management scores. The first measures the effect of the environment on the firm, while the second gauges the level of preparation for environmental-related risks. The MSCI E-score measures a firm's readiness to handle climate risks and exposure. It assesses firm-level vulnerability to climate effects and the preparedness of management to deal with these exposures.

Furthermore, according to Berg et al. (2022), the MSCI ESG rating exhibits a greater divergence from other prominent ESG rating agencies due to heterogeneity in scope, measurement and weighting. Other ESG rating systems, however, focus on measuring greenness. This explains why the MSCI E score has the lowest correlation with the E scores assigned by other ESG assessors. In particular, Berg et al. (2022) report that the correlation between the MSCI E score and other ESG E scores is below 0.37. In contrast, the correlation between the Moody and S&P E scores is 0.7. As an illustration of how different ESG ratings prioritize different aspects within the same category, Table III of Berg et al. (2022) offers a comparison of indicators that rating agencies assign to the water category. Refinitiv's water category assigns indicators including Emission

[7] https://www.bloomberg.com/graphics/2021-what-is-esg-investing-msci-ratings-focus-on-corporate-bottom-line/

Reduction/Discharge into the Water System, Resource Reduction/Water Recycling, and Resource Reduction/Water Use. In contrast, the MSCI water category score is related to the firm's water stress management capacity.

3.2 MSCI E and corporate climate risk exposure

To further establish the fact that the MSCI E score is more about climate preparation and less about exposure to climate risk, we source data on exposure to climate risk from Sautner, Van Lent, Vilkov, and Zhang (2023). We estimate fixed-effect panel regression with MSCI E as the dependent variable and exposure to physical shocks, denoted by ph_expo_ew, as the predictor. The results of the panel regressions of individual stock MSCI E scores by quarters on ph_expo_ew are given in Table 1.

Although there is a statistically significant relationship between exposure to climate risk, measured by ph_expo_ew, and the MSCI E score, the extremely low values of R^2 and negative adjusted R^2 indicate that this relationship accounts for virtually none of the variation in the MSCI E score. This suggests that the MSCI E score may primarily reflect climate risk preparation or other factors, rather than direct exposure to climate risk.

Table 1 MSCI E and climate risk exposure. We estimate quarterly panel regressions using data from Q4 2012 through Q4 2022. The dependent variable is MSCI E, and the independent variable is ph_expo_ew in Sautner et al. (2023).

	Dependent variable:
	E
ph_expo_ew	-228.401^{***}
	(24.002)
Observations	62,355
R^2	0.002
Adjusted R^2	-0.045
F Statistic	90.551^{***} (df = 1; 59599)
Note:	*p<0.1; **p<0.05; ***p<0.01

3.3 Summary statistics of factors

We collect monthly stock returns from the CRSP. Our sample data start in November 2012 and end in December 2022. In line with Pástor et al. (2022), we start from November 2012 because that is the month that the MSCI coverage of firms became more comprehensive. We merge MSCI E-score data with CRSP return data that have share codes 10 or 11, which typically represent common stocks. We also excluded financial firms, identified by SIC codes ranging from 6000 to 6999. To estimate the effect of climate preparedness on the pricing of the cross sections, we construct the climate preparedness factor, the E factor, using the 3 by 2 sorting method in Fama and French (1993). The other four factors, the market factor Mkt, firm size SMB, profitability RMW and investment CMA, come from Kenneth R. French - Data Library.[8]

Panel (A) in Table 2 reports the mean, standard deviation, *t* statistic, and Sharpe ratio of the constructed slope factors from November 2012 to November 2022. As expected, the market factor exhibits the highest Sharpe ratio. In addition, the risk premium of the market factor is the highest. The E factor also has a positive risk premium during the sample period. This observation is consistent with the findings suggested by our theory. In particular, the risk premium is high, second only to the market factor when we exclude the effect of the pandemic, as shown in Panel (B). According to Tollefson (2021), carbon dioxide emissions decreased by 6.4% in 2020 compared to 2019, as the COVID-19 pandemic slowed economic and social activities around the world. During the pandemic, companies were less likely to focus on climate preparation as they struggled with unexpected disruptions to demand and supply chains. Furthermore, the worldwide decline in carbon emissions reduced the probability of climate-related events. As a result, the risk premium for the E factor can be seen to increase markedly when years of the pandemic are excluded.

In terms of correlations, as shown in Table 3 Panel (A), the E factor is most correlated with CMA and least correlated with Mkt. The latter is also true when the years of the pandemic are excluded.

[8] Download from `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

Table 2 Factor premiums: mean, standard deviation, t-statistic, and Sharpe Ratio. Panel (A) shows that E factor has a positive risk premium. The risk premium is high, second only to the market factor when we exclude the effect of the pandemic, as shown in Panel (B).

	Mean	SD	t-statistic	SR
	Panel (A): November 2012 - December 2022			
E	0.09	3.26	0.32	0.01
Mkt	1.01	4.40	2.53	0.22
SMB	-0.04	2.66	-0.15	-0.03
RMW	0.28	2.03	1.53	0.11
CMA	0.13	2.18	0.65	0.03
	Panel (B): November 2012 - December 2019			
E	0.50	2.74	1.70	0.16
Mkt	1.13	3.31	3.18	0.33
SMB	-0.10	2.39	-0.39	-0.07
RMW	0.07	1.45	0.43	0.01
CMA	-0.14	1.47	-0.90	-0.14

Table 3 Correlation matrix of a slope factor set. The E factor is most correlated with CMA and least correlated with Mkt. The latter is also true when the years of the pandemic are excluded.

	E	Mkt	SMB	RMW	CMA
	Panel (A): November 2012 - December 2022				
E	1				
Mkt	-0.162	1			
SMB	-0.209	0.308	1		
RMW	-0.323	0.083	-0.383	1	
CMA	-0.519	-0.197	-0.004	0.173	1
	Panel (B): November 2012 - December 2019				
E	1				
Mkt	-0.109	1			
SMB	-0.125	0.314	1		
RMW	-0.232	-0.13	-0.478	1	
CMA	-0.491	-0.197	0.022	0.161	1

4 Factor risk premia

In this section, we estimate the factor risk premia based on the Bayesian method developed by Chib and Zeng (2020). Specifically, let CLP5 factors be potential risk factors in the SDF. Suppose the SDF consists of the risk factors $\boldsymbol{x}_{j,t} : k_{x,j} \times 1$, and a complementary set of factors (the non-risk factors) $\boldsymbol{f}_t \backslash \boldsymbol{x}_{j,t} = \boldsymbol{w}_{j,t} : k_{w,j} \times 1$. Let the SDF be

$$M_{j,t} = 1 - \boldsymbol{\lambda}'_{x,j} \Omega_{x,j}^{-1} \left(\boldsymbol{x}_{j,t} - \mathbb{E}[\boldsymbol{x}_{j,t}] \right), \tag{18}$$

where $\boldsymbol{b}_{x,j} \triangleq \Omega_{x,j}^{-1} \boldsymbol{\lambda}_{x,j} : k_{x,j} \times 1$ are the unknown risk factor loadings, and $\Omega_{x,j} : k_{x,j} \times k_{x,j}$ is the covariance matrix of $\boldsymbol{x}_j$. Enforcing the pricing restrictions implied by the no-arbitrage condition

$$\mathbb{E}[M_{j,t} \boldsymbol{x}'_{j,t}] = \mathbf{0} \quad \text{and} \quad \mathbb{E}[M_{j,t} \boldsymbol{w}'_{j,t}] = \mathbf{0}$$

for all t, we get that

$$\mathbb{E}[\boldsymbol{x}_{j,t}] = \boldsymbol{\lambda}_{x,j} \quad \text{and} \quad \mathbb{E}[\boldsymbol{w}_{j,t}] = \Gamma_j \boldsymbol{\lambda}_{x,j},$$

for some matrix $\Gamma_j : k_{w,j} \times k_{x,j}$.

If we assume that the joint distribution of $(\boldsymbol{x}_j, \boldsymbol{w}_j)$ is Gaussian, then the latter pricing restrictions imply that under a marginal-conditional decomposition of the factors, $\mathbb{M}_j$ has the restricted reduced form given by

$$\boldsymbol{x}_j = \boldsymbol{\lambda}_{x,j} + \varepsilon_{x,j}, \tag{19}$$

$$\boldsymbol{w}_j = \Gamma_j \boldsymbol{x}_j + \varepsilon_{w \cdot x,j}, \tag{20}$$

where the errors are block independent Gaussian

$$\begin{pmatrix} \varepsilon_{x,j} \\ \varepsilon_{w \cdot x,j} \end{pmatrix} \sim \mathbb{N}_K \left(\mathbf{0}, \begin{pmatrix} \Omega_{x,j} & \mathbf{0} \\ \mathbf{0} & \Omega_{w \cdot x,j} \end{pmatrix} \right), \tag{21}$$

and $\Omega_{w\cdot x,j} : k_{w,j} \times k_{w,j}$ is the covariance matrix of the conditional residuals $\varepsilon_{w\cdot x,j}$.

We estimate the parameters in Eq. (19) - (21) with the data of the 5 factors as risk factors from November 2012 to December 2019, excluding the impacts of the Pandemic. The posterior means, standard deviations, and quantiles, given in Table 4. Both Mkt and E factors have significant factor risk premia, with both positive 5% quantile and 95% quantile. The marginal distributions of the 5 risk premia parameters are shown in Figure 7.

Table 4 Posterior Statistics of the Risk Premia Parameters in the CLP5 model. The sample ranges from November 2012 to December 2019, excluding the impacts of the Pandemic. These are based on 10,000 MCMC draws, with a burn-in of 1000 draws. This table reports posterior statistics, including posterior mean, posterior standard deviation, posterior median, 5% quantile, and 95% quantile in percentage for the risk premia in λ_x in the CLP5 model with Mkt, E, SMB, CMA and RMW as risk factors. Both Mkt and E factors have significant factor risk premia, with both positive 5% quantile and 95% quantile.

	Posterior mean	Standard deviation	Posterior median	5% quantile	95% quantile
Mkt	0.12	0.04	0.12	0.05	0.20
E	0.10	0.06	0.10	0.01	0.20
SMB	-0.04	0.06	-0.04	-0.15	0.07
CMA	0.03	0.11	0.03	-0.14	0.20
RMW	0.12	0.11	0.12	-0.06	0.29

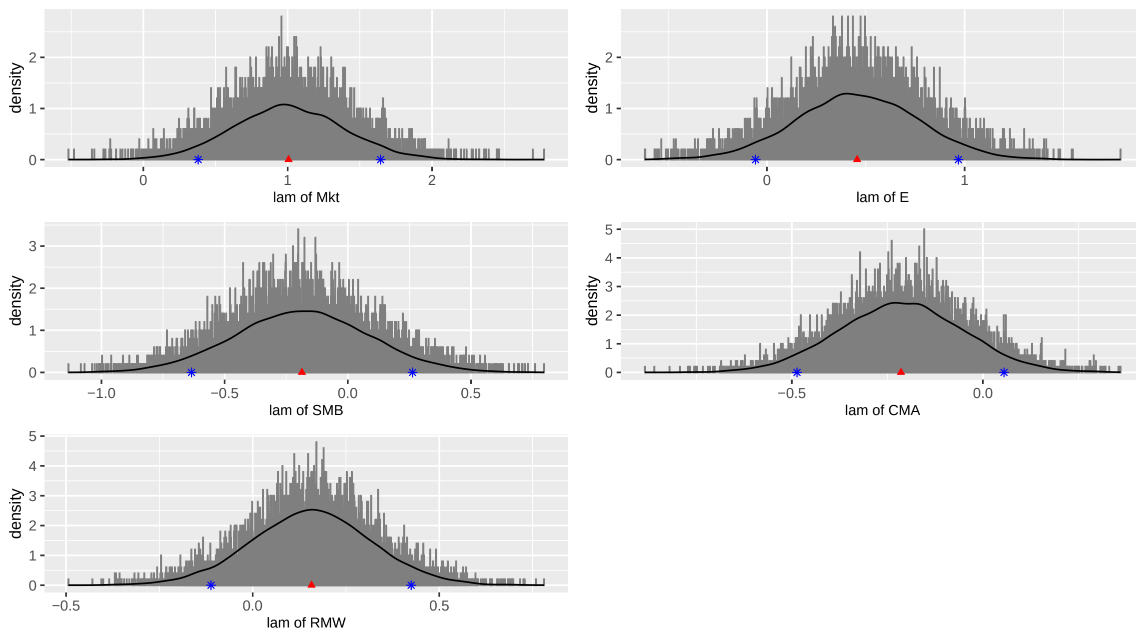

Figure 7 Posterior distribution of the risk premia parameters of the CLP5 model. The sample ranges from November 2012 to December 2019, excluding the impacts of the Pandemic. These are based on 10,000 MCMC draws, with a burn-in of 1000 draws. The error is a multivariate Gaussian distribution. The posterior 0.025 and 0.975 quantities are marked by blue crosses. The posterior means are marked by red triangles.

5 Pricing of the cross-section

Our theoretical model posits that the expected return is influenced by several characteristics of the firm, including the size of the firm, investment, profitability, and readiness for the climate. In terms of factors, the empirical model for pricing assets takes the form

$$Re_{i,t} = \beta_{i,Mkt}\mathrm{Mkt}_t + \beta_{i,e}\mathrm{e}_t + \beta_{i,SMB}\mathrm{SMB}_t + \beta_{i,RMW}\mathrm{RMW}_t + \beta_{i,CMA}\mathrm{CMA}_t + \varepsilon_{i,t} \tag{22}$$

where $Re_{i,t}$ is the excess return on equity of asset i. Mkt denotes the market factor, SMB is the size factor, CMA is the investment factor, RMW is the profitability factor, and e is the climate preparation factor.

5.1 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

$$r^e = \boldsymbol{\beta}_0' \boldsymbol{x}^* + \varepsilon_0, \tag{23}$$

and mispriced if

$$r^e = \alpha + \boldsymbol{\beta}_1' \boldsymbol{x}^* + \varepsilon_1. \tag{24}$$

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, the null is rejected, and the asset is not-priced. In the Bayesian approach, both models are estimated, and the respective log-marginal likelihoods are compared. From this approach, we can obtain evidence in favor of pricing at different levels of posterior confidence. Let m_0 denote the log-marginal likelihood of the regression model that assumes that the asset is priced, and let m_1 denote the log-marginal likelihood of the regression model that assumes that the asset is not priced. Then, the probability that the risk factors price the asset given the data is

$$\Pr(r^e \text{ is priced by } \boldsymbol{x}^* | \text{Data}) = \frac{1}{1 + e^{-d}} \tag{25}$$

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 (25) 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 considered a sample of 2990 stocks (CRSP share codes 10 and 11) with at least 60 months of data from November 2012 to December 2022. Stocks of financial firms (SIC codes 6000-6999), negative book equity, and price per share below \$5 per share are excluded. Given their higher volatility, stocks present a greater challenge for pricing models compared to portfolios. In Table 5 we compare the pricing performance of models with and without the E factor. As can be seen in the table, under the 2:1 criteria, 2439 of 2990 stocks are priced by the model with the E factor, as opposed to 2398 of 2990 stocks without the E factor. The model with the E factor also outperforms other benchmark models.

We apply the same testing approach to a sample of 948 ETFs from November 2012 to December 2022. ETFs are diversified portfolios that are liquid, transparent, and inexpensive 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. 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 holding 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. Additionally, we exclude foreign and global ETFs that have 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 any levered ETFs. The levered ETFs are usually very small compared to their unlevered counterparts. As we see in Table 5, under the 2:1 criteria, the model with the E factor prices 701 of 948 ETFs, compared to 598 of 948 ETFs without the E factor.

Finally, we use two sources of anomalies as test assets. The first set of anomalies comes from Hou, Xue, and Zhang (2020) (HXZ anomalies) covering the period from November 2012 to December 2021. The second set of anomalies comes from decile portfolios in Chen and Zimmermann (2021) (CZ anomalies) covering the period from November 2012 to December 2022. In particular, for anomalies in this source without missing data, we construct long-short portfolios using the top minus the bottom deciles. The comparison results, presented in Table 5, indicate that, while the models with and without the E factor demonstrate similar effectiveness in pricing the CZ anomalies, the model with the E factor outperforms the model without in pricing the HXZ anomalies, at all odds.

Table 5 Bayesian pricing results on a large collection of test assets: # of assets being priced. This table reports the number of priced stocks, ETFs and anomalies for the CLP5 and the CLP4 model. 2990 stocks are obtained from CRSP (with share codes 10 and 11) that have at least 60 months of data from November 2012 to December 2022. Stocks of financial firms (SIC codes 6000-6999), negative book equity, and price per share below $5 per share are excluded. Our 948 ETFs are from the CRSP (share code 73) from November 2012 to December 2022. 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. Additionally, we exclude foreign and global ETFs that have a Lipper Class Name containing a country or global region name or the words "global" or "international". HXZ anomalies come from Hou et al. (2020) (HXZ anomalies) from November 2012 to December 2021 and CZ anomalies are from Chen and Zimmermann (2021) (CZ anomalies), constructed by balanced long-short portfolios using the top minus the bottom deciles from November 2012 to December 2022. The number of priced assets is reported for posterior odds of priced vs not priced of 2:1 and 3:1.

Risk factors set	# priced at 2:1	# priced at 3:1	# priced at 4:1
		2990 Stocks	
CLP5	2439	1996	1488
CLP4	2398	1936	1355
		948 ETFs	
CLP5	701	541	366
CLP4	598	440	283
		188 HXZ anomalies	
CLP5	113	81	50
CLP4	83	56	27
		185 CZ anomalies	
CLP5	108	67	37
CLP4	101	71	40

6 Conclusion

In this paper, we studied the link between firm climate preparation and investment returns in a two-date stochastic general equilibrium model. Although there has been much analysis on how portfolio choices can mitigate climate risks for investors, and the impact these portfolio choices have on financial market prices and returns, the question we address in this paper, related to the impact on the cross-section of returns of actions taken by firms to mitigate or prepare for climate change, is new.

Our analysis is based on a parsimonious model in which 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 model includes a possible climate change-induced event that can occur on the second date and cause firm-specific damage. The firm engages in two distinct investments: investment in climate preparation and physical investment. Our analysis shows that, in equilibrium with an interior solution, the expected return on equity is positively related to the firm's initial climate preparation. Moreover, a high initial climate preparation leads to a low or zero E investment. Those relationships are robust to changes in model parameters.

Our theoretical implications are supported by empirical evidence. Based on the E-score provided by MSCI, a measure that is a suitable proxy for the variable in our model, we construct a climate preparedness factor, the E factor, using the 3 by 2 sorting method. We show that this E factor has a positive risk premium during the sample period, which is consistent with the implications of our theoretical model. This risk premium is high, second only to the market factor when we exclude data from the pandemic years.

Our theoretical model suggests that a five-factor empirical asset pricing model consisting of the market factor and factors corresponding to the E score, profitability, size, and investment, can be used to price traded equity-based assets. On a large set of test assets consisting of stocks, ETFs and portfolios, we show that the model with the E factor improves on the model without the E factor, which supports our theoretical analysis, and the positive role that the E factor can play in pricing the cross-section.

Appendices

A Media Climate Change Concerns

We assume that the climate preparedness function exhibits concavity. Consequently, firms with low e-scores should spend more on the E investment, although such data is not available. To justify this assumption, we examine firm behavior as the probability of a CE changes. Given the concavity of the E investment, firms with low e-scores derive greater marginal benefits from these investments. Therefore, these firms are more likely to increase their climate preparedness efforts when the perceived probability of a CE is high. We employ the climate concern index as a proxy for the probability of a CE. When climate concerns are high, firms anticipate a higher probability of such events.

We hypothesize that firms with low e-scores will respond more positively to increases in the probability of a CE. The rationale is straightforward: as the anticipated probability of a CE rises, firms are more incentivized to invest in climate preparedness. Given the concave nature of the climate preparedness function, firms with low e-scores experience greater marginal returns from these investments.

We use the Media Climate Concerns Index (MCCC) data in Ardia, Bluteau, Boudt, and Inghelbrecht (2023) as a proxy for the probability of a CE.[9] The MCCC is constructed from U.S. newspapers and newswires. Figure A.1 plots the daily MCCC from January 2003 to 2022 August, which exhibits pronounced variability and an upward trend. Additionally, we plot the daily Extreme Weather Index, which is more closely aligned with the concept of climate-related events, in Figure A.2. This index displays a trend similar to that of the MCCC.

We categorize firms into two groups: (1) well-prepared firms with high e-scores, and (2) less-prepared firms with low e-scores. We run regressions on individual stocks within each category.

[9] https://sentometrics-research.com/

The dependent variable is MSCI E, and the independent variables are market value of equity (mve) and MCCC. Our focus is on the MCCC loadings β_{MCCC} for stocks with varying e-scores.

We define the first 20% as the top decile and the last 20% as the bottom decile. To be included in the analysis, a stock must have at least 30 months of observation. There are 309 stocks in the top decile (stocks with high *e*-scores) and 318 stocks in the bottom decile (stocks with low *e*-scores) that meet this criterion. We observe significant positive *MCCC* loadings $\hat{\beta}_{MCCC}$ for less-prepared stocks, as shown in Figure A.3, where the upper panel is the distribution of $\hat{\beta}_{MCCC}$, and the lower panel is the distribution of the t-statistics of $\hat{\beta}_{MCCC}$. For less-prepared stocks, $\hat{\beta}_{MCCC}$ mainly falls between 0 and 1, indicating that stocks of less preparedness to climate risks tend to have high *E* investment when the climate concern is high. However, for stocks with high *e*-score, the MCCC loadings $\hat{\beta}_E$ do not have definite signs. In Figure A.4, the distribution of $\hat{\beta}_E$ ranges from -5 to 10 with its t-statistics from -1 to 8. These results validate our hypothesis that firms with low e-scores will respond more positively to MCCC.

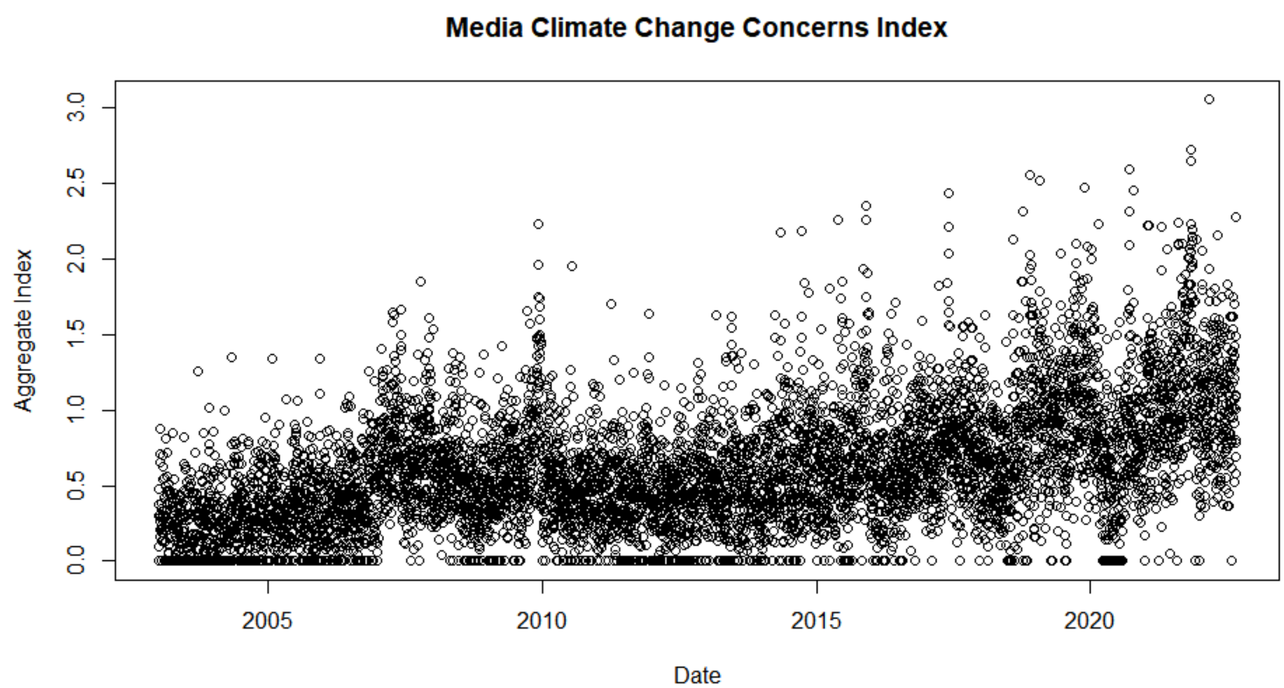

Figure A.1 The Daily Media Climate Change Concerns Index (MCCC): from Jan 2003 to August 2022

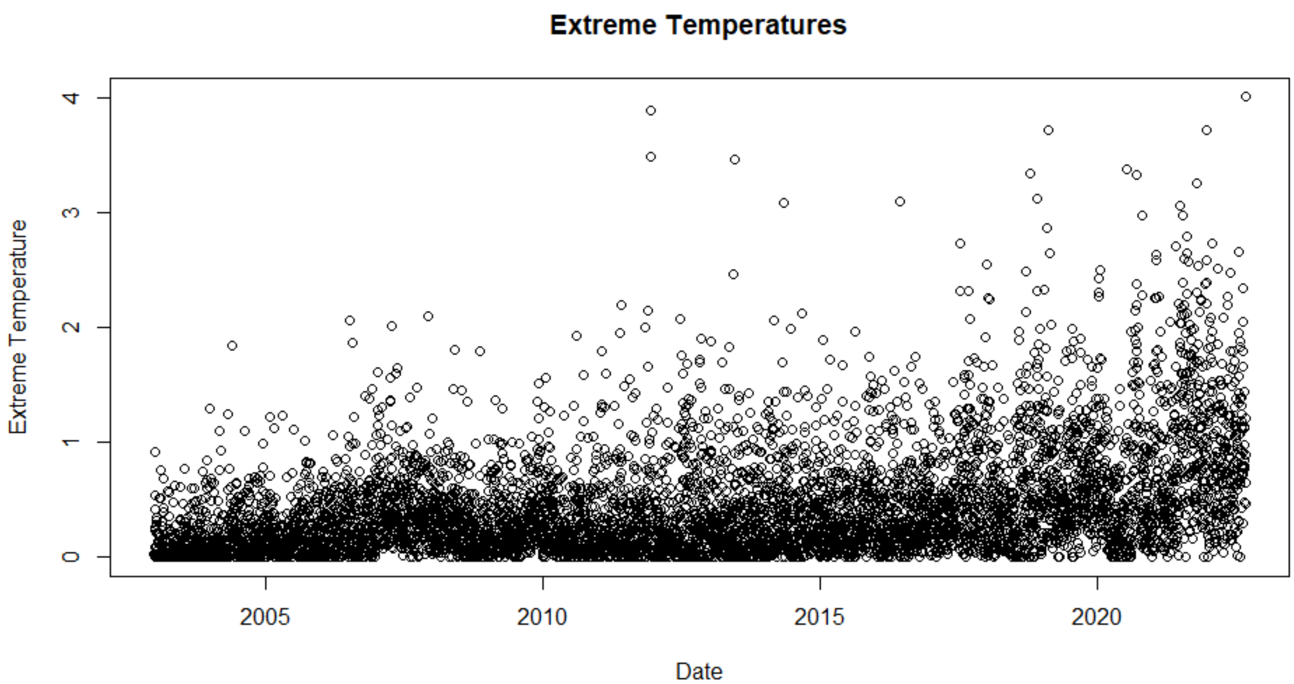

Figure A.2 The Daily Extreme Temperatures Index: from Jan 2003 to August 2022

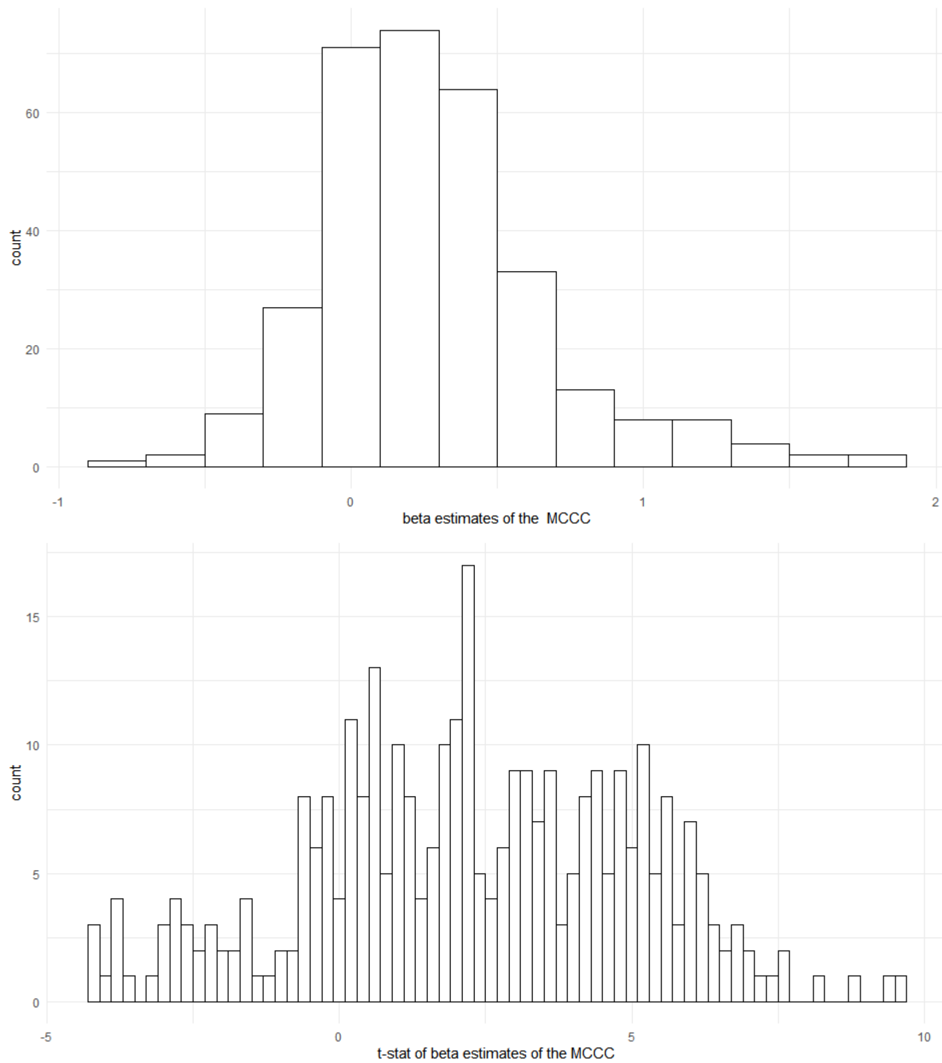

Figure A.3 Low-E stocks (N = 318): The distribution of $\hat{\beta}_{MCCC}$ and its t-statistics of stocks in the bottom E-decile

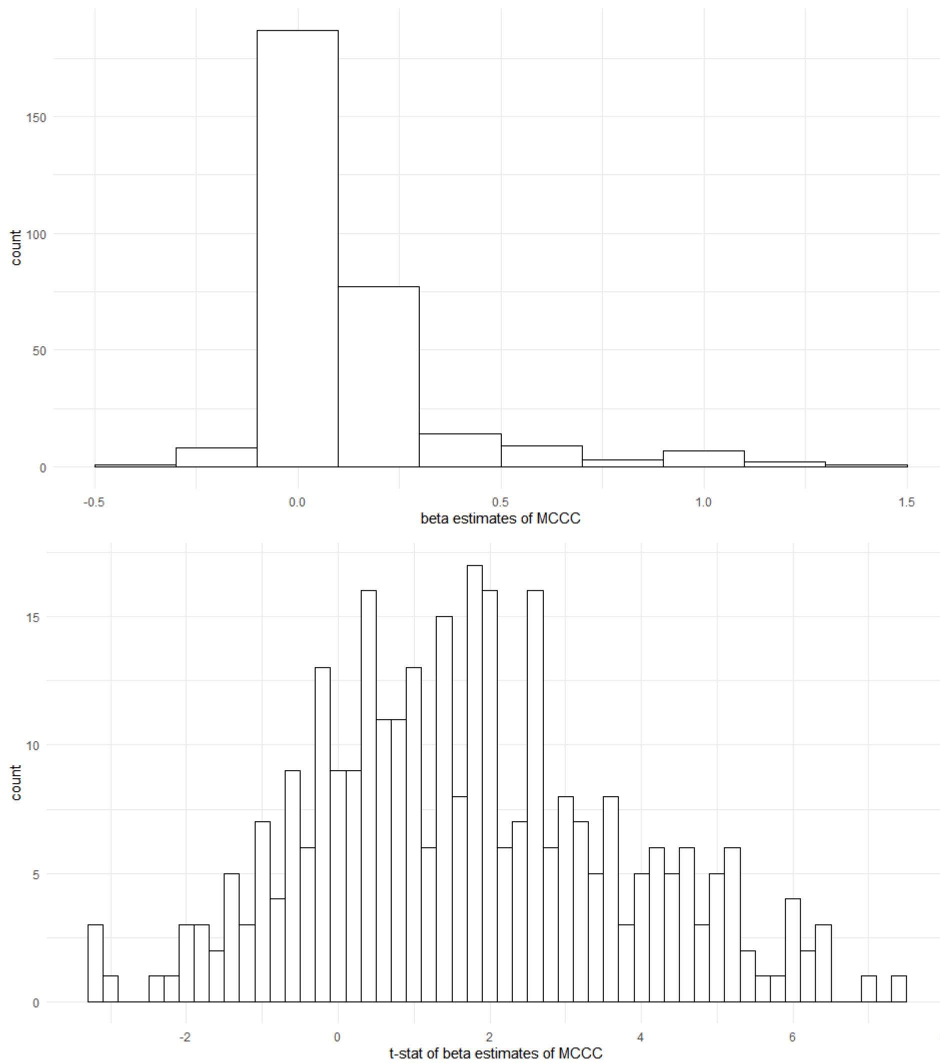

Figure A.4 High-E stocks (N = 309): The distribution of $\hat{\beta}_{MCCC}$ and its t-statistics of stocks in the top E-decile

B Figures

In Section 2.4, we study how firms' climate preparedness influences the expected equity return. In the corner solution where $\{E_0^* > 0, I_0^* = 0\}$, E_0^* is a function of e_0. To examine how $\mathbb{E}[R^E]$ is affected by e_0, it is sufficient to explore the relationship between e_1 and e_0 as $\mathbb{E}[R^E]$ is strictly over e_1. We plot this link in Figure B.1 and observe that e_0 is increasing in e_0.

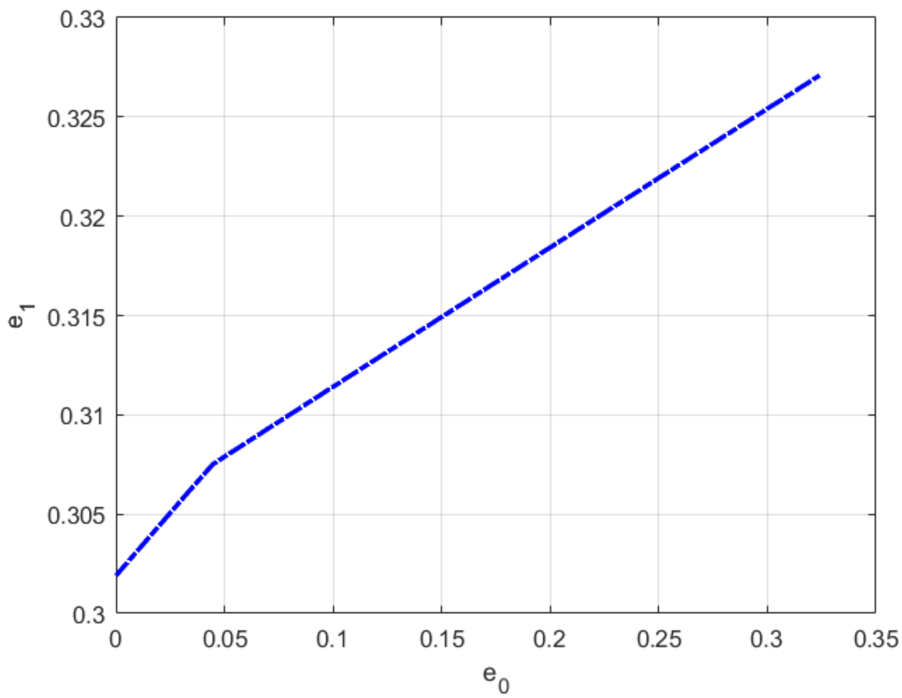

Figure B.1 e_1 in equilibrium. This figure plots how e_1, representing the level of climate preparedness at date-1, varies with e_0 within the range where E_0^* is positive. The parameters are set as follows: $K_0 = 2$, $\Pi = 1.05$, $a = 0.1$, $\beta = 0.98$, $\delta = 0.1$, and $p = 0.2$.

Bibliography

Jawad M Addoum, David T Ng, and Ariel Ortiz-Bobea. Temperature shocks and industry earnings news. *Journal of Financial Economics*, 150(1):1–45, 2023.

G Alekseev, S Giglio, Q Maingi, J Selgrad, and J Stroebel. A quantity-based approach to constructing portfolios to hedge climate risk. *Work. Pap., New York Univ*, 2021.

David Ardia, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632, 2023.

Ronald J Balvers and Dayong Huang. Productivity-based asset pricing: Theory and evidence. *Journal of Financial Economics*, 86(2):405–445, 2007.

Ronald J Balvers, Thomas F Cosimano, and Bill McDonald. Predicting stock returns in an efficient market. *The Journal of Finance*, 45(4):1109–1128, 1990.

Michael Barnett, William Brock, and Lars Peter Hansen. Pricing uncertainty induced by climate change. *The Review of Financial Studies*, 33(3):1024–1066, 2020.

Robert J Barro. Environmental protection, rare disasters and discount rates. *Economica*, 82(325): 1–23, 2015.

Florian Berg, Julian F Koelbel, and Roberto Rigobon. Aggregate confusion: The divergence of esg ratings. *Review of Finance*, 26(6):1315–1344, 2022.

Michele Boldrin, Lawrence J Christiano, and Jonas D M Fisher. Habit persistence, asset returns, and the business cycle. *American Economic Review*, 91(1):149–166, 2001.

Patrick Bolton and Marcin Kacperczyk. Do investors care about carbon risk? *Journal of Financial Economics*, 2021.

Patrick Bolton and Marcin Kacperczyk. Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754, 2023.

Andrew Y Chen and Tom Zimmermann. Open source cross-sectional asset pricing. *Critical Finance Review, Forthcoming*, 2021.

Siddhartha Chib and Xiaming Zeng. Which factors are risk factors in asset pricing? A model scan framework. *Journal of Business & Economic Statistics*, 38(4):771–783, 2020.

John H Cochrane. Production-based asset pricing and the link between stock returns and economic fluctuations. *The Journal of Finance*, 46(1):209–237, 1991.

John H Cochrane. A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104(3):572–621, 1996.

John H Cochrane et al. Financial markets and the real economy. *Foundations and Trends® in Finance*, 1(1):1–101, 2005.

Mariano Massimiliano Croce. Long-run productivity risk: A new hope for production-based asset pricing? *Journal of Monetary Economics*, 66:13–31, 2014.

Energy Policy Institute at the University of Chicago. The true cost of climate pollution: 44% of corporate profits, 2021. URL https://epic.uchicago.edu/news/the-true-cost-of-climate-pollution-44-of-corporate-profits/. Accessed: [2024].

Robert F Engle, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel. Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216, 2020.

EY. Businesses finding unexpected financial benefits from climate initiatives, 2022. URL https://www.ey.com/en_gl/news/2022/11/businesses-finding-unexpected-financial-benefits-from-climate-initiatives. Accessed: [2024].

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56, 1993.

Stefano Giglio, Bryan Kelly, and Johannes Stroebel. Climate finance. *Annual Review of Financial Economics*, 13:15–36, 2021.

Mikhail Golosov, John Hassler, Per Krusell, and Aleh Tsyvinski. Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88, 2014.

Harrison Hong, Frank Weikai Li, and Jiangmin Xu. Climate risks and market efficiency. *Journal of econometrics*, 208(1):265–281, 2019.

Harrison Hong, G Andrew Karolyi, and José A Scheinkman. Climate finance. *The Review of Financial Studies*, 33(3):1011–1023, 2020.

Harrison Hong, Neng Wang, and Jinqiang Yang. Mitigating disaster risks in the age of climate change. *Econometrica*, 91(5):1763–1802, 2023.

Kewei Hou, Chen Xue, and Lu Zhang. Replicating anomalies. *The Review of financial studies*, 33 (5):2019–2133, 2020.

William D Nordhaus. To tax or not to tax: Alternative approaches to slowing global warming. *Review of Environmental Economics and policy*, 2007.

Nora Pankratz, Rob Bauer, and Jeroen Derwall. Climate change, firm performance, and investor surprises. *Management Science*, 2023.

L'uboš Pástor, Robert F Stambaugh, and Lucian A Taylor. Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424, 2022.

Zacharias Sautner, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang. Firm-level climate change exposure. *The Journal of Finance*, 78(3):1449–1498, 2023.

S&P Global. Quantifying the financial costs of climate change physical risks, 2021. URL https://www.spglobal.com/esg/insights/featured/special-editorial/quantifying-the-financial-costs-of-climate-change-physical-risks. Accessed: [2024].

Johannes Stroebel and Jeffrey Wurgler. What do you think about climate finance?, 2021.

Jeff Tollefson. Covid curbed 2020 carbon emissions-but not by much. *Nature*, 589(343), 2021.

United Nations Environment Programme. Climate economics: Costs and benefits, 2021. URL https://eciu.net/analysis/briefings/climate-impacts/climate-economics-costs-and-benefits. Accessed: [2024].

Jules H Van Binsbergen and Ralph SJ Koijen. The term structure of returns: Facts and theory. *Journal of Financial Economics*, 124(1):1–21, 2017.