Climate Risk Preparedness and the Cross Section[*†]

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Abstract

We develop a parsimonious production-based equilibrium model that isolates the insurance channel of climate preparedness and delivers sign-identified predictions for discount rates. Greater readiness lowers required returns, generating a negative premium, whereas physical investment is procyclical and earns a positive premium. Empirically, using TCFD-based textual analysis of 10-K and 10-Q filings, we construct a preparedness proxy that reflects substantive readiness actions rather than generic "climate talk" or exposure. Preparedness predicts lower risk premia, higher subsequent physical investment, and lower subsequent readiness investment, consistent with the model's predictions about the insurance and substitution channels of climate preparedness.

JEL Classification: G11, G12, G14

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1 Introduction

Climate risk has become a first-order driver of firms' investment and risk management decisions. A large and rapidly expanding body of literature examines how investors hedge climate risk in their portfolios and how that demand is reflected in asset prices. Much less is known about how actions taken by firms to reduce climate vulnerability are valued in the cross-section of equity returns. This paper addresses that gap by asking a simple question: in what way do firms' own mitigation actions affect equilibrium expected returns, and can this mechanism help explain differences in expected returns across firms?

Our answer relies on a production-based asset-pricing model in which a representative firm allocates resources between traditional (physical) investment and *readiness* investment that reduces losses in a climate event. Readiness is, economically, an *insurance* technology: it raises cash flows *in bad states* by limiting damage without directly scaling output in normal times. In equilibrium, this insurance property implies a clear pricing sign: preparedness loads positively on the stochastic discount factor (SDF) in disaster states and therefore *lowers* the required return (a negative risk premium). Physical investment, in contrast, is procyclical and commands a positive premium. The firm chooses both margins until the SDF-weighted marginal benefits equal marginal costs, tightly linking preparedness, investment, and expected returns.

We deliberately keep preferences and pricing standard so that the mechanism is transparent. In a two-date general-equilibrium setting with log utility, the SDF is $m = \beta C_0/C_1$, the climate event arrives at $t+1$ with probability p, and readiness e attenuates damage via $d(e) = e^{-e}$ with diminishing returns. The firm's first-order conditions equate SDF-adjusted marginal products of physical and readiness investment. Two immediate testable implications follow. *First*, holding technology and the event probability fixed, greater preparedness (a higher stock of readiness) *reduces* the equity discount rate because it pays off precisely when marginal utility is high. *Second*, comparative statics predict greater readiness (and less physical investment) when the event is more likely or more damaging, sharpening the cross-sectional spread in required returns along

the preparedness dimension.

These theoretical objects map cleanly into standard factor language. The readiness margin has a negative "beta" with respect to bad-state payoff risk (equivalently, a positive covariance with the SDF), so its price of risk is negative, and its required return is below the risk-free rate. The physical margin loads in the opposite direction. Aggregating across margins at the optimum yields an equity discount rate that is decreasing in preparedness and increasing in exposure, a sign prediction we take to the data.

We construct a firm-level proxy for climate preparedness (*crp*) from textual disclosures in 10-K and 10-Q filings.The Task Force on Climate-related Financial Disclosures (TCFD) framework is particularly well-suited for this task because its structured pillars allow us to distinguish between disclosures of climate risk exposure and disclosures that signal tangible investment in preparedness. Our methodology relies on several downstream-task language models, built upon a climate-specific language model, that have been independently validated and show high classification accuracy for identifying climate text and TCFD-specific text (Webersinke, Kraus, Bingler, and Leippold, 2021; Bingler, Kraus, Leippold, and Webersinke, 2024). Specifically, the climate preparedness index counts disclosures that fall under the TCFD's Governance and Risk Management pillars and are simultaneously classified as containing a corporate commitment. Disclosures in these sections are direct evidence of a preparatory framework. They identify the investment in the systems and processes a firm has established to oversee, assess, and manage that risk (e.g., "board oversight of climate risk," "processes for managing climate risk"). By focusing on this process infrastructure, we are able to isolate the costly, tangible investments in the firm's capacity to act. As a result, we are able to filter out generic climate discussions and capture a more credible signal of preparedness.

Our theory yields two empirical implications that we test. First, we examine the real, production-based mechanism. If preparedness works as the model predicts, it should shift firms' investment policies. Using panel regressions, we test whether higher current preparedness leads

to more physical investment (as capital moves from "insurance" to "growth") and less readiness investment (as marginal returns fall). This confirms the intertemporal substitution channel at the core of the model. Second, we test the asset-pricing implication. In Fama and MacBeth (1973) regressions, preparedness, by serving as insurance in adverse states, is associated with lower average excess returns after controlling for firm characteristics.

Our theoretical framework also generates more granular predictions, such as how the required returns on the separate margins of readiness versus physical investment might differ, or how the premium scales with aggregate disaster beliefs. These hypotheses are difficult to test cleanly. The marginal returns on specific investments are not directly observable. Likewise, aggregate disaster beliefs are a difficult-to-observe state variable. We therefore focus this paper on the two most direct and clearly testable implications: the firm's observable real investment behavior and its primary aggregate asset-pricing outcome.

We perform a series of robustness tests to ensure that the premium reflects risk rather than temporary mispricing. First, we test for return reversals. Our Fama and MacBeth (1973) estimates show that the negative association persists well beyond the first year, with no evidence of a subsequent positive reversal in the following three years. The result also holds when using our alternative measure, which is scaled by the climate discussion itself rather than by the total file size. Second, we disentangle our preparedness measure from general climate exposure. The *crp* premium remains negative and significant even when controlling for the full set of physical and transition risk measures from Li, Shan, Tang, and Yao (2024) (LSTY) and Sautner, Van Lent, Vilkov, and Zhang (2023) (SVVZ). Finally, we show that our measure is not redundant with other preparedness-like proxies. Notably, when we include *crp* alongside thematically similar measures, such as LSTY's proactive transition risk (*ln_tran_pro*) or SVVZ's opportunity exposure (*ln_op_expo*), our *crp* index remains priced in the cross-section, while these other measures do not. This distinction reinforces the value of our construction. By sourcing information from 10-K and 10-Q filings and isolating TCFD-based Governance and Risk Management commitments, our index captures a substantive, priced dimension of preparedness not found in earnings call

transcripts.

Finally, we pinpoint the economic channel driving this premium using a time-series return decomposition (Campbell and Shiller, 1988; Vuolteenaho, 2002). A negative premium could theoretically arise either because preparedness lowers the firm's risk (a discount-rate effect, consistent with our insurance mechanism) or because investors expect such investments to dissipate value (a cash-flow effect). Decomposing the variance of our preparedness hedge portfolios at the 12-, 18-, and 24-month horizons reveals a consistent pattern. Across all portfolio definitions, the discount-rate channel is the dominant driver of the premium's variance. For our primary *crp* portfolio, discount-rate news accounts for 66.9% of the variance at the 12-month horizon, and this dominance holds for our other portfolios and at longer horizons. This finding provides evidence that the market prices climate preparedness primarily as a risk characteristic rather than as a signal of future operational performance.

Our paper contributes to two strands of literature. The first strand is climate finance. Giglio, Kelly, and Stroebel (2021a) and Hong, Karolyi, and Scheinkman (2020) review the literature on this rapidly growing field, summarizing theoretical and empirical contributions. On the theoretical side, recent papers include, for example, Barro (2015), Van Binsbergen and Koijen (2017), and Giglio, Maggiori, Rao, Stroebel, and Weber (2021b); and on the empirical side, for example, Bolton and Kacperczyk (2021), Hong, Li, and Xu (2019), Engle, Giglio, Kelly, Lee, and Stroebel (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 based on incentives to invest in climate risk preparation and mitigation, as well as 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) shows 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). We extend these models to tackle the question of how investments in a firm's climate risk preparedness influence asset pricing.

The rest of the paper proceeds as follows. Section 2 develops the equilibrium model, derives the SDF-weighted first-order conditions, and shows that greater preparedness lowers required returns while satisfying intuitive comparative statics. Section 3 details the construction of the preparedness index from TCFD-based textual analysis of 10-K and 10-Q filings. Section 4 presents the empirical analysis: we test both the model's real-investment mechanism and its asset-pricing implications. Section 5 concludes.

2 Theoretical Model

We present a compact two-date general equilibrium model in which a representative firm allocates resources between traditional (physical) investment and climate-readiness investment. Climate readiness, summarized by an E-score, reduces losses in a potential climate event (CE) at $t = 1$. Preferences and pricing are kept standard so that asset-pricing objects follow directly from the stochastic discount factor (SDF). To focus on the economic trade-off (insurance vs. growth), we impose conditions that yield an *interior* solution and avoid corner cases.

2.1 Economic environment

Time is $t \in \{0,1\}$. The representative household owns the representative firm and has time-additive expected utility

$$U \;=\; u(C_0) + \beta\, \mathbb{E}[\,u(C_1(s))\,], \qquad u(C) = \ln C, \quad \beta \in (0,1).$$

The state $s \in \{T,F\}$ indicates whether a climate event occurs at $t=1$; $\Pr(s=T) = p \in (0,1)$ and $\Pr(s=F) = 1-p$. The SDF is

$$m(s) \;=\; \frac{\beta\, u'(C_1(s))}{u'(C_0)} \;=\; \beta\, \frac{C_0}{C_1(s)}. \tag{1}$$

Technology and exposure. The firm starts with capital $K_0 > 0$ and profitability $\Pi > 0$. It chooses physical investment $I_0 \geq 0$ and readiness investment $E_0 \geq 0$. Capital evolves as

$$K_1 \;=\; (1-\delta)K_0 + I_0, \qquad \delta \in (0,1). \tag{2}$$

Readiness is summarized by $e_1 = e_0 + E_0$ with $e_0 \geq 0$. If a CE occurs ($s=T$), a fraction $d(e_1)$ of operating cash flow is destroyed; otherwise ($s=F$) there is no damage. We assume

$$d(e_1) \;=\; e^{-e_1} \in (0,1), \qquad d'(e_1) = -e^{-e_1} < 0, \quad d''(e_1) = e^{-e_1} > 0, \tag{3}$$

so readiness reduces expected damage with diminishing returns. Operating cash flow at $t=1$ is

$$Y_1(s) \;=\; \Pi K_1\,[\,1 - \mathbf{1}_{\{s=T\}}\, d(e_1)\,]. \tag{4}$$

At $t=0$, the firm faces a quadratic adjustment cost in I_0,

$$\mathrm{Adj}(I_0; K_0) \;=\; \frac{a}{2}\Big(\frac{I_0}{K_0}\Big)^2 K_0, \qquad a > 0, \tag{5}$$

and treats E_0 as a direct outlay. Consumption at $t = 0$ equals output net of investments:

$$C_0 \;=\; \Pi K_0 - I_0 - E_0 - \mathrm{Adj}(I_0; K_0). \tag{6}$$

At $t = 1$, household consumption equals firm output $C_1(s) = Y_1(s)$.

2.2 Pricing and the firm's problem

Because the representative household owns the firm, the firm's investment and readiness choices (I_0, E_0) are chosen to maximize the household's expected utility

$$\max_{I_0, E_0} \; u(C_0) + \beta\, \mathbb{E}[\,u(C_1(s))\,], \tag{7}$$

subject to

$$C_0 = \Pi K_0 - I_0 - E_0 - \tfrac{a}{2}\left(\tfrac{I_0}{K_0}\right)^2 K_0, \qquad C_1(s) = Y_1(s) = \Pi K_1[1 - \mathbf{1}_{\{s=T\}} d(e_1)]. \tag{8}$$

This problem internalizes ownership: the household directly chooses investment and climate-readiness spending to balance current consumption against future payoffs in both states.

The first-order condition with respect to a generic control $x \in \{I_0, E_0\}$ is obtained by differentiating the objective

$$0 \;=\; \frac{\partial U}{\partial x} \;=\; u'(C_0)\frac{\partial C_0}{\partial x} + \beta\, \mathbb{E}\left[u'(C_1(s))\frac{\partial Y_1(s)}{\partial x}\right]. \tag{9}$$

The two terms reflect the effect of x on current and future consumption, respectively. Dividing through by $u'(C_0)$ and defining the stochastic discount factor $m(s) = \beta\, u'(C_1(s))/u'(C_0)$ gives

$$0 \;=\; \frac{\partial C_0}{\partial x} + \mathbb{E}\left[m(s)\frac{\partial Y_1(s)}{\partial x}\right]. \tag{10}$$

The first term, $\partial C_0/\partial x < 0$, is the marginal cost of investing in x. It captures the reduction in current consumption. The second term is the expected discounted marginal benefit, which is the increase in future output valued at the household's intertemporal marginal rate of substitution. Rearranging yields the fundamental intertemporal efficiency condition

$$-\frac{\partial C_0}{\partial x} = \mathbb{E}\left[m(s)\frac{\partial Y_1(s)}{\partial x}\right]. \tag{11}$$

This equality states that one unit of consumption forgone today must deliver an expected discounted benefit of exactly one unit in present-value terms.

Since $C_0 = \Pi K_0 - I_0 - E_0 - \frac{a}{2}(I_0/K_0)^2 K_0$, we have

$$\frac{\partial C_0}{\partial I_0} = -\left(1 + a\frac{I_0}{K_0}\right), \qquad \frac{\partial C_0}{\partial E_0} = -1. \tag{12}$$

The marginal effects on future output are

$$\frac{\partial Y_1(s)}{\partial I_0} = \Pi[1 - \mathbf{1}_{\{s=T\}} d(e_1)], \qquad \frac{\partial Y_1(s)}{\partial E_0} = \Pi K_1 \mathbf{1}_{\{s=T\}} e^{-e_1}. \tag{13}$$

Substituting these derivatives into (11) yields the compact FOCs:

$$1 + a\frac{I_0}{K_0} = (1-p)m(F)\Pi + p\,m(T)\Pi[1 - d(e_1)], \tag{14}$$

$$1 = p\,m(T)\Pi K_1 e^{-e_1}. \tag{15}$$

With logarithmic utility, $m(F) = \beta C_0/(\Pi K_1)$ and $m(T) = \beta C_0/[\Pi K_1(1-d(e_1))]$, so the right-hand sides are explicit in (I_0, E_0).

Assumption 1 (Interior solution)**.** *Parameters* $(\Pi, K_0, \delta, a, \beta, p, e_0)$ *lie in a compact set such that* (14)–(15) *has a unique solution with* $I_0^* > 0$*,* $E_0^* > 0$*, and* $C_0^* > 0$*.*

Assumption 1 rules out corner cases and keeps attention on the core trade-off: readiness

spending hedges against the bad state, while capital deepening raises baseline production.

2.3 Comparative statics

Let (I_0^*, E_0^*) solve (14)–(15) under Assumption 1.

Proposition 1 (Comparative statics)**.** *With d given by (3) and log utility*

(a) $\dfrac{\partial E_0^*}{\partial p} > 0$ *and* $\dfrac{\partial I_0^*}{\partial p} < 0$*: a higher CE probability shifts resources toward readiness and away from physical investment.*

(b) $\dfrac{\partial E_0^*}{\partial e_0} < 0$ *and* $\dfrac{\partial I_0^*}{\partial e_0} > 0$*: greater initial preparedness lowers the marginal value of additional readiness and frees resources for capital deepening.*

(c) $\dfrac{\partial E_0^*}{\partial K_0} > 0$ *(more baseline at risk raises the value of protection);* $\dfrac{\partial I_0^*}{\partial K_0}$ *is ambiguous due to the opposing effects of scale and convex adjustment costs.*

Proof. Differentiate (14)–(15) via the implicit function theorem. Monotonicity of d and the SDF components $m(F), m(T)$ (through C_0/C_1 under log utility) delivers the signs. Details are standard and omitted. □

Remark 1 (Economic interpretation)**.** *Readiness E_0 insures the bad state by reducing $d(e_1)$. Because marginal utility is high when output is low, $m(T)$ is large, amplifying the value of readiness. As p rises, the bad state matters more, raising E_0^*. As e_0 rises, diminishing returns (d' less negative) reduce the payoff for additional readiness and tilt toward I_0.*

This model clarifies the readiness-growth trade-off. Readiness investment acts like insurance (it does not raise K_1 directly) but commands a high price through $m(T)$; physical investment raises baseline production but is partially exposed in the bad state. In equilibrium, the firm equates pricing-adjusted marginal returns across the two margins, and comparative statics follow directly from how parameters shift the value of insuring the bad state versus scaling the good and average states.

2.4 Further implications of the model

The first-order conditions (14)–(15) imply that, at the optimum, the marginal cost of each investment equals its expected discounted marginal payoff

$$c_x \;=\; \mathbb{E}\big[m\,G_x\big], \qquad x \in \{I,E\}, \tag{16}$$

where

$$G_I(s) = \frac{\partial Y_1(s)}{\partial I_0} = \Pi[1 - \mathbf{1}_{\{s=T\}}\, d(e_1)], \qquad G_E(s) = \frac{\partial Y_1(s)}{\partial E_0} = \Pi K_1\, \mathbf{1}_{\{s=T\}}\, e^{-e_1}, \tag{17}$$

and $c_I = 1 + aI_0/K_0$, $c_E = 1$ are their respective marginal costs in units of current consumption. These Euler equations can be rewritten in the familiar asset-pricing form

$$1 \;=\; \mathbb{E}\big[mR^x\big], \qquad R^x(s) := \frac{G_x(s)}{c_x}, \tag{18}$$

so that $R^x(s)$ plays the role of the stochastic gross return on margin x. Taking expectations and using $R_f^{-1} = \mathbb{E}[m]$ yields the standard decomposition

$$\mathbb{E}[R^x] - R_f \;=\; -R_f\,\mathrm{Cov}(m, R^x), \qquad x \in \{I,E\}. \tag{19}$$

The pricing identities above allow for a clear interpretation of the two investment margins. Physical investment (I_0) generates payoffs that are high during good times, while readiness investment (E_0) generates payoffs that materialize during bad times when a climate event occurs. Hence, the two margins differ fundamentally in how their payoffs covary with the pricing kernel $m(s)$: one is risk-exposed, while the other provides insurance. The following proposition formalizes this contrast.

Proposition 2 (Insurance versus exposure)**.** *Under log utility and $d(e_1) \in (0,1)$, we have $m(T) >$*

$m(F)$, $G_I(T) < G_I(F)$, *and* $G_E(F) = 0 < G_E(T)$. *Consequently,*

$$\mathrm{Cov}(m, R^E) > 0 \;\Rightarrow\; \mathbb{E}[R^E] < R_f \quad \textit{(readiness provides insurance, lower required return),}$$

$$\mathrm{Cov}(m, R^I) < 0 \;\Rightarrow\; \mathbb{E}[R^I] > R_f \quad \textit{(physical investment is risk-exposed, higher required return).}$$

Proof. With $u(C) = \ln C$, $m(s) = \beta C_0 / C_1(s)$, so $C_1(T) < C_1(F)$ implies $m(T) > m(F)$. Since $G_I(T) = \Pi[1 - d(e_1)] < G_I(F) = \Pi$ and $G_E(F) = 0 < G_E(T) = \Pi K_1 e^{-e_1}$, m and G_E move together (positive covariance) while m and G_I move oppositely (negative covariance). Substituting into (19) gives the stated inequalities. □

Remark 2 (Connection to "negative beta" language)**.** *In linear-factor terms, the readiness payoff loads more in the bad state, so its "beta" with the pricing kernel is* negative *(i.e., positive covariance with m), yielding a* lower *required return. Physical investment loads less in bad times, giving a positive risk premium. This matches the intuition stated earlier and is exactly what the FOCs encode: at the optimum, the m-priced marginal benefits equal marginal costs, but the* physical *expected returns of the two margins differ relative to R_f according to their covariance with m.*

The next result formalizes how greater climate preparedness affects pricing through its impact on the distribution of future payoffs. As readiness investment raises e_1, the bad-state outcome $Y_1(T)$ improves, reducing consumption volatility across states. Because the stochastic discount factor $m(s)$ is inversely related to $Y_1(s)$ under log utility, this compression of payoffs lowers the covariance between m and returns, and hence reduces the equilibrium risk premium. The following lemma makes this relation explicit in closed form.

Proposition 3 (Preparedness lowers the risk premium)**.** *Given $u(C) = \ln C$, $C_1(s) = Y_1(s)$, $m(s) = \beta\, C_0 / Y_1(s)$, and*

$$Y_1(F) = \Pi K_1, \qquad Y_1(T) = \Pi K_1 \,[1 - d(e_1)], \quad d'(e_1) < 0.$$

Let $P_0 = \mathrm{E}[mY_1]$, $R(s) = Y_1(s)/P_0$, $R_f^{-1} = \mathrm{E}[m]$, *and denote probabilities by* $(1-p, p)$. *Then:*

(i) ***Price:*** $P_0 = \beta C_0$ *(independent of* e_1*'s effect on the split across states).*

(ii) ***Risk-free rate:*** $R_f^{-1} = \mathrm{E}[m] = \beta C_0 \left(\frac{1-p}{Y_1(F)} + \frac{p}{Y_1(T)} \right)$ *decreases in* e_1 *(so* R_f *increases).*

(iii) ***Risk premium:*** *The expected* excess *return*

$$\mathrm{E}[R] - R_f \;=\; \frac{1}{\beta C_0} \left(\underbrace{(1-p)\,Y_1(F) + p\,Y_1(T)}_{\textit{arithmetic mean}} \;-\; \underbrace{\frac{1}{\frac{1-p}{Y_1(F)} + \frac{p}{Y_1(T)}}}_{\textit{harmonic mean}} \right)$$

is strictly decreasing *in* e_1, *with* $\mathrm{E}[R] - R_f = 0$ *if and only if* $Y_1(F) = Y_1(T)$.

Proof. (i) With $m(s) = \beta C_0 / Y_1(s)$, $\mathrm{E}[mY_1] = \beta C_0$. (ii) As e_1 increases, $Y_1(T)$ rises, $\Rightarrow \mathrm{E}[m]$ falls, $\Rightarrow R_f$ rises. (iii) For positive numbers, the arithmetic mean $\geq$ is less than the harmonic mean, with strict inequality unless they are equal. As e_1 rises, $Y_1(F)$ and $Y_1(T)$ move closer (dispersion falls), shrinking the A-H gap. Hence, $\mathrm{E}[R] - R_f$ strictly decreases in e_1 and vanishes only when $Y_1(F) = Y_1(T)$. □

The previous result focused on how preparedness affects pricing by compressing the dispersion of payoffs across states. We now turn to the complementary question of how the probability of the adverse state itself shapes the equilibrium risk premium. When natural disasters or climate events are extremely rare, their contribution to aggregate risk is limited. However, as their likelihood rises, even slightly, the covariance between returns and the pricing kernel increases sharply. The next proposition formalizes this comparative-static result, showing that the risk premium rises monotonically with the probability of the bad state.

Proposition 4 (Rare natural disasters and risk premium)**.** *Given* $u(C) = \ln C$, $C_1(s) = Y_1(s)$, $m(s) = \beta C_0 / Y_1(s)$, *and*

$$Y_1(F) = \Pi K_1, \qquad Y_1(T) = \Pi K_1 \left[1 - d(e_1)\right], \quad d'(e_1) < 0.$$

Assume that $Y_1(T) > Y_1(F)$. *Let* $f(p) = \mathrm{E}[R] - R_f$, $D(p) = (1-p)/Y_1(F) + p/Y_1(T)$ *and denote probabilities by* $(1-p, p)$ *with* $p \ll 0.5$. *Then, the risk premium is strictly increasing in* p.

Proof. Taking the excess expected return with respect to p, we have

$$f'(p) = \frac{1}{\beta C_0}(Y_1(T) - Y_1(F))\left[1 - \frac{1}{Y_1(F)Y_1(T)D(p)^2}\right].$$

Setting $f'(p) = 0$ gives

$$D(p) = \frac{1}{\sqrt{Y_F Y_T}} \quad \Longrightarrow \quad p^* = \frac{\sqrt{Y_T}}{\sqrt{Y_1(T)} + \sqrt{Y_1(F)}} > \frac{1}{2}.$$

$f(p)$ is increasing on $(0, p^*)$. □

The preceding two results examined how preparedness and the likelihood of a climate event affect the equilibrium risk premium through changes in payoff dispersion and state probabilities. We now consider how firm characteristics, specifically scale and profitability, enter into this relationship. Larger or more productive firms generate proportionally higher payoffs in all states, which amplifies both the level of consumption and the magnitude of risk compensation required by investors. The next proposition formalizes this homogeneity property, showing that the equilibrium risk premium rises proportionally with firm size (K_1) and profitability (Π).

Proposition 5 (Firm size, profitability and risk premium)**.** *Given* $u(C) = \ln C$, $C_1(s) = Y_1(s)$, $m(s) = \beta C_0 / Y_1(s)$, *and*

$$Y_1(F) = \Pi K_1, \qquad Y_1(T) = \Pi K_1 [1 - d(e_1)], \quad d'(e_1) < 0.$$

Let $f(K_1, \Pi) = \mathrm{E}[R] - R_f$, $C = [(1-p) + p[1-d(e_1)]] - 1/[(1-p) + p/(1-d(e_1))]$ *and denote probabilities by* $(1-p, p)$. *Then, the risk premium is strictly increasing in* K_1 *and* Π.

Proof. Since $Y_1(F) = \Pi K_1$ and $Y_1(T) = \Pi K_1 [1 - d(e_1)]$, the arithmetic-harmonic mean gap is

homogeneous of degree one. Hence, the excess expected return can be written as

$$f(K_1, \Pi) = \frac{1}{\beta C_0} K_1 \Pi C,$$

where $C \geq 0$ and $C > 0$ if and only if $d(e_1) > 0$ (because for positive numbers, the arithmetic mean exceeds the harmonic mean unless the two arguments are equal).

Differentiating,

$$\frac{\partial f}{\partial K_1} = \frac{1}{\beta C_0} \Pi C \qquad \text{and} \qquad \frac{\partial f}{\partial \Pi} = \frac{1}{\beta C_0} K_1 C.$$

Therefore, f is (weakly) increasing in both K_1 and Π, and strictly increasing when $d(e_1) > 0$; it is flat only when $d(e_1) = 0$. □

2.5 Summary and connection to empirics

The theory we have developed provides a coherent set of testable implications. First, comparative statics establish that firms facing greater climate risk or lower initial preparedness allocate more resources toward readiness investment (Proposition 1). Second, the two investment margins differ fundamentally in pricing: readiness delivers payoffs in bad states and therefore commands a lower required return, whereas physical investment is procyclical and earns a positive premium (Proposition 2). Third, greater preparedness compresses payoff dispersion across states, reducing the covariance between returns and the stochastic discount factor, thereby lowering the equilibrium risk premium (Proposition 3). Fourth, as the probability of a climate event rises, the equilibrium risk premium increases monotonically (Proposition 4). Fifth, the magnitude of the premium scales with firm size and profitability, amplifying heterogeneity across firms (Proposition 5).

These results yield two core empirical predictions: preparedness should be associated with lower expected excess returns, and its cross-sectional variation should covary with firms' investment and profitability patterns. The next section describes how we construct a novel firm-level measure of climate risk preparedness from corporate disclosures to test these implications in

the data.

3 Data

A key empirical challenge we address is the absence of any dataset that directly measures firms' climate preparedness, that is, their forward-looking actions to anticipate, mitigate, and adapt to climate risk. Existing proxies, such as carbon emissions, environmental ratings, or textual exposure metrics, capture dimensions of risk or disclosure intensity but not the extent of organizational readiness. To test our model's predictions, we construct a novel firm-level index of climate risk preparedness (*crp*) that quantifies substantive readiness commitments, as opposed to generic "greenness" or exposure. The construction of this variable is described below.

3.1 Construction of climate risk preparedness (*crp*) index

Our textual data consist of corporate financial disclosures filed with the U.S. Securities and Exchange Commission (SEC). We collect all quarterly (Form 10-Q) and annual (Form 10-K) reports available on the SEC's EDGAR system for the period spanning 2003 to 2022. As discussed in Jiang, Lee, Martin, and Zhou (2019), the corporate reporting landscape experienced a significant structural break following the passage of Regulation Fair Disclosure in 2000 and the Sarbanes-Oxley Act (SOX) in 2002. These regulations fundamentally altered the content, quality, and availability of corporate filings.

Unlike LSTY and SVVZ, we focus our textual analysis on formal SEC filings instead of earnings conference calls. Statements made in 10-K and 10-Q filings are subject to a higher degree of legal and regulatory scrutiny. Under Section 10(b) and Rule 10b-5 of the Securities Exchange Act of 1934, material misstatements or omissions in these documents can expose a firm and its management to significant liability, including shareholder litigation and SEC enforcement actions. This stringent legal environment compels firms to be more cautious and precise in their formal

written disclosures. In contrast, while earnings calls are also subject to anti-fraud provisions, their unscripted, real-time nature provides a venue for more qualitative and sometimes aspirational statements that may be characterized as "cheap talk." Since our focus is on capturing tangible investment in climate preparedness, commitments documented in 10-K/10-Q filings constitute higher-cost and, thus, more credible signals of corporate intent than contemporaneous verbal statements made during earnings calls.

To process these filings, we perform the following steps. For HTML files, we parse the raw structure, extracting textual content from common tags (e.g., `<p>`, `<div>`). For plain text files, we reconstruct paragraphs by identifying and joining consecutive lines of text separated by blank lines. For both formats, we filter out non-substantive content by retaining only paragraphs with a minimum length of 100 characters.

Following the cleaning stage, each paragraph is processed through a series of machine learning classifiers built on climate-specific language models. General language models often fail to capture the nuanced and specialized vocabulary prevalent in climate-related corporate disclosures (Webersinke et al., 2021). To overcome this limitation, we use classifiers fine-tuned from ClimateBERT. The foundation of this model is the Bidirectional Encoder Representations from Transformers (BERT) architecture, which later underwent additional domain-specific pre-training on over two million climate-related paragraphs from corporate reports, news articles, and research papers. Webersinke et al. (2021) shows that this domain-adaptive pre-training results in a 48% improvement on a masked language modeling objective and achieves an F1-score of 0.99 on climate-related text classification. Building on this foundation, further fine-tuned models for specific downstream tasks, such as the one developed by Bingler et al. (2024) to classify commitments and actions, have also demonstrated strong performance, achieving an F1-score of 0.81 in manual validation exercises.

The initial classification step determines whether a paragraph is climate-related. For all paragraphs identified as pertinent, we apply a subsequent set of specialized models, similar to the

approach used by Bingler et al. (2024), to classify them along several dimensions: the presence of corporate commitments, the relevant TCFD category (Governance, Strategy, Risk Management, or Metrics and Targets), and the overall sentiment. This hierarchical classification approach generates a paragraph-level dataset, which we then aggregate to the filing level to construct our final firm-date observations for the empirical analysis.

A simple tally of climate-related paragraphs offers a limited view of a firm's climate preparedness, failing to distinguish between disclosures of risk awareness and substantive preparatory actions. To construct a more meaningful measure, we leverage the framework developed by TCFD. The TCFD framework is structured around four core pillars: Governance, Strategy, Risk Management, and Metrics and Targets (Task Force on Climate-related Financial Disclosures, 2023; Bingler et al., 2024).

The TCFD framework provides a critical distinction between disclosures that primarily describe a firm's *climate risk exposure* and those that demonstrate its *climate risk preparedness*. Disclosures of exposure involve identifying and quantifying potential climate-related harms. This includes describing identified risks and opportunities (TCFD Recommendation: Strategy a), assessing their impact on the business (TCFD Recommendation: Strategy b), and reporting relevant metrics, such as GHG emissions (TCFD Recommendations: Metrics and Targets a, b). In contrast, preparedness involves the systems and actions a firm has implemented to monitor and manage those risks. While related, the two are not interchangeable; a firm can disclose extensive exposure without demonstrating any meaningful preparation. Preparedness is not signaled by the mere act of disclosure but by the substantive content described within the specific TCFD pillars. For instance, existence of board oversight (TCFD Recommendation: Governance a), management roles (TCFD Recommendation: Governance b), and the processes for identifying, assessing, and managing climate risks (TCFD Recommendations: Risk Management a, b, c) are direct evidence of a preparatory framework. These elements point to tangible investments in established processes necessary to address climate challenges.

To illustrate this distinction in practice, consider two disclosures from Etsy, Inc. In its 2016 10-K, the company includes a standard risk factor paragraph:

"Natural disasters and other adverse weather and climate conditions...could disrupt our operations...For example, when Hurricane Sandy struck New York in October 2012, our headquarters in Brooklyn were closed for five days...If any of these events occur, our business could be adversely affected." 2016 10-k Etsy, Inc.

Our classification pipeline correctly identifies this text as climate-related, but it does not contribute to the *crp* index. It is categorized under the TCFD's "Strategy" pillar as it describes the impact of risks on the business and is not flagged by our model as containing a commitment. This is an example of disclosing risk exposure, a form of general "climate talk" that acknowledges a vulnerability without detailing investments or efforts to manage it.

In contrast, a section from Etsy's 2018 10-K details specific goals and actions:

"Utilize and source energy responsibly so that we can power our operations with 100% renewable electricity by 2020 and reduce the intensity of our energy use by 25% by 2025...In February 2019, we announced that we would offset 100% of our emissions from shipping through investment in verified emissions reductions..." 2018 10-k Etsy, Inc.

This disclosure is also identified as climate-related, but it is counted in our *crp* index. It falls under the "Risk Management" TCFD pillar and is classified as a commitment. The text moves beyond acknowledging risk to articulating a concrete, measurable plan for readiness. This contrast highlights the ability of our framework to filter out generic risk exposure and isolate the disclosures that signal tangible investment in preparedness, which involves actions that fall under the TCFD framework, in addition to a clear commitment.

Based on this distinction, we construct our index of climate risk preparedness by focusing on disclosures that most credibly signal action. While elements such as strategy, resilience, and targets are important outputs of this capacity, the core infrastructure for preparedness is detailed in the Governance and Risk Management pillars. These disclosures describe the systems a firm

establishes to oversee, identify, assess, and manage climate-related risks. To further refine our measure and ensure we are capturing intended action rather than passive description, we count only those paragraphs within these two pillars that are also flagged by the classifier as containing a corporate commitment. We call this measure the Climate Risk Preparedness, or *crp*, defined as follows:

$$crp_{i,f} = \frac{\sum_{p=1}^{N_f} \mathbb{I}(\text{TCFD_Pillar}_p \in \{\text{Governance, Risk Management}\}) \times \mathbb{I}(\text{Commitment}_p = 1)}{\text{Size}_{f,\text{KB}}} \tag{20}$$

$$crp_{i,t} = \frac{1}{K} \sum_{k=0}^{K-1} crp_{i,f_{t-k}} \tag{21}$$

where $crp_{i,f}$ is the preparedness score for firm i in a single filing f, calculated by summing an indicator function ($\mathbb{I}$) over all paragraphs p in the filing (up to N_f). The indicator equals one if a paragraph's TCFD classification, TCFD_Pillar_p, is either Governance or Risk Management and is also identified as containing a commitment. Size is the size of the file in kilobytes. The final index, $crp_{i,t}$, is the average of these scores across the K most recent filings available for firm i over the past four quarters.

To ensure our results are not driven by the choice of scaling by the overall document size, we construct an alternative preparedness measure, $crp_alt_{i,t}$. This measure retains the same numerator as $crp_{i,f}$—the count of paragraphs signaling a commitment within the Governance or Risk Management pillars—but scales it by the total number of climate-related paragraphs in the filing rather than by file size. This alternative index captures the *proportion* of a firm's climate discussion that is dedicated to substantive preparedness actions. It is defined as:

$$crp_alt_{i,f} = \frac{\sum_{p=1}^{N_f} \mathbb{I}(\text{TCFD_Pillar}_p \in \{\text{Governance, Risk Management}\}) \times \mathbb{I}(\text{Commitment}_p = 1)}{\sum_{p=1}^{N_f} \mathbb{I}(\text{Climate}_p = 1)} \tag{22}$$

$$crp_alt_{i,t} = \frac{1}{K}\sum_{k=0}^{K-1} crp_alt_{i,f_{t-k}} \tag{23}$$

This methodology allows us to isolate disclosures that articulate a clear act or intent to act within an established framework, providing a proxy for climate risk preparedness as opposed to mere risk exposure disclosure or general climate-related discussions. While works like SVVZ and Ilhan, Krueger, Sautner, and Starks (2023) use textual analysis to quantify a firm's exposure to climate risk, our *crp* index is designed to distinguish this awareness of risk from the establishment of a framework for managing it. By focusing on disclosures within the Governance and Risk Management pillars that also contain a clear commitment to act, our measure isolates signals of substantive preparedness, ie., the systems, processes, and stated intentions to manage climate challenges, rather than simply the volume of discussion about climate issues.

In addition to preparedness, we measure the overall tone of a firm's climate disclosure by constructing a climate sentiment index (*Sent*). This index represents the difference between the number of paragraphs classified as conveying climate-related opportunities and those conveying risks, scaled by the document's length. A higher value indicates a more optimistic framing of climate issues. We define this measure as follows:

$$sent_{i,f} = \frac{\sum_{p=1}^{N_f}\left(\mathbb{I}(\text{Opportunity}_p = 1) - \mathbb{I}(\text{Risk}_p = 1)\right)}{\text{Size}_{f,\text{KB}}} \tag{24}$$

$$sent_{i,t} = \frac{1}{K}\sum_{k=0}^{K-1} sent_{i,f_{t-k}} \tag{25}$$

where $sent_{i,f}$ is the net sentiment score for firm i in a single filing f, calculated by summing an indicator function ($\mathbb{I}$) for all paragraphs mentioning a climate opportunity and summing an indicator function for all paragraphs mentioning a climate risk over all paragraphs p in the filing (up to N_f). Then we take the difference and scale by file size. The final $sent_{i,t}$ is the average of these scores across the K most recent filings available for firm i over the past four quarters.

Finally, to capture the extent of general climate discussion not involving investment, we create

a measure of non-specific climate content (*climate_general*) as follows:

$$climate_general_{i,f} = \sum_{p=1}^{N_f} \mathbb{I}(\text{Climate}_p \notin \text{Commitment}) \tag{26}$$

$$climate_general_{i,t} = \frac{1}{K} \sum_{k=0}^{K-1} climate_general_{i,f_{t-k}} \tag{27}$$

where $climate_general_{i,f}$ is the number of climate-related paragraphs that do not have a commitment for firm i in a single filing f. The final $climate_general_{i,t}$ is the average of these scores across the K most recent filings available for firm i over the past four quarters.

3.2 Climate risk data

The recent climate finance literature has made advances in capturing climate risk exposure using textual analysis of corporate disclosures. LSTY measures various aspects of climate risk from earnings call transcripts by manually constructing and validating dictionaries to identify climate-related discussions in earnings calls. Their methodology distinguishes between physical and transition risks. Physical risk corresponds to the potential for damage. More specifically, *phy_risk_acute* captures discussions of acute events like hurricanes and wildfires. *phy_risk_chronic* captures longer-term issues, such as abnormal temperatures and precipitation. LSTY constructs another set of variables focused on opportunities and risks arising from the shift to a greener economy. They decompose this measure into two components based on the firm's tone. *tran_pro* identifies firms that discuss transition risk using active language (e.g., "build", "invest") and *tran_npro* captures discussions without such active language. The *tran_pro* can be viewed as an alternative climate readiness measure, similar to our *crp* measure. We examine the asset pricing implications of these two variables side-by-side in our analysis.

SVVZ developed a set of climate risk measures using machine learning to discover climate-related phrases from a global sample of earnings call transcripts. Their focus is on the attention paid

to climate change by market participants. *cc_expo* captures the overall frequency of climate-related discussions. They further decompose this measure into three distinct themes: *phy_expo* captures physical climate shocks, such as wildfires; *op_expo* captures the upside potential from climate change, such as developing green technologies; and *rg_expo* captures risks from climate-related policies, such as carbon taxes or cap-and-trade schemes. Again, *op_expo* should be related to climate preparedness, and we therefore examine its implications side by side with our *crp* measure in our analysis.

We include these measures from LSTY and SVVZ as they represent the closest thematic proxies for proactive climate action in the existing literature. However, our *crp* index is designed to be fundamentally distinct and, we argue, theoretically better suited for capturing substantive preparedness. First, our index is derived from 10-K and 10-Q filings, which are subject to higher legal and regulatory scrutiny than the earnings call transcripts used to construct the LSTY and SVVZ measures. This sourcing is chosen to mitigate potential "cheap talk" and capture more credible, high-cost signals. Second, our measure is explicitly grounded in the TCFD framework, a global standard that provides a clear structure for what constitutes meaningful preparation. By focusing specifically on the "Governance" and "Risk Management" pillars, we isolate the procedural and structural investments firms make, which is a more targeted approach than identifying proactive verbs (*ln_tran_pro*) or general opportunity discussions (*ln_op_expo*). Finally, our index imposes an additional filter by requiring these TCFD-aligned disclosures to also be classified as a "commitment." This additional step ensures our measure captures substantive intent to act, providing a more robust proxy for the tangible preparedness central to our theoretical model.

3.3 Other data

Our analysis incorporates a set of firm characteristics and market data that serve as control variables in our empirical tests. Monthly stock returns are from CRSP, and accounting variables are from

Compustat. The sample comprises all non-financial and non-utility firms for which the requisite data are available, ensuring broad coverage while avoiding sectors with distinct regulatory and capital-structure regimes. The choice of controls follows the established literature on the cross-section of stock returns, notably the study by Green, Hand, and Zhang (2017).

These characteristics can be broadly categorized as follows. Firm size is proxied by the natural logarithm of market equity (*ln_mve*), and value by the (log) book-to-market ratio (*ln_bm*). To capture the firm's leverage, we use *lev*, which is measured as total debt divided by total assets. Dividend yield *dy* is calculated as dividends per share divided by the stock price. Sales growth (*sgr*) captures the firm's annual sales growth, while operating profitability (*operprof*) follows Fama and French (2015) and is defined as revenue minus the cost of goods sold, minus SG&A expenses and interest expenses, divided by lagged common shareholders' equity. We also include R&D expenses scaled by assets (*rd_assets*) to account for innovation intensity. To control for momentum effects, we include the 12-month momentum (*mom12*), calculated as the cumulative return from month $t-12$ to $t-2$. We measure idiosyncratic risk by the standard deviation of daily returns over the prior 12 months (*volat*). Finally, we include the natural logarithm of firm age (*ln_age*) to control for life-cycle effects. All accounting-based variables are matched to stock returns with a minimum six-month lag to ensure that the information is publicly available at the time of portfolio formation.

3.4 Summary statistics

Tables 1 and 2 present summary statistics for the climate-related variables derived from our textual analysis and the standard firm characteristics used in our empirical tests, respectively. Our sample covers 6021 unique firms between 2003 and 2024, with available filings and market data.

Table 1 reports the summary statistics of the climate disclosure variables. On average, firms discuss climate with a negative tone (mean paragraph count of 22.41) much more frequently than they discuss climate with a positive tone (9.90). On average, firms disclose 2.78 paragraphs in

which they commit to governance or risk management TCFD recommendations. Our primary measure of climate risk preparedness, *crp* , has a median score of zero, indicating that more than half of the firm-month observations contain no disclosures that signal a commitment within the governance or risk management TCFD pillars. The mean *crp* is 0.4, which means that each filing has 0.4 climate preparedness paragraphs per megabyte. The alternative climate preparedness measure, *crp_alt* has a mean of 0.03, which means that on average, a filing has about 3% of climate-related paragraphs discussing climate preparedness commitments. The climate sentiment index, *sent*, has a mean of -1.94, indicating that the overall tone of climate disclosure tends to emphasize risk more than opportunity.

Table 2 summarizes the firm characteristics for our sample. The average firm has a market capitalization (*mve*) of approximately $6.6 billion and a book-to-market ratio (*bm*) of 0.65. Financially, the average firm is moderately leveraged, with total debt to total assets (*lev*) averaging 2.72. In terms of performance and growth, the average firm exhibits positive annual sales growth (*sgr*) and a 12-month momentum (*mom12*) of 12%. The average dividend yield (*dy*) is low at 2%. The average firm age is about 22 years. The median firm generates operating profits equal to 19% of its book value. Innovation intensity, measured by R&D expenses to assets (*rd_assets*), is 8% on average. Finally, the average stock has a return volatility (*volat*) of 14%.

Table 3 reports pairwise correlations between our climate-readiness index (*crp*) and firm-level climate-risk measures from LSTY and SVVZ. Correlations with *crp* are uniformly small (max = 0.235), underscoring that *crp* captures a distinct disclosure dimension. Our climate-readiness index (*crp*) captures managerial preparedness and mitigation efforts, whereas existing climate-risk indices primarily measure exposure to climate events. Consistent with this distinction, correlations between *crp* and physical-risk exposure are negligible—0.041 with LSTY's acute physical risk (*ln_phy_risk_acute*) and 0.102 with SVVZ's physical exposure (*ln_ph_expo*). Thus, *crp* is not a proxy for weather-event discourse but for structured, managerial responses to climate change.

Our climate-readiness index (*crp*) aggregates a broad spectrum of corporate preparedness

information. Despite some thematic overlap with LSTY's proactive transition risk (*ln_tran_pro*) and SVVZ's opportunity exposure (*ln_op_expo*), *crp* is only modestly correlated with these measures (0.198 and 0.164, respectively). The distinction is conceptual: *ln_tran_pro* flags proactive language, and *ln_op_expo* reflects discussions of green technologies, whereas *crp* isolates formal commitments in 10-K/10-Q filings under the TCFD Governance and Risk-Management pillars. These disclosures are subject to greater legal and regulatory scrutiny than earnings calls. The low correlations indicate that *crp* contributes distinct and novel information on corporate readiness.

4 Empirical Results

We now test the predictions of our theoretical model. Our empirical strategy proceeds in four parts. First, in Section 4.1, we validate the model's internal mechanics by testing its predictions for firms' real investment decisions. We use firm-year panel regressions to show that *crp* positively predicts future physical investment and negatively predicts future readiness investment, consistent with the substitution channel in Proposition 1. Second, in Section 4.2, we test the model's central pricing-implication. Using Fama and MacBeth (1973) cross-sectional regressions, we show that *crp* robustly predicts lower subsequent stock returns at 6-, 12-, and 24-month horizons, confirming the existence of a negative risk premium as predicted by our insurance channel (Proposition 3). Third, in Section 4.3, we establish that our *crp* measure captures substantive readiness, distinct from general climate talk or risk exposure, by showing that our negative premium persists after controlling for other prominent climate measures. Finally, in Section 4.4, we arbitrate between the risk-based and performance-based explanations for this premium. We use a Campbell (1991) return decomposition to show that the *crp* premium is consistently driven by discount-rate (risk) news, not cash-flow news, providing direct support for our model's insurance-based mechanism.

4.1 Climate preparedness, readiness and physical investment

Our theoretical model predicts that firms with higher initial preparedness (e_0) allocate more to physical investment and less to readiness investment (see Proposition 1(b)). The intuition is straightforward: when a firm is already well prepared, the marginal benefit of an additional dollar spent on readiness—an insurance-like outlay—declines. This lowers the shadow value of further preparedness and encourages the reallocation of the capital budget toward growth-oriented physical investment, which enters the risk premium linearly in the model.

First, empirically, this proposition implies a positive association between current preparedness and subsequent physical investment. We test this using firm–year panels where the dependent variables are one-year-ahead physical investment, $invest_{t+1:t+12}$, and asset growth, $agr_{t+1:t+12}$. The measure $invest_{t+1:t+12}$ captures accounting-based additions to capital expenditures and inventory, whereas $agr_{t+1:t+12}$ provides a broader gage of firm expansion. The key regressors are lagged preparedness measures, crp_t and alt_crp_t. Specifically, we estimate

$$Y_{i,t+1:t+12} = \beta\, prep_{i,t} + X'_{i,t}\gamma + \mu_{s(i)\times t} + \varepsilon_{i,t}, \tag{28}$$

with $Y \in \{invest, agr\}$, $prep \in \{crp, alt_crp\}$, and $X_{i,t}$ denoting standard firm controls and textual-analysis controls. Following LSTY, we include interacted industry×time fixed effects ($\mu_{s(i)\times t}$) and compute two-way clustered standard errors (by firm and by year). Under the model, we expect $\beta > 0$ for both dependent variables.

The estimation results for future investment are reported in Table 4. In columns (1) and (2), *crp* is positively and significantly associated with both physical investment and asset growth. Using the alternative index *alt_crp* yields similar results (columns (3) and (4)). All specifications include standard firm and textual controls and interacted industry×time fixed effects, with two-way clustered standard errors by firm and year. The pattern is consistent with the model's central trade-off: as preparedness rises, firms shift resources from insurance-like readiness toward growth-

oriented physical investment.

Second, Proposition 1(b) implies that, empirically, a firm's current level of preparedness should be negatively related to its incremental readiness investment. We test this using firm-year panel regressions, where the dependent variable is the one-year-ahead change in preparedness, measured as $\Delta crp_{t+1:t+12} \equiv crp_{t+1:t+12} - crp_{t:t+12}$ and, alternatively, $\Delta alt_crp_{t+1:t+12} \equiv alt_crp_{t+1:t+12} - alt_crp_{t:t+12}$. Specifically, we estimate

$$\Delta prep_{i,t+1:t+12} = \beta\, prep_{i,t} + X_{i,t}'\gamma + \mu_{s(i)\times t} + \varepsilon_{i,t}, \tag{29}$$

where $\Delta prep_{i,t+1:t+12} \in \{\Delta crp_{i,t+1:t+12}, \Delta alt_crp_{i,t+1:t+12}\}$ and the notation for regressors, fixed effects, and standard errors is the same as above. The model predicts $\beta < 0$.

Table 5 shows that changes in preparedness are negatively predicted by current preparedness. In column (1), $\Delta crp_{t+1:t+12}$ is negatively and significantly associated with crp_t, indicating that firms with higher baseline readiness increase their preparedness by a smaller amount over the subsequent year. Column (2) confirms—and strengthens—this result using the alternative measure: $\Delta alt_crp_{t+1:t+12}$ loads negatively and highly significantly on alt_crp_t. These patterns are consistent with the diminishing marginal returns to readiness investment implied by Proposition 1(b).

4.2 The Negative risk premium for climate preparedness

In this section, we estimate the risk premium associated with firm-level climate risk preparedness. Our index *crp* serves as a proxy for the firm's unobserved preparedness e_1. Proposition 3 shows that preparedness lowers the risk premium. The intuition is that preparedness improves payoffs in bad states; because the stochastic discount factor is higher in those states and is inversely related to payoffs, the covariance falls and the equilibrium risk premium declines.

Empirically, we expect a negative premium on climate preparedness: firms with higher *crp* should earn lower excess returns. To test this hypothesis, we employ the Fama and MacBeth (1973)

methodology. Each month, we estimate cross-sectional regressions of excess returns on climate-preparedness characteristics, alongside standard firm characteristics as controls. Specifically, for each month t and horizon h, let $\text{Ret}_{i,t+1:t+h}$ denote the excess returns over h-month horizons, $x_{i,t}$ the climate preparedness measures (either crp or alt_crp), $W_{i,t}$ the other climate related controls (for instance, $sent$, $\ln(climate_general)$, $\ln(filesize)$); $Z_{i,t}$ the vector of standard firm characteristics, which is summarized in Table 2, and $\mathbb{1}\{i \in j\}$ industry dummies (included when "Industry FEs = YES"). We estimate the monthly cross-section

$$\text{Ret}_{i,t+1:t+h} = \beta_{t,h} x_{i,t} + \gamma_{t,h}^{\top} W_{i,t} + \theta_{t,h}^{\top} Z_{i,t} + \sum_{j} \delta_{j,t,h} \mathbb{1}\{i \in j\} + \varepsilon_{i,t,h}, \tag{29}$$

We report time-series averages of the monthly slopes and compute t-statistics from the time series of the estimated slopes using Newey and West (1987) standard errors.

We start by evaluating whether the documented relation reflects a persistent risk premium rather than transitory mispricing by examining excess returns over 6- and 12-month horizons ($h = 6, 12$ in Eq.(29), respectively). A risk-based interpretation predicts a stable negative association that does not reverse within these windows, whereas temporary mispricing is expected to unwind at shorter horizons. Importantly, we match a firm's stock return to its most recently available annual crp measure, imposing a minimum seven-month lag from the fiscal year-end to ensure availability. To ensure that crp is public information before it is used to forecast returns, we additionally require at least six months between the accounting date underlying crp and the month for which the return is predicted. This process yields a time series of monthly slope coefficients on crp.

Table 6 reports risk premium estimates for crp. Columns (1) to (3) report estimates for the 6-month horizon $Ret_{i,t+h}, h \in [1,6]$ and columns (4) to (6) report estimates for the 12-month horizon $Ret_{i,t+h}, h \in [1,12]$. Across all specifications, including those with the full set of firm characteristics and industry fixed effects, the loading on crp is negative and statistically significant (at least at the 5% level). The magnitude remains meaningful when adding firm characteristics and industry fixed effects, as well as textual controls for sentiment ($sent$), overall climate discussion

(ln _*climate_general*), and filing length (ln _*filesize*). Based on the full specification in Column (6), a one-standard-deviation increase in our *crp* index (0.0017) is associated with a 0.87% lower monthly excess return (-5.107 $\times$ 0.0017), roughly -10% per year on a simple annualized basis. Overall, we conclude that the risk premium on climate preparedness (*crp*) is negative, which is consistent with Proposition 3. Firms with greater climate risk preparedness earn significantly lower subsequent returns, consistent with preparedness functioning as insurance for which investors pay through lower expected returns.

To further probe the persistence of this premium and rule out slow-moving return reversals, we extend our analysis to even longer horizons. If the negative premium were due to temporary mispricing that is slow to correct, we might expect to see a positive reversal in the years following our initial 12-month window. To accommodate long horizons, we consider $Ret_{i,t+h}, h \in [13,24]$ and $Ret_{i,t+h}, h \in [25,36]$ on the left side of Eq.(29), while keeping the right side. Table 7 presents the Fama and MacBeth (1973) estimates for excess returns over the second year ($Ret_{i,t+h}, h \in [13,24]$) and the third year ($Ret_{i,t+h}, h \in [25,36]$) after the crp measurement.

The results provide no evidence of such a reversal. For the second-year horizon in columns (1) to (3), the coefficient on crp is negative and statistically significant in the baseline specification but becomes statistically insignificant after including firm characteristics and industry fixed effects. Moving to the third-year horizon in columns (4) to (6), the coefficients on crp remain negative and are statistically insignificant across all specifications. The lack of any positive and significant coefficients in these subsequent years reinforces our main finding, suggesting that the negative premium is a persistent risk-based phenomenon rather than a temporary mispricing that reverses over time.

For robustness, we consider an alternative measure *alt_crp*. This index scales the number of commitment paragraphs in the Governance and Risk Management TCFD pillars by the total number of climate-related paragraphs, thus focusing the normalization on the scope of the climate discussion itself. A higher alt_crp means a larger share of the firm's climate disclosure is devoted

to concrete actions and governance structures rather than general discussions of climate-related topics. Table 8 reports risk premium estimates for alt_crp. Columns (1) to (3) report estimates for the 6-month horizon $Ret_{i,t+h}, h \in [1,6]$ and columns (4) to (6) report estimates for the 12-month horizon $Ret_{i,t+h}, h \in [1,12]$. The coefficient on *alt_crp* is negative and statistically significant across all specifications, confirming that the negative relationship between preparedness and future returns holds when we normalize by the extent of the climate discussion rather than the overall filing size. Overall, these findings support our result that firms with greater climate risk preparedness earn significantly lower subsequent returns.

4.3 Disentangling preparedness from general climate discussion

A central claim of this paper is that the *crp* index measures a firm's substantive preparedness, distinct from prominent climate-risk exposure and generic climate discourse measures (LSTY and SVVZ). To assess whether the negative premium associated with *crp* reflects preparedness rather than correlated climate exposures, we first re-estimate our baseline models while adding the climate-risk controls from LSTY. Conditioning on these measures allows us to test whether the *crp* premium persists net of both general climate-risk exposure and firms' stated transition posture.

Table 9 presents the results of our Fama and MacBeth (1973) regressions after adding different sets of LSTY variables as controls. In column (1), we additionally control for a set of physical risks, *ln_phy_risk_acute* and *ln_phy_risk_chronic*, derived from earnings-call text that explicitly links acute events (e.g., hurricanes, floods, wildfires) and chronic conditions (e.g., abnormal temperatures), respectively. We interpret these measures as proxies for the firm's underlying exposure to climate risk. In column (2), we include LSTY's transition-risk components-*ln_tran_pro* and *ln_tran_npro*, which split transition discussions into proactive versus non-proactive content based on a curated verb list (e.g., "invest", "build", "integrate", "reduce"). In column (3), we include both physical and transitional risks. Across all specifications, the loading on *crp* is negative and statistically significant, while the coefficients on all these LSTY variables

are statistically insignificant. The empirical results confirm that our constructed preparedness index crp measures a different climate-related dimension, specifically the firm's concrete efforts to mitigate losses from climate-related events.

Importantly, though *ln_tran_pro* also measures some dimension of preparedness, capturing proactive language (e.g., "invest", "build"), the insignificant loadings on *ln_tran_pro* in Columns (2) and (3) confirm that our constructed preparedness index measures a broader and more substantive facet of readiness. This divergence reflects both the source and the method. First, our preparedness index is constructed from corporate financial disclosures filed with the SEC, which are more formal and legally binding compared with the statements in earnings calls used by *ln_tran_pro*. Moreover, while *ln_tran_pro* captures proactive language using a manually constructed dictionary, our *crp* index is built on a multi-layered classification process designed to identify substantive, structured action.

We extend this analysis by controlling for the climate exposure measures from SVVZ. These measures are also derived from earnings call transcripts but use a machine learning approach to capture the degree of attention paid to climate-related topics. Their opportunity exposure measure, *ln_op_expo*, is particularly relevant as it quantifies discussions about green technologies and other climate-related upsides, making it an important conceptual benchmark for our preparedness index.

The results, presented in Table 10, reinforce our main conclusion that our constructed crp index measures a distinct aspect of climate-related topics. The coefficient on *crp* remains negative and statistically significant in both specifications. When controlling for all disaggregated SVVZ measures in Column (2), the *crp* coefficient is negative and statistically significant. This demonstrates that the preparedness premium is robust after controlling for various proxies of climate-related discussion.

4.4 Return decomposition analysis

Our Fama and MacBeth (1973) regressions show that firms with higher *crp* earn lower subsequent returns. This negative premium admits two competing interpretations. One is a risk-based explanation, consistent with our theory (Proposition 3), in which preparedness acts as insurance, making firms safer and lowering their required returns. The other is a performance-based view, where preparedness spending represents corporate inefficiency that leads investors to expect weaker future cash flows.

To distinguish between these channels, we decompose the return premium using the log-linear present-value framework of Campbell and Shiller (1988) and the VAR-based implementation of Campbell (1991). This approach separates the variance of portfolio returns into components driven by news about future cash flows (CF) and news about future discount rates (DR). A premium dominated by DR news supports the risk-based interpretation, whereas one driven by CF news favors the performance or mispricing view.

We apply the decomposition to three portfolios designed to capture the *crp* premium. Because many firms in our sample have a zero *crp* score, we avoid standard tercile or quartile sorts. Our primary portfolio, *crp* (Full Sample), is the monthly value-weighted excess return of firms with positive *crp* scores minus that of firms with $crp = 0$. To examine variation in the intensity of preparedness while retaining cross-sectional richness, we construct two additional hedge portfolios among positive-*crp* firms: *crp50*, defined as the top 50% of positive-*crp* firms minus zero-*crp* firms, and *crp30*, defined analogously for the top 30

We analyze these three return series at the 12, 18, and 24-month horizons, which align with our main Fama and MacBeth (1973) tests. Following the methodology in our code, we use H-month overlapping rolling-window data for all variables. We estimate a first-order VAR for each portfolio and horizon, using a state vector that includes the portfolio's own return, the market return ($CRSP_{vw}$), book-to-market (b/m), inflation ($infl$), and the default spread (dfy). Prior to estimation, all state variables were tested for stationarity, and any non-stationary predictors were included in

the VAR as first-differences. As detailed in the table notes, we follow the Vuolteenaho (2002) method to calculate the percentage shares of cash-flow and discount-rate news.

Table 11 reports the results. The findings are consistent across all portfolios and horizons. In all nine specifications, the discount-rate (DR) channel is the dominant source of variance. For the full *crp* portfolio at the 12-month horizon, DR news accounts for 66.9% of the variance. This pattern holds for the more concentrated portfolios and at longer horizons, reaching 77.7% for the *crp30* portfolio at the 24-month horizon. This provides evidence against a performance-based explanation. The finding that the premium is overwhelmingly driven by discount-rate news is consistent with our risk-based hypothesis. Investors view these prepared firms as safer and, consequently, require lower expected returns to hold them, as predicted by our theoretical model.

5 Conclusion

This paper provides a production-based equilibrium framework to understand how a firm's climate preparedness is priced. We model readiness as an insurance-like investment that pays off in bad states of the world. Our theory delivers clear, sign-identified predictions: preparedness, by reducing downside risk, lowers the firm's required return, generating a negative premium. To test this, we construct a new textual proxy for preparedness, *crp*, from 10-K and 10-Q filings that isolates substantive governance and risk-management actions from generic "climate talk."

Our empirical results validate this framework through three distinct tests. First, we confirm the model's real substitution channel: higher current preparedness predicts significantly more future physical investment and less future readiness investment. Second, we test the model's central pricing implication: in Fama and MacBeth (1973) regressions, *crp* predicts lower subsequent returns at 6- to 24-month horizons, confirming a negative risk premium. This result is robust to controlling for other climate-risk measures.

Finally, we disentangle the source of this premium using a VAR-based return decomposition.

This test confirms that the negative premium is not driven by expectations of poor performance (cash-flow news). Instead, the premium's variance is consistently dominated by discount-rate (risk) news at various longer horizons. This finding provides evidence that the market prices climate preparedness as a risk-mitigating characteristic. By integrating an equilibrium model, a novel textual measure, and a set of empirical tests, we show that the market is pricing the insurance value of corporate climate adaptation.

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Table 1 Climate Related Variables from Textual Analysis

	N	MEAN	P50	P10	P25	P75	P90	STD
climate_action	610,183	2.78	0.00	0.00	0.00	1.00	7.00	8.85
climate_positive	610,183	9.90	1.00	0.00	0.00	9.00	28.00	23.32
climate_negative	610,183	22.41	9.00	0.00	2.00	24.00	55.00	41.46
climate_general	610,183	41.88	14.00	1.00	5.00	39.00	103.00	84.32
file_size in kb	581,844	17951.06	6769.27	1812.89	3090.11	26402.26	45773.17	24511.46
crp	581,844	0.40	0.00	0.00	0.00	0.11	0.84	1.70
crp_alt	556,499	0.03	0.00	0.00	0.00	0.04	0.10	0.08
sent	581,844	-1.94	-0.37	-5.91	-1.86	0.00	0.48	8.14

This table reports summary statistics for the climate-related variables derived from our textual analysis of quarterly (10-Q) and annual (10-K) SEC filings from 2003 to 2022. The statistics are presented at the firm-month level. *crp* is our primary Climate Risk Preparedness index, calculated as the count of paragraphs classified as both a corporate commitment and falling under the TCFD Governance or Risk Management pillars, scaled by the filing size in megabytes. *crp_alt* is an alternative preparedness measure where the same numerator is scaled by the total number of climate-related paragraphs in the filing. *sent* is the climate sentiment index, calculated as the number of climate opportunity paragraphs minus the number of climate risk paragraphs, scaled by file size. The variables *climate_action*, *climate_positive*, *climate_negative*, and *climate_general* represent the raw paragraph counts for each respective classification.

Table 2 Firm Characteristics

	N	MEAN	P50	P10	P25	P75	P90	STD
mve	610,183	6559.56	569.84	39.25	136.22	2412.53	9686.07	41330.03
bm	610,183	0.65	0.40	0.08	0.21	0.69	1.09	26.84
lev	610,183	2.72	0.37	0.06	0.15	0.84	1.81	331.78
sgr	583,556	1.10	0.08	-0.17	-0.02	0.22	0.49	79.27
dy	609,471	0.02	0.00	0.00	0.00	0.01	0.03	1.19
age	610,183	21.68	17.00	5.00	9.00	30.00	48.00	16.62
operprof	607172	0.85	0.19	-0.56	-0.02	0.36	0.64	214.74
rd_assets	601,840	0.08	0.01	0.00	0.00	0.09	0.22	0.23
volat	600,742	0.14	0.12	0.06	0.08	0.17	0.25	0.12
mom12	599,384	0.12	0.12	-0.54	-0.17	0.39	0.73	0.65

This table reports summary statistics for the firm-month sample and for the firm-level control variables used in the analysis. Variables are defined as follows: *mve* is the market value of equity (millions of dollars); *bm* is the book-to-market ratio; *lev* is total debt divided by total assets; *sgr* is the percentage growth in annual sales; *dy* is the dividend yield, calculated as dividends per share divided by the stock price; *age* is the number of years the firm has been covered in CRSP; *operprof* is operating profitability, defined following Fama and French (2015) as revenue minus cost of goods sold, SG&A, and interest expense, all scaled by lagged common shareholders' equity; *rd_assets* is research and development expense scaled by total assets; *volat* is the standard deviation of daily stock returns over the prior 12 months; and *mom12* is the cumulative stock return from $t-12$ to $t-2$.

Table 3 Correlations between *crp* and Climate Risk Metrics from LSTY and SVVZ

Variable	*crp*	*ln_phy_risk_acute*	*ln_phy_risk_chronic*	*ln_tran_pro*	*ln_tran_npro*	*ln_cc_expo*	*ln_ph_expo*	*ln_op_expo*
crp	1							
ln_phy_risk_acute	0.041	1						
ln_phy_risk_chronic	0.053	0.158	1					
ln_tran_pro	0.198	0.053	0.038	1				
ln_tran_npro	0.223	0.055	0.039	0.683	1			
ln_cc_expo	0.235	0.034	0.030	0.561	0.663	1		
ln_ph_expo	0.102	0.010	0.101	0.073	0.089	0.201	1	
ln_op_expo	0.164	0.021	0.010	0.470	0.571	0.899	0.103	1
ln_rg_expo	0.196	0.031	0.021	0.407	0.420	0.516	0.124	0.299

This table reports the correlation matrix for our climate readiness proxy (*crp*) and alternative firm-level climate risk measures from Li et al. (2024) (LSTY) and Sautner et al. (2023) (SVVZ). The LSTY measures capture acute physical risk (*ln_phy_risk_acute*), chronic physical risk (*ln_phy_risk_chronic*), proactive transition risk (*ln_tran_pro*), and non-proactive transition risk (*ln_tran_npro*). The SVVZ measures capture overall climate change exposure (*ln_cc_expo*) and its components related to physical (*ln_ph_expo*), opportunity (*ln_op_expo*), and regulatory (*ln_rg_expo*) aspects. The sample period is from 2003 to 2022.

Table 4 Panel Regressions of Future Investment on Preparedness

Dependent Variable:	(1) $invest_{t+1,t+12}$	(2) $agr_{t+1,t+12}$	(3) $invest_{t+1,t+12}$	(4) $agr_{t+1,t+12}$
crp	5.419***	3.861***		
	(4.26)	(2.91)		
alt_crp			0.042**	0.111*
			(2.64)	(1.88)
sent	-0.592*	0.363	-0.589*	0.338
	(-1.86)	(0.77)	(-1.75)	(0.69)
climate_all	0.006***	0.002	0.010***	0.003
	(4.48)	(1.05)	(6.41)	(0.92)
ln_filsz	-0.001	-0.001	-0.003	-0.003
	(-0.13)	(-0.05)	(-0.74)	(-0.30)
Intercept	0.090	0.197	0.123*	0.237
	(1.40)	(1.27)	(1.84)	(1.46)
Firm Characteristics	YES	YES	YES	YES
Industry × Time FEs	YES	YES	YES	YES
Observations	38,055	38,532	35,002	35,437
Adj. R-sq	0.04	0.06	0.04	0.06

This table reports annual panel annual regressions that relate future investment to climate preparedness measures (*crp* and *alt_crp*). The dependent variables are one-year-ahead investment ($invest_{t+1,t+12}$) and asset growth ($agr_{t+1,t+12}$). All specifications include interacted industry-time fixed effects, firm characteristics and textual analysis variables. The sample covers the period from 2003 to 2024. T-statistics, reported in parentheses, are based on standard errors two-way clustered by firm and year. All independent variables are lagged. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Panel Regressions of Future Change in Preparedness on Current Preparedness

Dependent Variable:	(1) $\Delta crp_{t+1,t+12}$	(2) $\Delta alt_crp_{t+1,t+12}$
crp	-31.991**	
	(-2.65)	
alt_crp		-1.933***
		(-8.02)
sent	-2.346	0.841
	(-0.97)	(0.74)
climate_all	0.028	-0.007
	(0.63)	(-0.44)
ln_filsz	0.423**	-0.065**
	(2.09)	(-2.09)
Intercept	-6.604**	1.168**
	(-2.14)	(2.39)
Firm Characteristics	YES	YES
Industry × Time FEs	YES	YES
Observations	12,512	13,184
Adj. R-sq	0.10	0.03

This table reports panel annual regressions that relate future changes in climate risk preparedness measures to the current climate preparedness measures (*crp* and *alt_crp*). The dependent variables are the one-year-ahead change in the preparedness indices, $\Delta crp_{t+1,t+12}$ and $\Delta alt_crp_{t+1,t+12}$. All specifications include interacted industry-time fixed effects, firm characteristics and textual analysis variables. The sample covers the period from 2003 to 2024. T-statistics, reported in parentheses, are based on standard errors two-way clustered by firm and year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Risk Premium for Climate Risk Preparedness Measure

	(1)	(2)	(3)	(4)	(5)	(6)
	$Ret_{i,t+h}, h \in [1,6]$			$Ret_{i,t+h}, h \in [1,12]$		
crp	-10.696***	-6.613**	-7.536***	-8.980***	-4.962**	-5.107**
	(-3.16)	(-2.50)	(-2.92)	(-2.64)	(-2.06)	(-2.08)
sent			-0.48			0.293
			(-1.26)			(1.02)
ln_climate_general			0.000			0.000
			(-0.16)			(-0.33)
ln_filesize			-0.003***			-0.003***
			(-3.13)			(-3.55)
Intercept	-0.022***	-0.071***	-0.02	-0.023***	-0.084***	-0.043***
	(-3.91)	(-6.81)	(-1.35)	(-3.67)	(-6.93)	(-3.66)
Firm Characteristics	NO	YES	YES	NO	YES	YES
Industry FEs	NO	YES	YES	NO	YES	YES
Adj. R-sq	0.07	0.10	0.11	0.06	0.09	0.10
obs	287,737	260,724	260,724	558,089	506,340	506,340

This table reports the time-series averages of slopes from monthly Fama and MacBeth (1973) cross-sectional regressions. The dependent variables are future monthly excess returns over different horizons. Columns (1)-(3) use monthly returns from 1 to 6 months ahead ($Ret_{i,t+h}, h \in [1,6]$). Columns (4)-(6) use monthly returns from 1 to 12 months ahead ($Ret_{i,t+h}, h \in [1,12]$). In each monthly cross-sectional regression of $Ret_{i,t+h}$ on $crp_{i,t}$, we use the most recently available annual *crp* measure, imposing a minimum seven-month lag from the fiscal year-end. We add firm characteristics as indicated. Columns 3 and 6 add the textual controls. Industry FEs are included as indicated. The sample period is from 2003 to 2024. T-statistics, reported in parentheses, are based on Newey and West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Risk Premium for Climate Risk Preparedness Measure (Long Horizons)

	(1)	(2)	(3)	(4)	(5)	(6)
	$Ret_{i,t+h}, h \in [13,24]$			$Ret_{i,t+h}, h \in [25,36]$		
crp	-6.045**	-2.923	-3.711	-3.647	-1.362	-2.544
	(-2.21)	(-1.17)	(-1.41)	(-1.61)	(-0.81)	(-1.22)
sent			0.177			0.177
			(0.49)			(0.43)
ln_climate_general			0.000			0.000
			(0.53)			(-0.41)
ln_filesize			-0.002**			-0.002***
			(-2.58)			(-4.30)
Intercept	-0.023***	-0.079***	-0.054***	-0.023***	-0.076***	-0.039***
	(-3.70)	(-8.56)	(-4.01)	(-4.94)	(-9.69)	(-3.70)
Firm Characteristics	NO	YES	YES	NO	YES	YES
Industry FEs	NO	YES	YES	NO	YES	YES
Adj. R-sq	0.06	0.09	0.10	0.07	0.10	0.10
obs	494,403	451,823	451,823	442,815	407,138	407,138

This table reports the time-series averages of slopes from monthly Fama and MacBeth (1973) cross-sectional regressions. The dependent variables are future monthly excess returns over different horizons. Columns (1)-(3) use monthly returns from 13 to 24 months ahead ($Ret_{i,t+h}, h \in [13,24]$). Columns (4)-(6) use monthly returns from 25 to 36 months ahead ($Ret_{i,t+h}, h \in [25,36]$). In each monthly cross-sectional regression of $Ret_{i,t+h}$ on $crp_{i,t}$, we use the most recently available annual *crp* measure, imposing a minimum seven-month lag from the fiscal year-end. We add firm characteristics as indicated. Columns 3 and 6 add the textual controls. Industry FEs are included as indicated. The sample period is from 2003 to 2024. T-statistics, reported in parentheses, are based on Newey and West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8 Risk Premium for Alternative Climate Risk Preparedness Measure

	(1)	(2)	(3)	(4)	(5)	(6)
	$Ret_{i,t+h}, h \in [1,6]$			$Ret_{i,t+h}, h \in [1,12]$		
alt_crp	-0.019***	-0.019***	-0.015***	-0.021***	-0.016***	-0.012***
	(-3.07)	(-3.05)	(-2.63)	(-3.60)	(-3.82)	(-2.69)
sent			-0.583			0.179
			(-1.64)			(0.59)
ln_climate_general			-0.001			-0.001
			(-0.87)			(-1.18)
ln_filesize			-0.003**			-0.002***
			(-2.34)			(-2.61)
Intercept	-0.020***	-0.068***	-0.024	-0.022***	-0.084***	-0.053***
	(-4.06)	(-7.10)	(-1.31)	(-3.55)	(-6.49)	(-4.34)
Firm Characteristics	NO	YES	YES	NO	YES	YES
Industry FEs	NO	YES	YES	NO	YES	YES
Adj. R-sq	0.06	0.10	0.11	0.06	0.10	0.10
obs	275,137	249,314	238,904	534,655	484,778	463,946

This table reports the time-series averages of slopes from monthly Fama and MacBeth (1973) cross-sectional regressions. The dependent variables are future monthly excess returns over different horizons. Columns (1)-(3) use monthly returns from 1 to 6 months ahead ($Ret_{i,t+h}, h \in [1,6]$). Columns (4)-(6) use monthly returns from 1 to 12 months ahead ($Ret_{i,t+h}, h \in [1,12]$). In each monthly cross-sectional regression of $Ret_{i,t+h}$ on $alt_crp_{i,t}$, we use the most recently available annual alt_crp measure, imposing a minimum seven-month lag from the fiscal year-end. We add firm characteristics as indicated. Columns 3 and 6 add the textual controls. Industry FEs are included as indicated. The sample period is from 2003 to 2024. T-statistics, reported in parentheses, are based on Newey and West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Future Returns, *crp* and LSTY Climate Risk Measures

	(1)	(2)	(3)
	$Ret_{i,t+h}, h \in [1,12]$		
crp	-5.253**	-4.941**	-5.043**
	(-2.31)	(-2.37)	(-2.41)
ln_phy_risk_acute	0.000		0.000
	(0.12)		(-0.25)
ln_phy_risk_chronic	0.001		0.001
	(1.46)		(1.36)
ln_tran_pro		0.000	0.000
		(-0.29)	(-0.19)
ln_tran_npro		0.000	0.002
		(-0.11)	(0.76)
sent	0.247	0.276	0.276
	(0.62)	(0.70)	(0.70)
ln_filesize	-0.002**	-0.002**	-0.002**
	(-2.30)	(-2.22)	(-2.24)
Intercept	-0.040***	-0.040***	-0.041***
	(-3.60)	(-3.54)	(-3.60)
Firm Characteristics	YES	YES	YES
Industry FEs	YES	YES	YES
Adj. R-sq	0.10	0.10	0.10
obs	368,700	368,700	368,700

This table reports the time-series averages of slopes from monthly Fama and MacBeth (1973) cross-sectional regressions. The dependent variables are future monthly excess returns over different horizons. We use monthly returns from 1 to 12 months ahead ($Ret_{i,t+h}, h \in [1,12]$). In each monthly cross-sectional regression of $Ret_{i,t+h}$ on $crp_{i,t}$, we use the most recently available annual *crp* measure, imposing a minimum seven-month lag from the fiscal year-end. We include a set of climate risk control variables from Li et al. (2024) (LSTY). The LSTY measures include acute physical risk (*ln_phy_risk_acute*), chronic physical risk (*ln_phy_risk_chronic*), proactive transition risk (*ln_tran_pro*), and non-proactive transition risk (*ln_tran_npro*). We add firm characteristics, textual variables and Industry FEs. The sample period is from 2003 to 2024. T-statistics, reported in parentheses, are based on Newey and West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Future Returns, *crp* and SVVZ Climate Risk Measures

	(1)	(2)
	$Ret_{i,t+h}, h \in [1,12]$	
crp	-4.673**	-4.415**
	(-2.13)	(-1.99)
ln_cc_expo	-0.727	
	(-1.07)	
ln_ph_expo		-6.315
		(-0.53)
ln_op_expo		-1.147
		(-1.22)
ln_rg_expo		-6.306
		(-0.76)
sent	0.443	0.485
	(1.06)	(1.17)
ln_filesize	-0.002**	-0.002**
	(-2.21)	(-2.12)
Intercept	-0.042***	-0.044***
	(-3.52)	(-3.51)
Firm Characteristics	YES	YES
Industry FEs	YES	YES
Adj. R-sq	0.11	0.11
obs	401,369	401,369

This table reports the time-series averages of slopes from monthly Fama and MacBeth (1973) cross-sectional regressions. The dependent variables are future monthly excess returns over different horizons. We use monthly returns from 1 to 12 months ahead ($Ret_{i,t+h}, h \in [1,12]$). In each monthly cross-sectional regression of $Ret_{i,t+h}$ on $crp_{i,t}$, we use the most recently available annual *crp* measure, imposing a minimum seven-month lag from the fiscal year-end. We include a set of climate risk control variables from Sautner et al. (2023) (SVVZ). The SVVZ measures capture overall climate change exposure (*ln_cc_expo*) and its thematic components related to physical (*ln_ph_expo*), opportunity (*ln_op_expo*), and regulatory (*ln_rg_expo*) aspects. We add firm characteristics, textual variables and Industry FEs. The sample period is from 2003 to 2024. T-statistics, reported in parentheses, are based on Newey and West (1987) standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11 Campbell-Shiller Time-Series Decomposition

	Horizon (H)	Channel Importance CF (%)	DR (%)
Panel A: *crp* Portfolio (Full Sample)			
crp	12	33.09	66.91
	18	40.72	59.28
	24	47.28	52.72
Panel B: crp30 Portfolio			
crp30	12	45.81	54.19
	18	37.48	62.52
	24	22.27	77.73
Panel C: crp50 Portfolio			
crp50	12	46.78	53.22
	18	42.23	57.77
	24	36.02	63.99

This table presents a Campbell-Shiller variance decomposition for three hedge portfolios designed to capture the *crp* premium. Our primary portfolio, *crp* (Full Sample), is the monthly value-weighted excess return of firms with positive *crp* scores minus that of firms with $crp = 0$. *crp30* and *crp50* are constructed analogously, using the top 30% and top 50% of positive-*crp* firms, respectively, against the $crp = 0$ portfolio. The analysis is conducted at 12, 18, and 24-month horizons using H-month overlapping rolling-window data. We estimate a first-order Vector Autoregression (VAR) for each portfolio, with state variables including the portfolio's own return, the market return ($CRSP_{vw}$), book-to-market (b/m), inflation ($infl$), and the default spread (dfy). Prior to estimation, all state variables are checked for stationarity using an Augmented Dickey-Fuller test and are first-differenced if the p-value exceeds 0.10. The R^2 column reports the R-squared from the VAR's return-forecasting equation. *Channel Importance* (CF % and DR %) is the variance share of cash-flow news (NCF) and discount-rate news (NDR), where the unexpected return is defined as $r_{t,t+H} - E_t[r_{t,t+H}] = \text{NCF}_{t,H} - \text{NDR}_{t,H}$. Following Vuolteenaho (2002), the shares are calculated to sum to 100% as: $\text{CF Share} = \text{Var}(\text{NCF}_{t,H})/(\text{Var}(\text{NCF}_{t,H}) + \text{Var}(\text{NDR}_{t,H})) \times 100\%$, and $\text{DR Share} = 100\% - \text{CF Share}$.