Explaining Greenium in a Macro-Finance Integrated Assessment Model

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ABSTRACT

How do firms' environmental performances affect cross-sectional expected stock returns? Using a third-party ESG score, I find that greener stocks have lower expected returns. This greenium remains significant after controlling for systematic and idiosyncratic risks. Green stocks hedge climate-related disasters, contributing to the greenium. A macro-finance integrated assessment model featuring time-varying climate damage intensity, recursive preferences, and investment frictions quantitatively explains the empirical findings. The model implies a positive covariance between climate damages and consumption, which justifies a high discount rate and a low present value of carbon emission.

Keywords: Climate change, Macrofinance, Greenium

JEL classification: G12, Q43, Q5.

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I. Introduction

Climate change has been accelerating over the last decades. As shown in Figure 1, global temperature has increased around one degree Celsius over the previous forty years, accompanied by an increasing frequency of climate-related disasters. Nordhaus (2019) considers climate change the "ultimate challenge" for economics, as it affects many aspects of human society. Despite a growing literature that studies the socioeconomic impact of climate change, little is known about how climate disasters affect the cross-section of the asset market. Understanding the answer to this question is vital for individual investors to self-insure against climate risk.

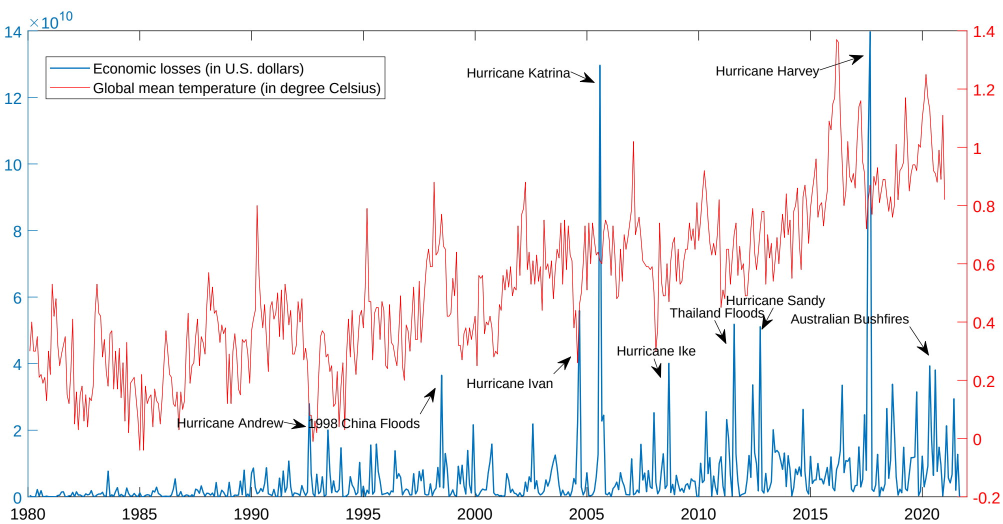

Figure 1: **Global temperature anormaly and economic losses due to climate disasters, 1980-2021**: Economic losses are monthly aggregated across more than 10,000 individual disasters related to climate change. Data collected from the International Disaster Database

This paper addresses two questions. First, given the recent global trend of investing sustainably,[1] what are the asset pricing implications of climate change consequences, such as disasters, on green and brown stocks? I find that, relative to brown stocks, green stocks are less exposed to climate disaster shocks. Thus, a strategy that longs the green and shorts the brown hedges against climate risk. This finding explains the negative *greenium*, i.e., lower expected returns of green stocks, documented by recent literature (Bolton and Kacperczyk, 2021a). Second, how to model climate feedback into the asset market? Current literature on climate economics usually relies on the

[1]For example, the Global Sustainable Investment Review shows that sustainable investing assets in Europe, the U.S., Japan, Canada, Australia, and New Zealand grow from USD 13.3 trillion in 2012 to USD 35.3 trillion in 2020, a 165% increase.

Integrated Assessment Modeling (IAM), such as Nordhaus (1992)'s Dynamic Integrated Climate Change (DICE) model. However, traditional IAM cannot price climate risk in the stock market. To bridge the gap, I provide a unified study that links IAM and production-based asset pricing models to provide a macro-finance IAM (MFIAM). The model simultaneously explains macroeconomic and environmental quantities and asset prices. In sum, my paper offers a detailed study on how climate risks materialize in the cross-section of the stock market.

To begin with, I present evidence of the negative greenium, which identifies the relationship between a firm's greenness and expected stock return. Specifically, I use the environmental pillar score (*ENSCORE*) from Refinitiv ASSET4 ESG Dataset as a measure of greenness (Miroshnychenko et al., 2017; Tarmuji et al., 2016). The ENSCORE covers nearly four thousand global firms as of 2019 and provides a comprehensive measure of firms' environmental responsibilities reflecting three main categories: emission, innovation, and resource use. I sort firms with available ENSCOREs into quintile portfolios from 2003 to 2019. The sorting method eliminates the industry effect and look-ahead bias. I find that the portfolio of stocks in the highest quintile (the green one) has, on average, 3.83% ($t = 2.76$) lower annualized return compared to the portfolio of stocks in the lowest quintile (the brown one). This difference remains significant after controlling for global asset pricing factors such as the CAPM (Sharpe, 1964), the Fama-French three (FF3) and five (FF5) factors (Fama and French, 1993, 2015). Results are robust to alternative greenness measures. These findings indicate a negative premium associated with green stocks, a "greenium."

To eliminate the possibility that firms' idiosyncratic risks drive the greenium, I implement double-sortings with respect to the ENSCORE and firms' financial (such as the size, book-to-market, investment over asset, etc.) and geographic (such as latitude, distance to the sea, exposure to drought risk) characteristics.[2] The greenium survives all double-sortings. Moreover, it is concentrated within big firms. To further illustrate the predictive power of the ENSCORE, I run Fama-Macbeth regression (Fama and MacBeth, 1973) of individual stock return on ENSCORE and various sets of control variables. The result shows that, *ceteris paribus*, a one-standard-deviation increase of a firm's ENSCORE decreases its annual stock return by 0.86% - 1.37% in the next year.

I explain the greenium by showing that greener stocks are less exposed to physical climate

[2]Geographic characteristics control firms' direct exposures to physical climate risks. I show that the greenium is not driven by the fact that green and brown firms locate in areas with different exposures to disasters. In fact, Addoum et al. (2020) find that geographic locations do not matter much when accounting for climate-related damages.

risks. That is, green stocks appreciate during climate-related disasters relative to brown stocks. Specifically, I regress risk-adjusted stock return on the time series of climate damages in Figure 1, and an interaction between the firm's ENSCORE and the damage series. The result shows that both green and brown stocks depreciate during a disaster shock. However, green stocks experience 13% less depreciation than brown stocks. Further investigation shows that it is the firms in the brownest quintile that depreciate the most. To study the real effect of climate risk, I run a similar regression with firm-level investment as the dependent variable. I find that green (brown) firms experience increased (decreased) investments when a climate disaster shock happens. These results are robust with alternative measures and event studies on individual disasters, such as Hurricane Katrina. The evidence presented here clearly shows that green stocks provide insurance against climate-related disasters. Thus investors demand a lower premium from them in equilibrium.[3]

I provide a simple, analytically solvable model to rationalize the above findings. In a two-period production economy, a representative agent optimally allocates investments between a green sector (G) and a brown sector (B). Investing in sector B leads to pollution and climate damage. I assume that an exogenous disaster increases the perception of climate severity and the perceived marginal damage from pollution (i.e., the *damage intensity*). This assumption results from the representative agent's learning process using disasters as signals (Hong et al., 2020; Ortega and Taspınar, 2018; Gibson et al., 2017). In sum, a disaster shock leads to higher perceived marginal costs of investing in sector B. It is then socially desirable to refrain from using fossil fuels and invest more in green energy. Under convex investment frictions from standard q-theory (Hayashi, 1982), this reallocation causes green stocks to appreciate. Consequently, sector G offers insurance for climate disasters and carries a lower premium than sector B. This model qualitatively explains the empirical findings in a simple setting. The main objective is to present a clear underlying mechanism that enables the MFIAM, a more generalized framework, to explain the data quantitatively.

The novelty of my MFIAM compared to traditional IAM lies in three aspects. First, as a dynamic stochastic general equilibrium (DSGE) model, my model accounts for shocks in productivity growth and damage intensity. These shocks are essential to generate the equity premium and

[3]One may argue that the responses of asset prices to disasters reflect investors' expectations of regulatory change (i.e., transition risk). However, previous papers (e.g., Hsu et al., 2020) usually model transition risk as exogenous regulation change and neglect the climate feedback. In this respect, the regulation change induced by disaster is still part of the physical risk. In a follow-up paper, I study the endogenous policy response to natural disasters and consider both transition risk and physical risk in a decentralized economy.

the greenium. Second, borrowing insights from the macrofinance literature, I assume agents have recursive preferences (Epstein and Zin, 1989; Weil, 1990). These preferences generalize constant relative risk aversion (CRRA) preferences and are useful in capturing aversions toward long-run climate risks (Bansal et al., 2016a).[4] Third, investment incurs an adjustment cost following standard q-theory (Jermann, 1998; Zhang, 2005). This cost, along with recursive preferences and long-run productivity risk, justifies equity premium in production economies (Croce, 2014).

My model provides rich implications for investment flows and stock valuations. I provide a novel and comprehensive examination of economic quantities and asset prices' responses to exogenous shocks that degrade environmental conditions (i.e., shocks that increase damage intensity). Specifically, I find that such a shock (i) increases the stochastic discount factor (SDF), indicating a higher marginal utility of consumption or a bad economic state; (ii) promotes a reallocation of both labor and investment toward sector G, indicating that our economy relies more on green energy; (iii) causes Tobin's q in sector G (B) to increase (decrease) due to reallocation adjustment costs, meaning that sector G (B) becomes more (less) valuable. As a result, green stocks appreciate relative to the brown stocks. These findings imply that sector G is safer since it is less exposed to ecological disasters. Thus, green stocks carry lower premium in equilibrium. In sum, my model quantitatively matches multiple aspects of the data, including economic and climate quantities. More importantly, my model improves traditional IAMs by explaining asset pricing facts, such as the equity premium and the greenium. At last, the model generates impulse response functions (IRF) of returns and investments to a disaster shock, consistent with the data.

While capable of explaining key asset pricing facts in the stock market, my model also answers an important open question: what is the sign of the *climate beta*. The climate beta measures the covariance between the future damage flow caused by marginal carbon emission today and future consumption (Giglio et al., 2020). In other words, climate beta captures the riskiness of damage flows and the discount rate to get the shadow cost of carbon emission. The sign of the climate beta is not clear *ex-ante*, with two forces moving in the opposite direction. On the one hand, climate change would cause greater damage in a world with higher GDP or consumption. Thus climate beta tends to be positive. On the other hand, great climate damage causes economic downturns and

[4] This model is based on Bansal et al. (2016a) but differs from theirs in several aspects. First, I introduce carbon-free energy with endogenous R&D. Second, I extend their endowment economy to a production economy. These aspects enable me to shed light on the dynamics of cross-sector investment allocations and stock returns.

lowers consumption, leading to a negative climate beta. Which force dominates the other remains an open question. Calibrated using economic data and asset prices, my model implies a positive climate beta (Dietz et al., 2018; Gollier, 2021), that is, the risk stemming from economic activities overwhelms the risk stemming from the climate process. As such, future climate damages caused by marginal carbon emission are risky and command a positive premium. With given damage flow, this premium depresses the shadow price of carbon substantially (27%) compared to the deterministic equilibrium with zero climate beta. Jaccard et al. (2020) show that the shadow cost of carbon in a centralized economy equals the social cost of carbon (SCC), a Pigouvian tax that corrects the market distortion caused by negative externality due to carbon emission. Therefore, my model implies that it is socially desirable to start with a relatively low carbon tax.[5]

Traditional IAMs usually adopt CRRA preferences due to mathematical tractability. However, CRRA implicitly assumes that agents' risk aversion is reciprocally related to their intertemporal elasticity of substitution (IES). Therefore, a high risk aversion, implied by the equity premium, indicates an unwillingness to substitute across time and thus a counterfactual high risk-free rate. Recent studies used recursive preferences to evaluate the SCC and climate policy from an asset pricing perspective (Ackerman et al., 2013; Jensen and Traeger, 2014; Daniel et al., 2016; Bansal et al., 2016b,a; Lemoine and Rudik, 2017; Lemoine, 2021; Jaccard et al., 2020). These preferences extend CRRA ones by separating the risk aversion from the IES. In line with the long-run risks literature about coping with the equity premium puzzle, I choose an IES larger than the reciprocal of the risk aversion, suggesting that agents prefer early resolution of uncertainty. My model shows that CRRA preference leads to under-reaction of investments and returns to the disaster shock, thus failing to generate a sizeable greenium.

The rest of the paper is organized as follows. In Section II, I discuss my contribution to related literature. Section III provides a concise but informative empirical analysis of the greenium and how green and brown firms respond to climate disaster shocks. Section IV illustrates the economic intuition of the mechanism through a simplified two-period model. In Section V, I present the MFIAM and solve the social planner's optimization problem. Section VI discusses the quantitative

[5]Following mainstream calibration on the magnitude of climate damage, my model implies an SCC equal to 40.4 U.S. dollars per metric ton of carbon (tC). This is about 9 cents per gallon of gasoline. Previous IAMs, which do not account for climate beta, usually generate higher SCC estimates. For example, \$135/tC in Nordhaus (2019) and \$60/tC in Golosov et al. (2014).

results. Section VII summarizes my findings.

II. Contribution to Literature

This paper contributes to the growing literature in the field of climate economics and finance. Existing literature has already found that climate risk materializes in the cross-section of economic sectors (Colacito et al., 2018) and stock market (Bansal et al., 2016a). In addition, stocks with different levels of greenness can be used to hedge climate risk (Engle et al., 2020). However, the literature presents mixed evidence regarding the relationship between a firm's expected stock return and greenness. While one strand of literature finds that being "eco-friendly" is associated with a lower expected return (see, for example, Chava, 2014; Bolton and Kacperczyk, 2021a,b; Hsu et al., 2020), the other reaches an opposite conclusion (see, for example, Guenster et al., 2011; Cai and He, 2014; In et al., 2017). In line with the first strand of literature, I document a negative greenium using a comprehensive greenness measure and a large sample of global firms. The novelty in this paper is to reveal a new channel through which physical climate risks drive cross-section investment flows and asset prices, along with both empirical supports and theoretical considerations.

The literature chiefly explains the green premium through non-pecuniary utility from holding green (Pastor et al., 2019) or environmental policy uncertainty (*transition risks*). For example, Hsu et al. (2020) find that green stock carries a low premium because it is positively exposed to environmental policy shocks (policies that restrain emission). However, their model considers exogenous policy shocks and neglects the climate feedback. Thus it is unclear whether an environmental policy shock is a good or bad shock: in the short run, it could be a bad shock due to higher production cost, while in the long run, it could be a good shock since it alleviates climate-change issues. Other papers that are closely related to mine include Barnett (2017) and Hong et al. (2021). Barnett (2017) explains greenium through aversion to model uncertainty in a production economy. Hong et al. (2021) attribute greenium to firms' endogenous choice of decarbonization due to sustainable finance pledges. My paper offers a new approach to explaining the greenium through green stocks' potential to hedge *physical risks*.[6] Compared to the works mentioned above, my model stands out in two aspects. First, it matches a wide range of economic and environmental quantities and asset

[6] Several papers have explored this potential (e.g., Choi et al., 2020; Engle et al., 2020; Faccini et al., 2021), but none of those studies address the mechanism through which green stock appreciates upon climate-related disasters.

prices. Second, it sheds light on how various macro-finance elements affect the SCC.

Finally, this paper contributes to the literature of IAM, pioneered by the seminal work of Nordhaus (1992) with his DICE model. Other examples of IAMs, to list a few, include WITCH (Bosetti et al., 2006), MERGE (Manne et al., 1995), DEMETER (Van der Zwaan et al., 2002), and ENTICE-BR (Popp, 2006). I provide a first "handy" model to link the literature of IAM with investment-based asset pricing models (Jermann, 1998; Zhang, 2005; Croce, 2014). The model simultaneously matches the cross-sectional asset prices as well as economic and climate dynamics.

III. Empirical evidence

This section documents a greenium in the cross-section of the global stock market and provides evidence that the greenium is not absorbed by common asset pricing factors or firms' idiosyncratic risks. To this end, I first sort firms according to their greenness levels, measured by the environmental pillar score from the Refinitiv (formerly known as Thomson Reuters) ASSET4 ESG dataset.[7] The ENSCORE covers three major categories of firms' environmental responsibility: emission, innovation, and resource use. The score ranges from 0 to 100 and is updated annually. Firms with higher scores are more environmental-friendly. The available data begins in 2002, and the number of firms expanded from 925, in 2002, to 3927 in 2019.

In each year, I sort firms into quintile portfolios, using their ENSCOREs of the last year and relative to their industry peers according to the Fama-French 49 industries classifications.[8] Thus the sorting is based on relative greenness within industries and there is no look-ahead bias. Furthermore, I exclude firms in the finance industry following Hsu et al. (2020) and small firms, i.e., firms with market values smaller than the bottom 20% of all NYSE listed firms, following Engle et al. (2020). I then construct the monthly value-weighted stock returns for all quintile portfolios. I also collect various firm characteristics from the Refinitiv Eikon. I winsorize all variables at the 1% level to mitigate the impact of outliers.

[7]Refinitiv Asset4 ESG score covers around 70% of the world capitalization with over 450 ESG metrics, of which the 186 most comparable measures are sorted into ten category scores (e.g., emission, human rights, management, etc.) and three pillar scores (environmental, social, and governance). The information is mainly collected by Refinitiv from public information, e.g., firms' annual reports, corporate social reports (CRS), company websites, etc. There are over 9000 firms in the Asset4 universe as of July 2020.

[8]The cutoff points are specific for each industry to ensure that each quintile portfolio has a similar number of firms. In addition, I remove industry-year pairs where the number of firms with distinctive ENSCOREs is smaller than 5.

In the rest of this section, I provide several pieces of evidence showing the existence of the greenium. First, I regress portfolio returns on global asset pricing factors to see whether priced systematic risks drive the return differences across portfolios. Second, I implement double sorting to test whether the return difference exists within sub-samples divided by specific characteristics. Third, a Fama-Macbeth regression confirms that the predictive power of ENSCORE on stock return does not depend on firms' idiosyncratic risks, captured by both financial and geographic characteristics. Finally, I show green stocks hedge climate disaster shocks using evidence from panel regression and event studies on major natural disasters. In Appendix A, I implement several robustness tests. First, I show that the greenium exists when focusing on specific aspect of ENSCORE. Second, greenium is not driven by a certain sample period, and exists in a subsample with only U.S. firms. Third, I provide evidence of greenium when using alternative greenness measures, such as the emission intensity and MSCI E-score. In addition, I verify a greenium using ENSCORE before its revision.[9] Fourth, I use a factor-mimicking portfolio to show that the greenium is priced in a broad cross-section of global testing portfolios. This demonstrates that a greenium exists beyond my chosen sample.

A. Portfolio characteristics

Table I shows the time-series average of the cross-sectional mean of firm characteristics in the overall sample and in each quintile portfolio. The table covers both financial characteristics (Panel A) and geographic characteristics (Panel B). The sample period is from 2002 to 2019.

Panel A of Table I shows the financial characteristics including market value, book-to-market ratio, investment over asset,[10] revenue over asset, R&D over asset, PPE over asset, and leverage. Except for market value, all financial characteristics are in an annual frequency. Panel B shows the geographic information, including the latitude, distance to the nearest coast (Dist2Sea), and the trend of Palmer Drought Severity Index (PDSI) (Palmer, 1965) for the cities where firms' headquarter are located. Latitudes are obtained by double matching firms' address cities and

[9] Berg et al. (2020) find substantial rewritings of Refinitiv ESG scores in April 2020, due to changes in scoring methodology. They show that such changes affect tests related to ESG ratings. Therefore, I investigate the greenium using ENSCORE downloaded in February 2020, before the change happens. I thank Quentin Moreau for providing the data.

[10] Investment at year t is defined as change in total asset from year t to year $t+1$ following Fama and French (2015).

countries with those in the World Cities Database.[11] Dist2Sea is collected from NASA.[12] Finally, I follow Hong et al. (2019) to calculate the time trend in the PDSI as a measure of each city's vulnerability to droughts.[13] A lower value in the PDSI means higher vulnerability to droughts. Geographic characteristics are time-invariant during the sample period. The goal of introducing these characteristics is to control the *direct* exposure of each firm to physical climate change risk, so that the result is not driven by firms' geographic proximity to disasters.

In this paper, I define the portfolio with the highest (lowest) quintile of ENSCORE as the *green* (*brown*) portfolio. According to Table I, each quintile portfolio has a similar number of firms. ENSCORE increases monotonically from Quintile 1 to Quintile 5. Portfolios differ in terms of some financial characteristics. The most obvious difference is that greener firms tend to be bigger, which may not be surprising since bigger firms care more about their environmental profiles, and therefore put more emphasis on curbing emissions and utilizing clean energies. Thus they tend to achieve better environmental profiles. In addition, greener firms have smaller investments and R&D over asset. For geographic characteristics, I find that green firms, on average, are located in areas with higher latitude, nearer to the sea, and more vulnerable to droughts. A possible explanation is that green firms tend to settle in relatively developed areas, which have high latitudes and often are near the sea. These facts indicate that green firms may intrinsically have different exposures to physical climate risks, due to their geographic locations. However, I control all these characteristics in the later analyses, i.e., double sorting, Fama-Macbeth regression, and event studies, to ensure that these characteristics do not drive my results.

Finally, Table II shows the first few industries with the highest weights in the green and brown portfolios. The weight is the fraction of firms in a specific industry among all the firms in that portfolio. The top-weighted industries are similar for both brown and green portfolios, indicating that the sorting captures the relative greenness within industries.

[11]`https://simplemaps.com/data/world-cities`. Firms with missing or multiple matches are assigned to the capital of their country of domicile.

[12]`https://oceancolor.gsfc.nasa.gov/docs/distfromcoast/`

[13]PDSI uses temperature and precipitation data to estimate relative dryness. It is constructed by Dai et al. (2004) and collected from the National Center for Atmospheric Research (NCAR): `https://rda.ucar.edu/datasets/ds299.0/index.html#!description`.

Table I: **Portfolio summary statistics**

Quintiles	All	L	2	3	4	H
ENSCORE	30.50	0.13	12.57	27.55	45.09	68.99
Observations	2396	475	479	481	479	482
Panel A. Financial characteristics						
MV (billion $)	12.68	6.23	5.79	10.07	15.04	26.53
BV/MV (%)	58.93	53.77	62.43	60.16	60.06	60.41
I/A (%)	3.30	4.44	4.01	3.21	2.68	1.90
REV/A (%)	87.94	84.36	82.46	86.78	92.26	87.60
R&D/A (%)	3.70	6.07	2.91	3.41	3.16	3.12
PPE/A (%)	31.86	27.09	36.88	34.19	32.29	31.45
Lev (%)	38.88	38.35	39.50	38.69	38.91	40.68
Panel B. Geographic characteristics						
Latitude	36.12	34.25	34.48	34.78	37.36	39.98
Dist2Sea (km)	147.90	152.98	181.16	149.68	135.63	120.87
PDSI	-1.19	-0.89	-1.01	-1.22	-1.39	-1.57

Note: The table shows time-series averages of cross-section means of firm characteristics in the overall sample and in each of the quintile portfolios. All financial characteristics are annual except for market value (which is monthly). Geographic characteristics are static. Sample period is from 2002 to 2019.

Table II: **Industry decomposition**

High ENSCORE portfolio		Low ENSCORE portfolio	
Top-weighted industry	**FF49 code**	**Top-weighted industry**	**FF49 code**
Retail	43	Business Services	34
Utilities	31	Computer Software	36
Petroleum and Natural Gas	30	Retail	43
Communication	32	Communication	32
Business Services	34	Pharmaceutical Products	13
Transportation	41	Petroleum and Natural Gas	30

Note: The table shows the industry decomposition of high and low ENSCORE portfolios. The weight is the number of firms in a specific industry over the total number of firms in that portfolio. FF49 code is the Fama-French 49 industry classification code

B. Factor regressions

The first row of Table III reports the annualized value-weighted excess returns of the quintile portfolios. The portfolio with the highest ENSCORE (the green portfolio) has, on average, 3.83% lower annual return than the one with the lowest ENSCORE (the brown portfolio). To see whether this return difference is driven by priced systematic risks, I apply time-series regression of these

Table III: **Factor regressions**

	L	2	3	4	H	L - H
$E[R^{ex}]$	10.87	8.84	9.33	9.00	7.04	3.83***
	(4.16)	(4.24)	(4.2)	(3.58)	(3.25)	(1.39)
SR	0.20	0.17	0.18	0.20	0.16	0.17
			Panel A. CAPM			
α	2.84	0.89	1.52	2.11	0.41	2.43**
	(1.31)	(1.3)	(1.3)	(0.9)	(0.97)	(1.18)
			Panel B. FF3			
α	3.02	0.93	1.78	2.48	0.86	2.17**
	(1.02)	(1.3)	(1.32)	(0.81)	(0.84)	(0.98)
			Panel C. FF5			
α	4.99	0.78	2.21	2.72	1.07	3.91***
	(1.16)	(1.4)	(1.36)	(1.02)	(0.86)	(1.22)
			Panel D. FF5 & MOM			
α	5.04	0.79	2.17	2.66	1.06	3.98***
	(1.16)	(1.39)	(1.39)	(1.05)	(0.87)	(1.25)

Note: The table shows the excess returns and abnormal returns (α) of the quintile portfolios using the following time-series regression:

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum. Returns are value-weighted and annualized. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that the L-H return is positive at 10%, 5%, and 1% significance levels.

portfolio returns to global asset pricing factor models.[14] I use the CAPM (Sharpe, 1964), FF3 (Fama and French, 1993), FF5 (Fama and French, 2015) and FF5 plus the momentum factor to get the abnormal returns (α),[15]

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t}$$

where F_t is the list of factors listed above and $R_{i,t}$ equals the return of the quintile portfolio i at month t. The abnormal returns α are reported in panels A to D in Table III. The last column of this table also shows the α of the strategy that longs the brown portfolio and shorts the green one (i.e., the low-minus-high portfolio on ENSCORE).

[14]Appendix A shows that the result is robust among U.S. firms when using a set of U.S. risk factors.

[15]The global asset pricing factors are downloaded from Kenneth French's data library: `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

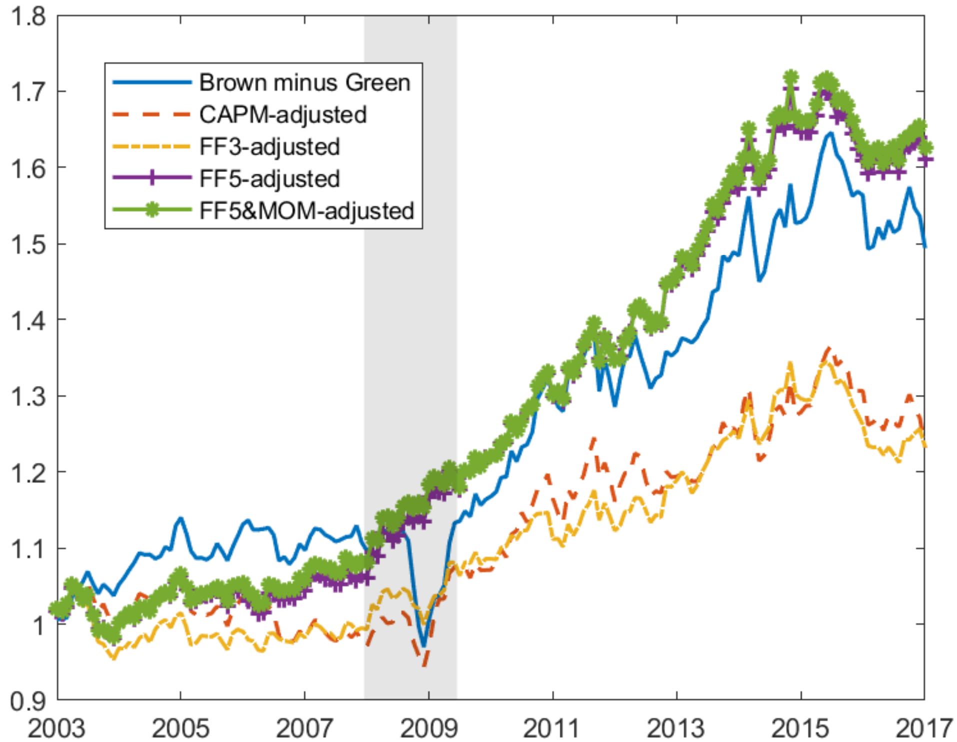

Figure 2: **Risk adjusted cumulative returns**

After controlling for these factors, the abnormal returns of the low-minus-high portfolio remain significantly positive. The α is 2.43% (t=2.06) for the CAPM, 2.17% (t=2.21) for the FF3, 3.91% (t=3.20) for the FF5, and 3.98% (t=3.18) for the FF5 plus momentum factor models. The results show that portfolios with higher ENSCORE carry lower expected returns after controlling for various global asset pricing factors that account for systematic risks. Figure 2 shows the cumulative abnormal return of the low-minus-high portfolio. When using the CAPM and FF3 factors, part of the greenium is absorbed. This is mainly because of the size effect since green firms tend to be bigger. However, when we broaden our examination to a more comprehensive set of asset pricing factors, i.e., the FF5 and FF5 plus momentum, the greenium becomes even more pronounced. Overall, the evidence presented here clearly shows that priced systematic risks cannot explain the greenium. In the next subsection, I investigate whether this return predictability remains after controlling for firm characteristics.

C. *Double sorting and Fama-Macbeth regression*

Since the firm characteristics of green versus brown portfolios differ in several aspects as shown in Table I, I implement two exercises to see whether these differences account for the greenium. In the first exercise, I double-sort the stocks using ENSCORE and another firm characteristic. For example, I first sort firms into *big* and *small* groups according to their market value in the last year relative to their industry peers.[16] Then, within the big and small groups, I sort firms into quintile portfolios according to their last year's ENSCOREs relative to their industry peers. Thus I create ten portfolios. I then compare these portfolios' annualized returns to see whether the lower expected return of the green portfolio exists within the big and small subsamples. I then repeat this double-sorting for all other characteristics.

Table IV shows the results. None of the firm characteristics affect the positive return obtained from a low-minus-high portfolio. In addition, the greenium is significant for all double-sortings except within small firms. This fact indicates that the greenium concentrates in big firms, consistent with In et al. (2017). A possible explanation of this phenomenon is that investors may not consider small firms as major contributors to climate change issues so that the risks associated with climate externality are attenuated in small firms.

In the other exercise, I run the Fama-Macbeth regressions of firm-level stock returns on their ENSCOREs and other characteristics, i.e.,

$$R_{i,t} = \beta_{0,t} + \beta_{1,t} ENSCORE_{i,t-12} + \beta_{2,t} X_{i,t-12} + \epsilon_{i,t}.$$

Where $R_{i,t}$ is the stock return of firm i at month t, X includes various sets of the firm characteristics listed before. All independent variables in the regression are standardized to have zero mean and unit variance for better inference on the coefficient. The estimation process consists of two steps. In the first step, I run the cross-sectional regression for each month to get the estimated slopes $\hat{\beta}_{i,t}$; in the second step, I take the average of the slopes over the whole sample period. Table V shows that a one-standard-deviation increase in the ENSCORE decreases a firm's annualized stock return in the next year by 0.86% to 1.37%, under different subsets of control variables. In other words,

[16] I use the median of market value as the cutoff point. Thus a firm with a market value smaller than the median of its industry peers is classified as "small" and vice versa.

Table IV: **Double sorting on ENSCORE and other characteristics**

	L	2	3	4	H	L - H	L	2	3	4	H	L - H
	Panel A. MV						Panel B. BV/MV					
L	12.71	12.53	11.93	10.80	11.85	0.87	10.18	8.42	7.35	8.77	7.07	3.11**
	(4.48)	(4.53)	(4.56)	(4.41)	(4.61)	(1.53)	(4.11)	(3.74)	(3.8)	(3.49)	(3.03)	(1.63)
H	9.63	9.42	8.92	7.36	6.61	3.02**	10.69	8.72	11.24	9.82	7.05	3.64**
	(4.1)	(4.29)	(3.73)	(3.29)	(3.24)	(1.44)	(4.25)	(4.79)	(4.55)	(3.74)	(3.93)	(1.59)
	Panel C. I/A						Panel D. REV/A					
L	9.46	10.13	8.07	6.33	6.32	3.14**	10.24	8.57	10.51	8.66	6.78	3.45**
	(3.99)	(4.32)	(3.8)	(3.49)	(3.33)	(1.53)	(4.42)	(4.32)	(4.1)	(3.82)	(3.34)	(1.58)
H	10.26	6.55	9.57	8.55	6.29	3.98***	11.80	9.22	8.29	8.90	7.42	4.39***
	(4.36)	(3.92)	(4.01)	(3.76)	(3.23)	(1.59)	(3.83)	(3.97)	(4.09)	(3.81)	(3.17)	(1.32)
	Panel E. R&D/A						Panel F. PPE/A					
L	10.90	10.23	10.30	8.74	7.42	3.48**	10.67	9.93	10.54	7.80	6.47	4.20***
	(4.44)	(4.34)	(4.1)	(3.36)	(3.4)	(1.71)	(4.07)	(4.45)	(4.51)	(3.45)	(3.4)	(1.58)
H	12.95	8.42	7.70	8.03	7.05	5.90***	10.92	7.99	8.80	9.52	8.02	2.90**
	(4.82)	(5.22)	(4.41)	(3.61)	(3.62)	(2.45)	(4.47)	(4.33)	(3.79)	(3.96)	(3.19)	(1.7)
	Panel G. Lev						Panel H. Latitude					
L	9.84	8.67	9.34	8.54	6.48	3.36**	10.81	8.46	8.77	9.31	6.81	4.00***
	(4.1)	(4.08)	(4.37)	(3.35)	(3.13)	(1.72)	(3.98)	(4.23)	(3.79)	(3.71)	(3.23)	(1.34)
H	11.72	9.18	9.63	8.27	8.02	3.69**	11.45	11.03	7.45	9.87	7.17	4.28***
	(4.54)	(4.19)	(3.72)	(4.04)	(3.4)	(1.64)	(4.43)	(4.32)	(4.65)	(3.36)	(3.36)	(1.76)
	Panel I. Distance to Sea						Panel I. PDSI					
L	11.66	9.99	10.49	9.42	7.64	4.03***	9.90	7.44	6.89	8.01	6.76	3.14**
	(4.2)	(4.42)	(3.88)	(3.37)	(3.46)	(1.24)	(4.04)	(3.91)	(4.32)	(3.67)	(3.26)	(1.59)
H	9.32	6.60	9.90	7.40	6.59	2.73**	11.93	9.19	9.42	12.65	7.48	4.44***
	(3.95)	(3.74)	(4.59)	(3.84)	(3.2)	(1.58)	(4.21)	(4.73)	(3.88)	(4.01)	(3.32)	(1.52)

Note: The table shows portfolio returns after double sorting according to the ENSCORE and one other firm characteristic. In the first step, I sort firms into two portfolios based on one of the following characteristics: market value, book-to-market ratio, investment over asset, revenue over asset, R&D over asset, PPE over asset, leverage, latitude, distance to the sea, and PDSI. Then within each portfolio I further sort firms into quintile portfolios according to the ENSCORE. The sortings are all based on last year's value, relative to industry peers. One, two, and three asterisks indicate that the L-H return is positive at the 10%, 5%, and 1% significance levels.

given that the sample standard deviation of ENSCORE is 28.4, an increase of ENSCORE from 0 (the lowest possible level) to 100 (the highest possible level) decreases the firm's annual stock return next year by 3.03% to 4.82%. This result is in line with the 3.83% greenium documented in the previous analysis.

Table V: **Fama-Macbeth regression on ENSCORE and other firm characteristics**

	(1)	(2)	(3)	(4)	(5)
ENSCORE	-1.37**	-1.02*	-0.96*	-0.86**	-0.86**
	(0.56)	(0.55)	(0.49)	(0.40)	(0.42)
MV		-0.94*	-0.52	-0.52	-0.51
		(0.53)	(0.47)	(0.37)	(0.35)
BV/MV		1.06	1.65	2.82*	2.89**
		(0.80)	(1.11)	(1.59)	(1.43)
I/A			-0.50	-0.88	-0.82
			(0.55)	(1.08)	(1.13)
REV/A			1.09***	1.37**	1.48**
			(0.38)	(0.64)	(0.64)
R&D/A				2.14**	2.03**
				(0.99)	(0.98)
PPE/A				-1.30*	-1.06
				(0.72)	(0.68)
Lev				0.85	0.83
				(0.81)	(0.80)
Latitude					0.30
					(0.70)
Dist2Sea					-0.42
					(0.42)
PDSI					1.42*
					(0.81)
Industry FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.110	0.118	0.118	0.147	0.165
Obs.	475128	446232	435264	203316	188712

Note: This table shows the results of the Fama-Macbeth regression

$$R_{i,t} = \beta_{0,t} + \beta_{1,t} ENSCORE_{i,t-12} + \beta_{2,t} X_{i,t-12} + \epsilon_{i,t}.$$

All independent variables are standardized with a zero mean and unit variance. I first run cross-section regression for each month. Then I report the average of the estimated slope. Newey-West adjusted standard errors of the average slopes are reported in the parentheses. One, two, and three asterisks indicate that the coefficient is significant at 10%, 5%, and 1% levels.

In sum, these two exercises provide valid evidence that the greenium is not attributable to firms' idiosyncratic risks, as captured by both financial and geographic characteristics.

D. Green stock hedges physical risks

D.1. Panel regression

In this section, I explain the greenium through the standard risk-return paradigm. Specifically, I investigate whether green stock provide a hedge against climate-related disasters. If green stock appreciates after a positive disaster shock, then investors demand a lower return for holding it. To implement this, I use granular data on firm-level return and a monthly measure of economic losses due to climate-related disaster. To begin with, I collect a list of global disasters from the International Disaster Database, and pick out disasters that are related to climate change.[17] I then construct a monthly index of climate economic damage by aggregating economic losses (in U.S. dollars) due to global climate disasters that happened in each month. To my knowledge, I am the first to construct a time-series of physical climate risk using real economic losses caused by climate disasters.

I then run a panel-data regression of firm-level returns on this climate damage index. To explore whether climate disasters impact green and brown firms differently, I introduce the interaction between climate damage and a firm's greenness. The specification is given by

$$AR_{i,t} = \alpha_i + (\beta_1 + \beta_2 \cdot ENSCORE_{i,t-12}) \cdot logdamage_t + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{1}$$

where $AR_{i,t}$ is the risk-adjusted return of firm i in month t. α_i is the firm fixed effect term, thus the specification exploits the time-series variation across firms. $logdamage_t = \log(damage_t + 1)$ where $damage_t$ is the economic losses due to climate disasters in month t, measured in thousand of U.S. dollars. For the control variable $X_{i,t}$, I include firm characteristics that are known to affect stock returns, such as the market value, book-to-market, momentum (cumulative returns of the last twelve months), investment over asset, revenue over asset, tangibility, and leverage. The parameter of interest is β_2. A significantly positive β_2 means that green stocks appreciate relative to brown ones upon a positive shock on climate disasters. To facilitate comparison between parameters β_1 and β_2, I normalized ENSCORE between zero to one.

[17] See `https://www.emdat.be/`. The database provides a long list of disasters (climatic or non-climatic) with rich information such as time, location, and economic losses. Climate-related disasters are defined by the following types: flood, wildfire, storm, extreme temperature, drought, and glacial lake outbreak. During my sample period, there are 5,892 disaster event, where more than 85% are storms and floods.

To have clear picture on how stocks in each quintile of ENSCORE response to disaster shock, I run an alternative regression where the continuous measure, ENSCORE, is replaced by a set of dummies indicating which greenness quintile the firm belongs to, i.e.,

$$AR_{i,t} = \alpha_i + (\beta_1 + \beta_2 \cdot Quintile_{i,t-12}) \cdot logdamage_t + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{2}$$

Column 1 and 2 of Table VI present the result from the equations (1) and (2), respectively. The result shows that the CAPM-adjusted return of a firm with zero ENSCORE (i.e., the brownest) decreases by 0.28 b.p. when the climate damage increases by 1%.[18] However, the coefficient of the interaction term is significantly positive. This indicates that, relative to brown firms, green firms suffer less damage from disasters. Specifically, the decrease in returns of green firms is 13% (0.038/0.282) less than that of the brown ones. A test on the sum of the two coefficients show that green stocks still depreciate significantly due to climate disasters, but to a less degree. Column 2 indicates that it is the brownest firms that depreciate the most, where firms in higher quintiles depreciate significantly less than the firms in the first quintile.

Column 3 and 4 of table VI show that the result is robust when using raw return as dependent variable and adding market return as a control. In Figure 2, the return on the BMG portfolio decreases significantly during the financial crisis. As such, to eliminate the possibility that the result is driven by that period. I run the same regressions but exclude the financial crisis episode (July 2017 to March 2019). Column 5 and 6 show that the result is consistent. Finally, Column 7 and 8 show result of a placebo test where I replace the series of climate damages using damages due to earthquakes, which is unrelated to climate change. Intuitively, returns depreciate significantly due to earthquakes. However, the interaction terms is now negative and weakly significant, and the coefficients for different quintiles are not significant. This means that only climate-related disasters lead to the relative appreciation of green stocks.

In a similar exercise, I investigate how investments of green/brown firms respond to climate damage shocks. I study investment to see whether there is a real effect (e.g., an investment re-allocation) caused by climate shocks. Specifically, I replace the dependent variable in regressions (1) and (2) by firm-level investment. I follow literature to define investment by log changes in the

[18] Result is consistent with returns adjusted using Fama-French factors.

Table VI: **Stock returns and climate damage**

	risk-adjusted return		raw return		no financial crisis		placebo	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
logdamage	-0.282***	-0.285***	-0.270***	-0.273***	-0.271***	-0.272***	-0.033***	-0.034***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.003)	(0.005)
$ENSCORE \times logdamage$	0.0380***		0.0439***		0.0374***		-0.011*	
	(0.006)		(0.007)		(0.007)		(0.006)	
Quintile 2		0.0239***		0.0263***		0.0181***		0.0030
		(0.004)		(0.004)		(0.004)		(0.005)
Quintile 3		0.0160***		0.0181***		0.0132***		-0.0079
		(0.004)		(0.004)		(0.004)		(0.005)
Quintile 4		0.0209***		0.0225***		0.0202***		-0.0042
		(0.005)		(0.005)		(0.005)		(0.005)
Quintile 5		0.0257***		0.0293***		0.0262***		-0.0061
		(0.005)		(0.005)		(0.006)		(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	384,224	381,554	384,224	381,557	351,641	349,169	384,224	381,554
Adj. R^2	0.04	0.04	0.20	0.20	0.04	0.04	0.04	0.04

Note: This table shows the results of the regression of stock returns on economic losses due to climate disasters. ENSCORE is normalized between zero and one. The risk-adjusted return controls for CAPM. Returns are in percentages. Standard errors are clustered at the firm level.

Table VII: **Investments and climate damage**

	$I \equiv \Delta A$		$I \equiv \Delta PPE$		$I \equiv \Delta CAPX$	
	(1)	(2)	(3)	(4)	(5)	(6)
logdamage	-0.110***	-0.121***	-0.065**	-0.071*	-0.339***	-0.444***
	(0.027)	(0.035)	(0.029)	(0.012)	(0.082)	(0.103)
$ENSCORE \times logdamage$	0.289***		0.161**		0.499***	
	(0.062)		(0.067)		(0.143)	
Quintile 2		0.037		-0.001		0.004
		(0.038)		(0.047)		(0.110)
Quintile 3		0.095**		0.045		0.271**
		(0.042)		(0.048)		(0.111)
Quintile 4		0.163***		0.094*		0.455***
		(0.044)		(0.049)		(0.110)
Quintile 5		0.231***		0.148***		0.565***
		(0.048)		(0.053)		(0.119)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	105,265	104,563	105,184	104,484	87,993	87,462
Adj. R^2	0.32	0.32	0.33	0.33	0.08	0.08

Note: This table shows the results of the regression of investments on economic losses due to climate disasters. ENSCORE is normalized between zero and one. Coefficients are in percentages. Standard errors are clustered at the firm level.

(i) total asset (Fama and French, 2015), (ii) net PPE (Thomas and Zhang, 2002), and (iii) capital expenditure (CAPX) (Lev and Thiagarajan, 1993). Data is collected from Global Compustat and matched with Datastream. I change the frequency of the regressions to quarterly to match the frequency of investment.[19] Finally, control variables include lagged total asset and PPE, revenue over asset, book-to-market, and leverage. All variables are winsorized at the 99% level.

Table VII shows the result. According to column 1 where investment is defined as change in the total asset, a shock of 1% increase in the climate damage decreases investment of the brownest firm by 0.11 b.p. However, the coefficient of the interaction term is significantly positive, indicating that green firms experience increased investment relative to brown firms. A test shows that the sum of the two coefficients is significantly positive. This means the green firms experience increased investment during climate disasters. Column 2 shows a monotonically increasing relationship between the investment and the greenness, consistent with result in column 1. Finally, the result is robust

[19]To get rid of seasonality, investment is measured by the log change of the variables (asset, PPE, or CAPX) in the current quarter with respect to the same quarter of the last year.

with other measures of investment. In sum, the evidence presented in Table VII clearly shows a reallocation of investment from brown firms to green firms when facing a positive climate damage shocks.

D.2. Event studies

The previous section exploits time-series variation to explore the responses of returns and investments toward climate disaster shocks. In this section, I implement an event study and uses firms' cross-sectional variation to see how stocks with different greenness respond to specific natural disasters during the sample period. First, I identify three major natural disasters during the sample period: Hurricane Katrina, the 2012 US drought, and the 2018 California wildfires. These three events are considered the most devastating hurricane/drought/wildfires by the National Oceanic and Atmosphere Administration (NOAA) during the period 2002-2019.[20]

I implement the following cross-sectional regression for each of the three disasters,

$$R_{i,t\to t+M} = \alpha + \beta \cdot Brown_{i,t} + \gamma X_{i,t-12} + \epsilon_{i,t},$$

where t is the month when the disaster happens.[21] $R_{i,t\to t+M}$ is the (annualized) cumulative return from month t to month $t+M$ of firm i; $Brown_{i,t}$ is a dummy variable equal to 1 (0) if firm i is in the lowest (highest) quintile of ENSCORE; $X_{i,t-12}$ are control variables including the industry dummies, firm size, momentum (cumulative return of past 12 months), book-to-market of the year prior to the disaster, and the three geographic characteristics previously identified. The variable of interest is β. A negative β indicates that brown stocks depreciate upon a natural disaster relative to green stocks. Thus longing green stocks and shorting brown stocks could offer insurance against climate change, which explains the negative greenium documented previously.

Table VIII shows that the estimated β are significantly negative for the horizon from one month to one year following Hurricane Katrina. Compared to green stocks, annualized cumulative returns of brown stocks decreased 19.6% in the first months after Hurricane Katrina. The effect fades out

[20]See `https://www.ncdc.noaa.gov/billions/events/US/2003-2019`, Hurricane Katrina costs 170 billion US dollars and 1833 lives, 2012 US drought leads to 34.8 billion US dollars and 123 deaths, 2018 California wildfires cause 25 billion US dollars and 106 deaths.

[21]For the Hurricane Katrina, t is August 2005; For the drought and wildfires, t is the July of 2012 and 2018, respectively.

Table VIII: **Event study on stock returns**

M	1m	2 m	3m	6m	12m
			Panel A. Hurricane Katrina		
β	-19.61**	-17.93***	-9.10*	-8.76**	-8.79***
	(8.48)	(6.18)	(5.19)	(3.74)	(2.34)
Adj. R^2	0.14	0.20	0.09	0.19	0.18
Obs.	721	721	721	721	721
			Panel B. 2012 US drought		
β	-22.61**	-11.83*	-6.53	-5.11	-7.18***
	(10.81)	(6.62)	(4.89)	(3.14)	(2.54)
Adj. R^2	0.16	0.13	0.12	0.04	0.22
Obs.	844	844	844	844	844
			Panel C. 2018 California wildfires		
β	-24.50***	-6.12	-5.49	-2.92	-0.62
	(6.88)	(5.2)	(4.37)	(3.44)	(2.41)
Adj. R^2	0.06	0.06	0.05	0.13	0.12
Obs.	1475	1475	1475	1475	1475

Note: This table shows the results for the event study

$$R_{i,t\to t+M} = \alpha + \beta \cdot Brown_{i,t} + \gamma X_{i,t-12} + \epsilon_{i,t},$$

where $R_{i,t\to t+M}$ is the annualized cumulative return of firm i from month t to month $t+M$. $Brown_{i,t}$ is a dummy variable indicating whether firm i is brown or not. $X_{i,t}$ includes the industry dummies, firm size, momentum (cumulative return of past 12 months), book-to-market, and the geographic characteristics. Newey-West adjusted standard errors are reported in the parentheses. One, two, and three asterisks indicate that the coefficient is significant at 10%, 5%, and 1% levels.

in one year but still induces a significant reduction in cumulative return (9%). For the 2012 US drought and 2018 California wildfires, the decreases of brown stock returns are more pronounced in the first month (22.6% and 24.5%, respectively). But the effects seem to be less long-lasting than those of Hurricane Katrina. Note that the regression controls firms' geographic proximity to disasters. Thus the responses are not driven by, for example, brown firms are more damaged due to disasters. In sum, the result confirms the role of green stocks as a hedge against climate-related natural shocks.

Finally, I examine the dynamics of investment flows across brown and green firms upon natural disasters. Specifically, I do the same event study on investments. Because the investment data is low-frequency, I focus on long-lasting natural disasters, the 2012 U.S. drought/heatwave and the 2018 California wildfires:

$$\Delta(I/A)_{i,t} = \alpha + \beta \cdot Brown_{i,t} + \gamma X_{i,t-1} + \epsilon_{i,t},$$

$\Delta(I/A)_{i,t}$ is the change of the investment-over-asset of firm i from year $t-1$ to year t. The investment is defined by change in total assets (ΔA) and change in PPE (ΔPPE). The control variable $X_{i,t}$ includes industry dummies, revenue over asset, leverage, and the geographic characteristics.

Table IX shows that during the 2012 U.S. drought (the 2018 California wildfires), the investment-over-asset ratio of brown firms decreases by 4.6% (4.3%) relative to green stocks. Results are consistent when the investment is defined by the change in tangible capitals (PPE). The different investment responses of green versus brown firms are not driven by their direct exposures to natural disasters, captured by geographic characteristics. The result indicates that upon climate-related disasters, investments flow from the brown sector to the green one.

The above findings are consistent with recent literature on how investors react to climate events by changing their trading behaviors. For example, Choi et al. (2020) find that investors revise their beliefs about climate change upward when experiencing extremely warm temperature. They find that (i) attention to climate change, as proxied by Google search volume, increases when temperature is abnormally high, and (ii) retail investors oversell carbon-intensity in such weather, leading to a depreciation of brown stocks. In a recent paper by Huynh and Xia (2021), they also find that investor react to natural disasters by overselling stock and bond when a firm is exposed

Table IX: **Event study on investment**

	$I \equiv \Delta$A	$I \equiv \Delta$PPE
	Panel A. 2012 US drought	
β	-4.62**	-6.73**
	(2.18)	(2.74)
Adj. R^2	0.02	0.01
Obs.	829	827
	Panel B. 2018 California wildfires	
β	-4.28**	-5.19**
	(2.02)	(2.25)
Adj. R^2	0.03	0.01
Obs.	1381	1374

Note: This table shows the results for the event study

$$\Delta(I/A)_{i,t} = \alpha + \beta \cdot Brown_{i,t} + \gamma X_{i,t-1} + \epsilon_{i,t},$$

where $\Delta(I/A)_{i,t}$ is the change of the investment-over-asset of firm i from year $t-1$ to year t. The investment is defined in two ways: (1) change in total assets, and (2) change in PPE. $Brown_{i,t}$ is a dummy variable indicating whether firm i is brown or not. The control variable $X_{i,t}$ includes industry dummies, revenue over asset, leverage, and geographic characteristics. Newey-West adjusted standard errors are reported in the parentheses. One, two, and three asterisks indicate that the coefficient is significant at 10%, 5%, and 1% levels.

to disaster, but greener firms experience lower selling pressures. Consistent with this literature, I find brown stocks depreciate more than green stocks during climate disasters. In addition, I find that green firms experience increased investment than brown firms. Under investment friction, this reallocation of investment increases the green sector's value and thus lead to higher returns. Based on this intuition, I provide a simple and analytically solvable model in the next section to build a causal link between climate disasters and investment/return movements.

IV. A two-period model

This section presents a simple two-period model that qualitatively explains the empirical findings. At $t = 0$, a representative agent invests in two production sectors: one uses fossil fuel which causes pollution (sector B); the other uses non-fossil fuel/green energy (sector G) which has no pollution issues. At $t = 1$, the agent observes an exogenous natural disaster shock ϵ and again makes investment decisions on the two sectors. At $t = 2$ the agent consumes all goods, and the economy is closed. I introduce climate damage as a mapping from time-1 investment in sector B and the shock to the time-2 output.

Agents have Epstein and Zin recursive preferences (Epstein and Zin, 1989) . For mathematical tractability, I assume the IES equals to one and take the logarithm of the utility:

$$u_t = \begin{cases} (1-\beta)\log C_t + \frac{\beta}{1-\gamma}\log E_t\left[\exp\left\{u_{t+1}(1-\gamma)\right\}\right] & \gamma \neq 1 \\ (1-\beta)\log C_t + \beta E_t\left[u_{t+1}\right] & \gamma = 1 \end{cases}$$

where u_{t+1} is the continuation utility at time $t+1$, $\beta \in (0,1)$ and $\gamma > 0$ are the subjective discount factor and relative risk aversion, respectively.

This model may be unrealistic and oversimplified in terms of climate-economy interactions from the perspective of standard IAM literature. However, the goal of this section is to provide a glimpse into the mechanism through which green stocks rise upon climate-related disasters, while maintaining analytical tractability. In the rest of this section, I show how investments and stock returns at *time 1* respond to the shock, and the assumptions imposed on the damage mapping that enable the model to qualitatively match data. Details of the derivation are presented in Appendix B.

Utility At $t = 1$, the agent's utility becomes certain since all uncertainties are resolved. Thus,

$$u_1 = (1-\beta)\log(C_1) + \beta\log(C_2). \tag{3}$$

Production I assume, for simplicity, Cobb-Douglas production function depending on the capital stocks of two sectors with full capital depreciation. I remove labor input and the productivity process. In addition, I include climate damage mapping D, such that

$$C_2 = Y_2 = \Big(1 - D(I_{B,1}, \epsilon)\Big) I_{B,1}^{\alpha} I_{G,1}^{1-\alpha}, \tag{4}$$

where $\alpha \in (0,1)$ is the weight of sector B in the production function; $I_{B,1}$ ($I_{G,1}$) is the time-1 investments in sector B (G); and $\epsilon \sim N(0,\sigma^2)$ is the shock of natural disaster. D is the climate damage, which depends on both the investment in sector B and the natural disaster shock. I assume that $D_1' > 0$, $D_2' > 0$, and $D_{12}'' > 0$. The last assumption is essential to making the model consistent with the data, thus generating a lower premium for the green stocks. It says that the marginal climate damage caused by pollution increases with the shock of natural disasters. For analytical convenience, I assume the following multiplicative functional form for the climate damage $D(\cdot,\cdot)$:

$$D(I_{B,1},\epsilon) = \begin{cases} \lambda(\epsilon)\log(I_{B,1}/\bar{I}), & I_{B,1} > \bar{I} \\ 0, & I_{B,1} \leq \bar{I} \end{cases} \tag{5}$$

where $\bar{I}$ is a scaling parameter, such that when the investment of sector B, $I_{B,1}$, is smaller than $\bar{I}$ there is no climate damage. $\lambda(\epsilon)$ is the damage intensity, which determines the marginal cost of investing in sector B. It is assumed that both $\lambda(\epsilon)$ and $\bar{I}$ are sufficiently small. In addition, $\lambda(\epsilon)$ is increasing on the disaster shock ϵ. Here is the micro foundation for this setting: Since the damage intensity parameter λ is intrinsically uncertain, agents learn the true value of λ from the noisy signal ϵ. When a natural disaster happens, agents revise their belief about λ upward. Thus, in a reduced form, the perceived value of λ is an increasing function on the shock ϵ. This assumption is consistent with the ideas in Ortega and Taspınar (2018) and Gibson et al. (2017) that perceived climate risks become more salient after the realization of climate-related natural disasters. Hong et al. (2020) provide details about how investors increase belief regarding the adverse consequences of global warming due to unexpected disaster arrivals.

Optimization The assumptions mentioned above simplify the mathematics and generate linear solutions. The social planner's problem at Time 1 is

$$\max_{I_{G,1},I_{B,1}} \quad u_1 = (1-\beta)\log C_1 + \beta \log C_2, \tag{6}$$

subject to the constraints in equations (4), (5), and the market clear condition $Y_1 = I_{B,1} + I_{G,1} + C_1$.

Solving the first order conditions (F.O.C.) of problem (6) gives the investment and consumption solutions. The solutions are linear functions of the state variable Y_1, where the coefficients depend on the damage intensity λ,

$$I_{B,1} = \frac{\beta(\alpha-\lambda)}{1-\beta\lambda}Y_1, \tag{7}$$

$$I_{G,1} = \frac{\beta(1-\alpha)}{1-\beta\lambda}Y_1. \tag{8}$$

In general, climate damages are small, so we can safely assume $\alpha > \lambda$ and ensure that investments are always positive. Note that $\frac{\partial I_{B,1}}{\partial \lambda} < 0$ and $\frac{\partial I_{G,1}}{\partial \lambda} > 0$. Thus a natural disaster shock (a positive ϵ), which is translated into an increase in the damage intensity λ, will lead to a higher (lower) investment in the sector G (B). Specifically, we can approximate the investment as a linear function of the steady-state investment and the shock,

$$I_{B,1} = \bar{I}_{B,1} + \theta_B \epsilon, \tag{9}$$

$$I_{G,1} = \bar{I}_{G,1} + \theta_G \epsilon, \tag{10}$$

where $\bar{I}_{B,1}$ ($\bar{I}_{G,1}$) is a steady-state investment which does not depend on the shock, $\theta_B = -\beta\frac{1-\alpha\beta}{(1-\beta\lambda)^2}\bar{\lambda}'$ and $\theta_G = \beta^2\frac{1-\alpha}{(1-\beta\lambda)^2}\bar{\lambda}'$ with $\bar{\lambda}' = \frac{\partial\lambda}{\partial\epsilon}\Big|_{\epsilon=0}$. Since $\lambda' > 0$, then $\theta_B < 0$ and $\theta_G > 0$. We reach the following proposition.

Proposition 1: *Under the assumption that climate damage intensity increases after a natural disaster, a positive shock of natural disaster decreases investment in the fossil fuel sector and increases investment in the non-fossil sector.*

The intuition is quite simple: a natural disaster leads to a higher perceived damage intensity, or a higher marginal cost of production using fossil fuel. As a result, a social planner would lessen the use of fossil fuel. This leads to a lower investment in sector B.

Linear approximation of the utility Using the Envelope Theorem, the partial derivative of utility to the shock is given by

$$\frac{\partial u_1}{\partial \epsilon} = \frac{\partial u_1}{\partial \lambda}\bar{\lambda}' = -\beta\log(I_{B,1}/\bar{I})\bar{\lambda}' < 0. \tag{11}$$

Thus utility decreases when there is a positive shock of natural disaster.

Stochastic discount factor The SDF at $t = 1$ is expressed as

$$M_1 = \frac{\partial u_0/\partial C_1}{\partial u_0/\partial C_0} = \beta \frac{C_0}{C_1} \frac{\exp\left(u_1(1-\gamma)\right)}{E_0\left[\exp\left(u_1(1-\gamma)\right)\right]} \tag{12}$$

Taking the logarithm to equation (12) and applying a linear approximation,

$$m_1 = \bar{m}_1 + \theta_m \epsilon, \tag{13}$$

where the $\bar{m}_1$ is the steady-state SDF and $\theta_m = \beta\left[(\gamma-1)\log(\bar{I}_{B,1}/\bar{I}) - \frac{1}{1-\beta\lambda}\right]\bar{\lambda}'$.

The sign of θ_m depends on two terms. The first term is caused by the disutility due to the shock, which increases the SDF. The second one decreases the SDF due to increase in the time-1 consumption since agents refrain from investing in sector B. How the SDF changes with respect to the shock depend on the interaction of these two terms.

Proposition 2: *When the agent is risk averse enough, so that* $\gamma > 1 + \frac{1}{(1-\beta\lambda)\log(\bar{I}_{B,1}/\bar{I})}$, *a positive disaster shock increases the SDF.*

When $\lambda << 1$ and $\bar{I} << \bar{I}_{B,1}$ the condition in the above proposition is easily satisfied for risk-averse agents.

Stock returns Hayashi (1982) shows that introducing adjustment cost into a firm's optimal investment problem rationalizes Tobin's conjecture that investment is a function of marginal q. A convex investment adjustment cost indicates that Tobin's marginal q is positive related to investments. Therefore stock returns, which equal levered investment return, are linked with investment flows (Zhang, 2005). Specifically, I change the assumption regarding the capital accumulation process to the following (still maintaining the assumption on full depreciation):

$$K_{i,t+1} = I_{i,t} - G(I_{i,t}, K_{i,t}), \quad \forall i \in \{B, G\},$$

where $G(I, K)$ reflects a convex adjustment cost, which satisfies $G'_I > 0, G'_K < 0$ and $G'_{II} > 0$. The adjustment cost G is generally much smaller compared to the investment, so the optimal investments derived in equations (7) and (8) remain good linear approximations.

The stock returns equal to the investment return under no leverage (Cochrane, 1991) (I neglect index i for simplicity):

$$R_{t+1} = \frac{-Q_{t+1}G'_{K,t+1} + MPK_{t+1}}{Q_t}, \tag{14}$$

where MPK is the marginal product of capital. $Q = \frac{1}{1-G'_I}$ is Tobin's q, which captures the unit of current consumption required to generate one additional capital in the next period. I assume the adjustment cost takes the following functional form $G(I,K) = I - \frac{a}{1-\xi}I^{1-\xi}K^{\xi}$ following Jermann (1998) and Croce (2014), where $\xi > 0$. $1/\xi$ represents the elasticity of investment rate with respect to Tobin's q.

To see how stock returns respond to the shock ϵ, note that the log return for sector i can be expressed as

$$r_{i,1} = \bar{r}_{i,1} + \kappa_i\theta_i\epsilon, \quad \forall i \in \{B, G\}, \tag{15}$$

where $\kappa_i = \frac{\partial r_{i,1}}{\partial I_{i,1}} > 0$. $\bar{r}_{i,1}$ is the steady-state log stock return at time 1. θ_B and θ_G are given in equation (9) and (10). Note that κ_B and κ_G are both positive, $\theta_B < 0$ and $\theta_G > 0$. Then,

Proposition 3: *A positive shock of natural disaster increases the stock return in sector G and decreases that in sector B.*

Note that both stock returns and the SDF are conditionally log-normal. Thus the risk premium is $E_0[r^{ex}_{i,1}] = -\text{Cov}_0(m_1, r_{i,1}) - \frac{1}{2}\text{Var}_0(r_{i,1})$. Namely,

$$E_0[r^{ex}_{i,1}] = -\kappa_i\theta_i\theta_m\sigma^2 - \frac{1}{2}\kappa_i^2\theta_i^2\sigma^2, \quad \forall i \in \{B, G\},$$

when the agent is risk averse enough, so that the condition of *Proposition 2* is satisfied and $\theta_m > 0$, the natural disaster shock carries a negative price of risk, as captured by $-\theta_m\sigma^2$. With a negative exposure to the shock, i.e., $\kappa_B\theta_B < 0$, sector B carries a positive risk premium. In contrast, sector G carries a negative risk premium due to the positive exposure, i.e., $\kappa_G\theta_G > 0$. In summary, sector G provides insurance against global warming and thus carries a lower risk premium, consistent with the data.

V. The macro-finance integrated assessment model

This section presents a DSGE model with infinite horizon, which unifies the standard IAM and production-based asset pricing models in the macro-finance literature. The model is based on, but differs significantly from, the model by Bansal et al. (2016a,b). First, I extend their endowment economy into a production economy with two production sectors using fossil and non-fossil fuels, respectively. Second, I include investment frictions, which explicitly relates investment decisions to stock returns. Third, I specify a time-varying damage intensity that depends on the shock of natural disasters. These model setups enable me to elicit moments of macroeconomic variables and stock returns and match them with the empirical facts. In the rest of this section, I describe the economic sector, climate change dynamics, preferences, and the welfare optimization problem.

A. *Economic sector*

Production function I assume a constant elasticity of substitution (CES) aggregation between the outputs of the two sectors, since the elasticity of substitution between the two energy sources is important for the equilibrium allocations (Acemoglu et al., 2012).

$$Y_t = \left(\omega Y_{B,t}^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega) Y_{G,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{16}$$

where Y_B and Y_G are outputs from sector B and G, respectively. ω is the fraction of final output from sector B. ε is the elasticity of substitution between the two sectors. When $\varepsilon > 1$ ($\varepsilon < 1$), outputs in the two sectors are substitutes (complements). A benchmark calibration indicates $\varepsilon > 1$ (Acemoglu et al., 2012; Van der Zwaan et al., 2002), suggesting that fossil and non-fossil fuels are usually substitutes.[22]

Outputs from the brown sectors are produced through Cobb-Douglas function using capital and labor as inputs:

$$Y_{B,t} = K_{B,t}^{\alpha}(A_t l_{B,t})^{1-\alpha}, \tag{17}$$

where K_t and l_t are the capital stock and labor input, A_t is productivity. Output in sector G is

[22]For example, both renewable energy and fossil fuel are widely used to produce electricity nowadays. In this case, these two inputs are highly interchangeable. Solar and geothermal energies are hard to replace fossil fuels in high-temperature heating systems, due to equipment cost constraints (IRENA, 2015). In this case, these two energy sources are imperfect substitutes.

determined by both physical and intangible capital (human knowledge):

$$Y_{G,t} = H_t^{\nu} \left(K_{G,t}^{\alpha} (A_t l_{B,t})^{1-\alpha} \right)^{1-\nu}, \tag{18}$$

where H_t is human knowledge of non-fossil fuel, accumulated through R&D which will be discussed later.

The inclusion of intangible capital for sector G reflects the empirical fact that the green sector is investing more R&D than the brown sector in dollar values. Moreover, recent literature in climate economics suggests that technical change on non-fossil fuel is essential for accurate policy analysis (Acemoglu et al., 2012), since it provides a growth option toward emission reduction in the future.

Unlike Popp (2006) and Golosov et al. (2014), I do not include energy as a direct input into the production function. Instead, output depends on the capital level, i.e., the quantity of machines that extract, transport, and convert energy sources into final products.[23] As in Van der Zwaan et al. (2002), raw energy inputs in each sector are proportional to the level of corresponding capital stocks. This approach has two advantages: first, energy extraction and conversion costs are usually hard to quantify. I transform this cost to the depreciation of capital and investments. Second, through this approach I explicitly derive the investment flows between two production sectors, thus shedding light on the cross-sector stock returns.

Capital accumulation For sector $i \in \{G, B\}$,

$$K_{i,t+1} = (1 - \delta_K) K_{i,t} + I_{i,t} - G_t(I_{i,t}, K_{i,t}), \tag{19}$$

where δ_K is the rate of depreciation of the capital and $I_{i,t}$ is the investment in sector i at time t. $G_t(\cdot, \cdot)$ introduces the adjustment cost for capital accumulation. As in section IV, I assume a convex adjustment cost following Jermann (1998) and Croce (2014):

$$G_t(I_{i,t}, K_{i,t}) = I_{i,t} - \left(\frac{a_1}{1-\xi} I_{i,t}^{1-\xi} K_{i,t}^{\xi} + a_0 K_{i,t} \right), \tag{20}$$

[23] This paper assumes infinity supply of raw energy sources. Thus production is only limited by the capital installation of the two sectors. Future extension of this paper could consider the exhaustibility of fossil fuel, as in Acemoglu et al. (2012).

where $\xi > 0$, a_1 and a_0 is chosen to satisfy the restriction that $G = \frac{\partial G}{\partial I} = 0$ at steady state.

Research & development Human knowledge capital is accumulated through R&D,

$$H_{t+1} = (1 - \delta_H)H_t + h(RD_t, H_t), \tag{21}$$

where δ_H is the depreciation of human knowledge capital and RD_t is the R&D investment directed to the sector G. $h(RD_t, H_t)$ is the *innovation possibility frontier*. I follow Popp (2004), with a modification to ensure constant return to scale, to specify the following functional form for h:

$$h(RD_t, H_t) = \frac{b}{1-\eta} RD_t^{1-\eta} H_t^{\eta}, \tag{22}$$

where η is between 0 and 1. This setting supports two standard assumptions in the literature about technological change: (1) a diminishing return for research in accumulating human knowledge, and (2) the positive externality of human knowledge.[24] It can also be considered as introducing an adjustment cost to the accumulation of intangible capital.

Sector stock returns Unlevered stock returns equal investment returns, which are derived from the Euler equation by solving the first order conditions of the intertemporal optimization problem:

$$R_{i,t+1} = \frac{Q_{i,t+1}(1 - \delta_K - G'_{K_{i,t+1}}) + MPK_{i,t+1}}{Q_{i,t}}, \quad \forall i \in \{B, G\}$$

where $Q_{i,t} = \frac{1}{1-G'_{I_{i,t}}}$ is the Tobin's q of sector i and MPK is the marginal product of capital. Note that the return of sector B is the return on physical capital, whereas the return of sector G is a composite return on both physical and intangible capital.

Productivity growth and climate damage I separate productivity growth into short-run fluctuations and a long-run trend following the long-run risks literature (Bansal and Yaron, 2004).

[24] The more human knowledge capital, the higher the marginal return of R&D. This is consistent with the public-good nature of innovation (Romer, 1990).

Specifically,

$$\log(A_t) = \log(A_{t-1}) + \mu + x_t + \sigma\epsilon_{A,t}, \tag{23}$$

$$x_t = \rho_x x_{t-1} + \varphi_x \sigma \epsilon_{x,t}, \tag{24}$$

where μ is the unconditional mean of productivity growth rate; x_t is the long-run trend; $\epsilon_{A,t}$ and $\epsilon_{x,t}$ are short- and long-run productivity shocks, which are assumed to be *i.i.d.* standard Gaussian.

Following Golosov et al. (2014), I assume that climate damage is a mapping from carbon concentration to total output. Specifically,

$$\tilde{Y}_t = \exp\left(-\lambda_t(M_t - \bar{M})\right) Y_t, \tag{25}$$

where $\tilde{Y}_t$ (Y_t) is the post- (pre-) climate damage output. M_t and $\bar{M}$ are atmospheric carbon concentrations at time t and at the pre-industrial era. λ_t is the damage intensity parameter which governs the marginal cost of pollution, i.e., the additional damage caused by a one unit increase in carbon concentration. I assume the following AR(1) process for λ_t:

$$\lambda_t = (1 - \rho_\lambda)\bar{\lambda} + \rho_\lambda \lambda_{t-1} + \sigma_\lambda \epsilon_{\lambda,t}, \tag{26}$$

where $\epsilon_{\lambda,t} \sim N(0,1)$ is a shock that affects the perceived value of λ. This could be a natural disaster that causes people to revise upward their beliefs in climate damage intensity.

Market clearing The labor market clearing condition requires that the total labor demand be less than the total labor supply, which is normalized to one,

$$l_{B,t} + l_{G,t} \leq 1. \tag{27}$$

The market clearing condition for consumption is given by

$$C_t = \tilde{Y}_t - I_{B,t} - I_{G,t} - k \cdot RD_t. \tag{28}$$

As discussed in Nordhaus (2002) and Popp (2006), the opportunity cost of research in renewable energy is multiple times its dollar cost. The parameter k reflects this opportunity cost.

B. Climate-change dynamics

Climate-change dynamics is a reduced form of that in the DICE model (Nordhaus, 1992):[25]

$$T_{t+1} = (1-\rho_T)\bar{T} + \rho_T T_t + \chi \log\left(\frac{M_{t+1}}{\bar{M}}\right) + \sigma_T \epsilon_{T,t+1} \tag{29}$$

$$M_{t+1} = (1-\rho_M)\bar{M} + \rho_M M_t + E_t + \sigma_M \epsilon_{M,t+1} \tag{30}$$

where T_t is the temperature anomaly (i.e., temperature above the pre-industrial level). M_t is the carbon concentration level. $\bar{T}$ and $\bar{M}$ are the equilibrium levels of T_t and M_t under no anthropogenic CO_2 emissions. The mapping from carbon concentration to temperature is represented by the *radiative forcing* term $\log\left(\frac{M_{t+1}}{\bar{M}}\right)$, according to Arrhenius's greenhouse law (Arrhenius, 1896). E_t is the endogenous carbon emission caused by human activities. ϵ_T, ϵ_M are exogenous variations which are *i.i.d.* standard Gaussian. Finally, to close the climate feedback loop, I assume E_t depends on the *standardized capital* in sector B:

$$E_t = \zeta \frac{K_{B,t}}{A_t}, \tag{31}$$

where ζ is the constant carbon intensity.[26] The idea behind this specification is that E_t depends on fossil fuel combustion and is thus determined by sector B's capital stock. In addition, as productivity increases, less fossil fuel is required to produce a certain amount of output, either because of higher burning efficiency or power recycling. I thus rescale capital by productivity. This setup is also necessary because it ensures a stationary path of CO_2 emission and temperature at equilibrium, where capital is growing at the same speed of productivity.

[25] The DICE model uses a two-dimensional vector to represent the temperature: a vector of temperature in the atmosphere and in the lower level of the ocean. Here I simplify the dynamics of temperature using a one-dimensional temperature, the combined land-surface air and sea-surface water temperature anomalies.

[26] The DICE model introduces the de-carbonization process (i.e., the transition from coal to oil, and oil to gas). That is, the carbon emission to output ratio is decreasing over time. For example, Nordhaus (2019) shows that the global average carbon intensity has decreased by 1.6 percent every year over the last six decades. This fact is consistent with my specification of a constant ζ. Note that $E_t = \frac{\zeta}{A_t} K_{B,t}$, thus the emission-output ratio decreases as productivity increases.

C. Preferences

A representative agent has the EZ preferences following Epstein and Zin (1989) and Weil (1990),

$$U_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{32}$$

where β is the discount rate, γ is the relative risk aversion, and ψ is the IES. When $\psi = 1/\gamma$, the utility function collapses to the CRRA utility, which is commonly used in standard IAMs (Nordhaus, 2010; Pindyck, 2012).

D. Optimization problem

Define the state variable vector as $\mathcal{S} = \{H, M, K_B, K_G\}$. The problem is

$$\max_{\substack{C_t, RD_t, I_{B,t}, I_{G,t}, \\ l_{B,t}, l_{G,t}, \mathcal{S}_{t+1}}} \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}(\mathcal{S}_{t+1})^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{33}$$

subject to the dynamics and constraints from equation (16) to (31). I solve the F.O.C. of the problem. The rest of the model dynamics is solved through perturbation methods using the MATLAB Dynare++ package.

E. Social cost of carbon

One of the most important concepts widely reported in the climate economics literature is the SCC. SCC measures the present value of the damage caused by one additional unit of CO_2 emission, as expressed in consumption units. My model provides a straightforward way to estimate the SCC by using the Envelope Theorem,

$$SCC_t = -\frac{\partial U_t}{\partial E_t} \Big/ \frac{\partial U_t}{\partial C_t} = -\frac{\partial \mathcal{L}_t}{\partial E_t} \Big/ \frac{\partial \mathcal{L}_t}{\partial C_t},$$

where $\mathcal{L}$ is the Lagrange function. The SSC is explicitly captured by the negative ratio between the shadow price of CO_2 emission and that of consumption.

VI. Quantitative results

This section shows the quantitative performance of the MFIAM. I first describe the calibration and the simulation results. Then I estimate the impulse response functions (IRF) to shocks that alter the damage intensity, i.e., ϵ_λ. Third, I calculate the SCC and show its determinants. Finally, I implement sensitivity analysis of the key parameters on the steady-state results.

A. Calibration

I calibrate the model to match aggregate and sectoral statistics of U.S. economic quantities and asset prices on a yearly frequency. The parameters and their descriptions are presented in Table X.

First, I calibrate most of the parameters of productivity dynamics, following macro-finance literature. The parameter μ is set to match the 1.8% average growth rate of the U.S. economy. Short-run volatility $\sigma = 3.35\%$ follows Croce (2014). The long-run component of the productivity growth, x_t, is set to be persistent ($\rho_x = 0.96$) and has a small volatility that is one-fifth of the short-run volatility ($\varphi_x = 0.2$), following the calibration of Bansal et al. (2016a). These calibrations ensure that the model roughly matches the standard deviation of output growth rate, market excess return, and risk-free rate simultaneously.

On the production side, the elasticity of substitution between green and brown sectors is 3 following Acemoglu et al. (2012). The fraction of brown sector (fossil fuel) is 0.59 following Golosov et al. (2014). Capital share in production is around 1/3. Depreciation of physical capital is 6% annually (Croce, 2014) and that for human knowledge capital is 10%, following Popp (2006). The opportunity cost of R&D is 4, following Nordhaus (2002). Finally, the equilibrium damage intensity $\bar{\lambda}$ is set to equal the average estimate by Golosov et al. (2014).[27] Under this damage intensity, the proportional damage on output when temperature anomaly reaches 2 $°C$ is 1.28%, which is similar to the estimate of 1.12% by Nordhaus and Sztorc (2013).[28]

On the preference side, the IES and risk aversion are set at 2 and 10, respectively, so that $\frac{1}{\psi} < \gamma$ and agents prefer early resolution of uncertainty. In the following subsections, I also explore the

[27] Golosov et al. (2014) calculates an average damage intensity of 2.379×10^{-5}. Note that they use GtC (Gigatonnes of Carbon) as the unit of carbon concentration, while this paper uses particle per million (ppm). Given the relation 1 ppm = 2.124 GtC, my calibration would be $\bar{\lambda} = 5.05 \times 10^{-5}$.

[28] Their climate damage function is given by $D(T) = 1 - \frac{1}{1+\theta T^2}$, where $\theta = 0.0028388$.

case where $\frac{1}{\psi} = \gamma$ and the preference reduces to CRRA. The subjective discount factor is set at $\beta = 0.974$ to match the risk-free rate.

Second, I calibrate the climate-change parameters through regressions using data on global temperature anomaly, carbon concentration, and anthropogenic CO_2 emission. For example, the autocorrelations and residual volatility of temperature and carbon concentration are estimated according to equations (29) and (30). $\bar{T}$ and $\bar{M}$ are estimated using average pre-industrial temperature and carbon concentration from AD 1 to 1750. All environment data is collected from NOAA, NASA, and the World Bank dataset.

Finally, I estimate the remaining parameters using GMM to match model-implied moments with those from the data. These include seven parameters: autocorrelation and residual volatility of damage intensity ρ_λ and σ_λ; investment adjustment cost ξ; parameters related to the human knowledge capital accumulation ν, b, and η; and the carbon intensity ζ. I choose the moments as follows: standard deviations of growth rates for output, consumption, carbon emission, and R&D; stock market premium; green premium; and the risk-free rate. Specifically, let Θ denote the set of these parameters, I choose Θ to minimize the following function:

$$\min_{\Theta} \quad \big(\mathcal{M} - f(\Theta)\big)' W^{-1} \big(\mathcal{M} - f(\Theta)\big),$$

where $\mathcal{M}$ is a vector of moments from data, W is the weighting matrix of the moments,[29] and $f(\Theta)$ are those same moments implied by model simulation. Panel C of Table X shows the point estimates.

B. Simulation

I provide two exercises based on the model simulation to show how my model replicates real-world observations. In the first exercise, I extract shocks from data and feed the model with the extracted shocks. Specifically, I extract short- and long-run productivity shocks following Croce (2014), and shocks on temperature and carbon concentration using equations (29) and (30). The shock on damage intensity is set as random noise. Figure 3 shows simulations of three series: (1)

[29] I follow Jermann (1998) in using the identity matrix. There are two reasons for this choice. First, these moments have different sample periods and frequencies. Thus it's impractical to draw their variance-covariance matrix. Second, economic moments usually have much smaller variances than financial moments. The identity weighting matrix ensures that all moments are equally weighted, so we will not lose too much fitting performances of financial moments.

Table X: **Calibration**

Description	Parameter	Value
Panel A: Literature based calibration		
Unconditional mean of productivity growth	μ	1.8%
Short-run growth volatility	σ	3.35%
Autocorrelation of long-run growth	ρ_x	0.96
Long-run growth volatility	φ_x	0.2
Fraction of brown sector	ω	0.59
Elasticity between two sectors	ε	3
Physical capital depreciation rate	δ_K	0.06
Share of capital in production	α	0.34
Subjective discount factor	β	0.974
Risk aversion	γ	10
IES	ψ	2
Equilibrium damage intensity	$\bar{\lambda}$	5.05×10^{-5}
Opportunity cost of R&D	k	4
Depreciation of human knowledge capital	δ_H	0.1
Panel B: Regression based calibration		
Autocorrelation of CO_2 concentration	ρ_M	0.98
Autocorrelation of temperature	ρ_T	0.17
Residual volatility of CO_2 concentration	σ_M	0.45
Residual volatility of temperature	σ_T	0.092
Sensitivity of temperature to CO_2 concentration	χ	3.088
Panel C. GMM based calibration		
Autocorrelation of damage intensity	ρ_λ	0.92
Residual volatility of damage intensity	σ_λ	2.5×10^{-5}
Investment adjustment cost	ξ	1.71
Share of human capital knowledge	ν	0.074
R&D parameter	η	0.67
R&D parameter	b	7.99
Carbon intensity	ζ	1.64

GDP growth rate, (2) temperature, and (3) carbon concentration. The simulated series closely matches those from the data, indicating that calibrated parameters lie in reasonable areas that are neither magnifying nor attenuating the shocks' effects.

In a second exercise, I calculate a number of moments from the simulations. These moments include standard deviations and autocorrelations of macroeconomic and climate variables as well as financial market moments. I simulate the model under the benchmark case, and a case where agents have CRRA utilities ($\frac{1}{\psi} = \gamma$), which is the standard specification under previous IAMs. For

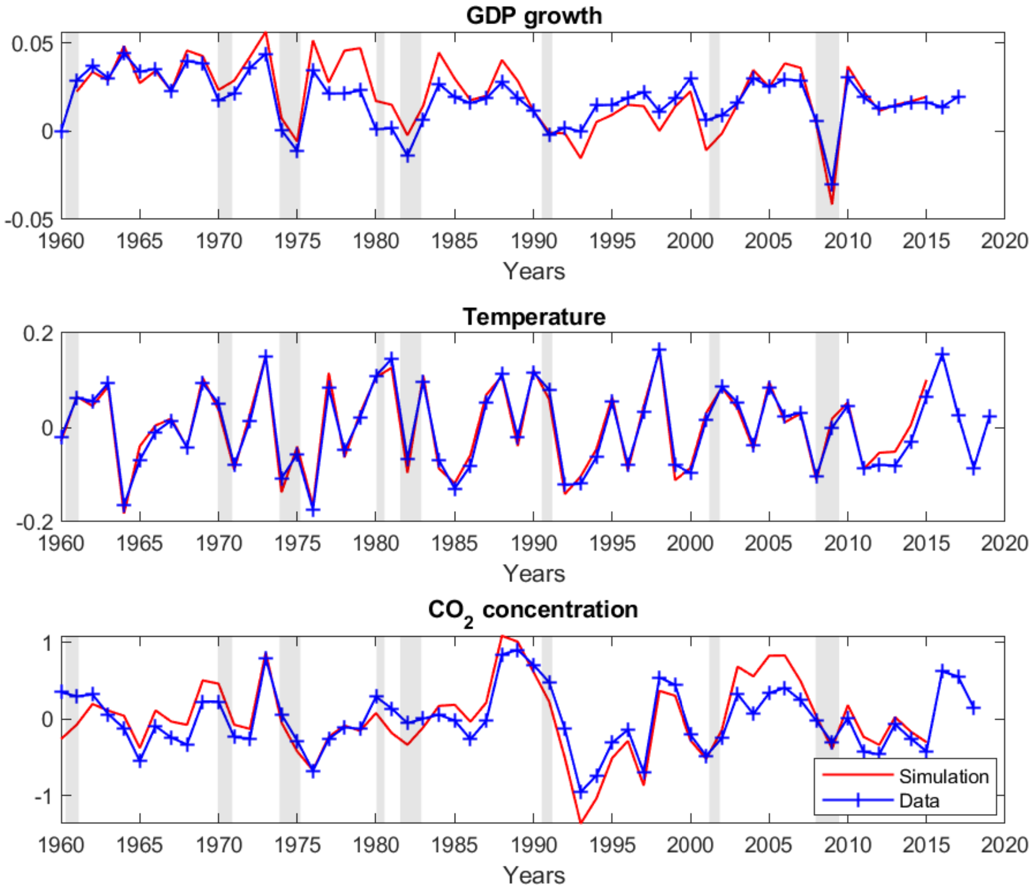

Figure 3: **Model simulation and data:** I simulated 60 time steps of the model as in the data. All the shocks are extracted from the data and are fed to dynare++ to get the simulation. Shocks on climate dynamics are extracted using equations (29) and (30). Short-run and long-run productivity shocks are extracted following Croce (2014):
$\Delta a_{t+1} = \mu + \underbrace{\beta_1 r_t^f + \beta_2 pd_t}_{x_t} + \epsilon_{a,t}, \quad x_t = \rho_x x_{t-1} + \epsilon_{x,t}.$
Where a_t, r_t^f and pd_t is the log TFP, risk-free rate and price-dividend ratio in U.S. $\epsilon_{a,t}$ and $\epsilon_{x,t}$ are extracted from short- and long-run shocks. Temperature and CO_2 concentration are detrended. Shaded areas indicate the NBER based recessions for the U.S.

both cases, I simulate the model for 60 time steps with 1,000 repetitions, consistent with the data length.

Table XI compares these model-generated moments with the data. The simulated moments under the benchmark calibration closely resemble the volatilities of most macroeconomic variables and environmental variables in the data. The model-implied volatility of consumption growth is slightly higher than that in the data. The model captures autocorrelations in the output, consump-

Table XI: **Simulated moments and data**

Moments	Data		Model	
	Estimate	SE	Benchmark	CRRA
Panel A. Macroeconomic variables				
$\sigma(\Delta y)$ (%)	2.43	(0.31)	2.42	2.25
$\sigma(\Delta c)$ (%)	2.05	(0.25)	2.77	2.57
$\sigma(\Delta i_B)$ (%)	3.32	(0.51)	2.98	6.24
$\sigma(\Delta i_G)$ (%)	6.52	(0.80)	6.40	23.27
$\sigma(\Delta RD)$ (%)	5.29	(0.63)	3.76	16.89
$AC1(\Delta y)$	0.36	(0.10)	0.40	0.26
$AC1(\Delta c)$	0.48	(0.10)	0.34	0.22
$AC1(\Delta i_B)$	0.00	(0.17)	0.25	0.05
$AC1(\Delta i_G)$	0.11	(0.31)	0.28	0.05
$AC1(\Delta R_G)$	-0.06	(0.07)	0.22	0.00
Panel B. Climate variables				
$\sigma(\Delta T)$ ($°C$)	0.12	(0.01)	0.13	0.13
$\sigma(\Delta M)$ (ppm)	0.65	(0.06)	0.53	0.55
$\sigma(\Delta E)$ (ppm)	0.06	(0.01)	0.07	0.04
$AC1(\Delta T)$	-0.33	(0.09)	-0.49	-0.49
$AC1(\Delta M)$	0.53	(0.13)	0.38	0.51
$AC1(\Delta E)$	0.34	(0.17)	0.08	0.44
Panel C. Asset prices				
$E(R_B - R_G)$ (%)	3.83	(1.54)	3.22	0.49
$\sigma(R_B - R_G)$ (%)	6.37	(0.49)	2.62	1.19
$E(R^{ex}_{MKT})$ (%)	6.68	(1.90)	6.43	-0.72
$\sigma(R^{ex}_{MKT})$ (%)	17.20	(1.47)	15.32	25.06
$E(r_f)$ (%)	0.85	(0.51)	0.79	19.86
$\sigma(r_f)$ (%)	2.12	(0.28)	0.63	8.93

Note: Δy is the output growth rate, Δc is the consumption growth rate, Δi_B (Δi_G) is the investment growth rate of sector B (G), and ΔRD is the R&D growth rate in sector G. ΔT is the temperature increment, ΔM is the carbon concentration increment, and ΔE is the carbon emission increment. $R_B - R_G$ is the difference between stock returns in sector B and G. R^{ex}_{MKT} is the market excess return. R_f is the risk-free rate. I simulate the model under the benchmark calibration and a case that the IES equals $1/\gamma$ (CRRA case). For both cases, I simulate 60 steps with 1000 repetitions. Excess returns have a leverage of two in the simulation. Annual data on Δy, Δc, ΔT, ΔM, R^{ex}_{MKT}, and r_B is from 1960-2018. Δi_B and Δi_G are calculated using the bottom and top quintile portfolios in Section III, respectively. $E(\cdot)$, $\sigma(\cdot)$ and $AC1(\cdot)$ are mean, standard deviation, and first-order autocorrelation, respectively. Numbers in the parentheses are Newey-West adjusted standard errors obtained through GMM. All statistics are in annual term.

tion, and temperature growth rate. In terms of the asset returns, the model quantitatively captures the greenium. A zero-cost strategy that longs the green stocks and shorts the brown ones delivers an expected annualized return of 3.83%. The model simulated return is 3.22%, which lies within the confidence interval of the data. The model-implied standard deviation of excess returns is lower compared to the data. This may be due to other unsystematic risks that are not captured in this model. The model-implied market return, which is constructed by averaging the stock returns of the two sectors weighted by their market values, replicates the average market return and its high volatility in the data.[30] Finally, the model generates a risk-free rate that is low enough to match that observed in the data.

In the other case, where agents have CRRA preferences instead of recursive ones, model-implied moments on economic quantities and asset prices fail to align with the data. For example, the investments and R&D become excessively volatile; autocorrelation of output and consumption is small. In addition, the difference between green and brown stocks becomes less pronounced. Finally, the most apparent discrepancy between a model with CRRA utilities and the data, as addressed in Bansal and Yaron (2004) and Croce (2014), is that the model-generated risk-free rate is extremely high and the market premium is too low. This is because CRRA agents do not price long-run shocks about productivity, so consumption risk is too low to justify a low risk-free rate and a high enough market premium.

C. Impulse response functions to a shock on damage intensity

I estimate the IRFs to a positive shock on the climate damage intensity parameter λ. The shock can be interpreted as an exogenous natural disaster that revises upward people's beliefs in the marginal damage caused by pollution. As a result, the externality of investing in fossil fuel increases, and agents refrain from using fossil fuel. These effects are all elaborated in Figure 4.

The solid blue lines in Figure 4 show the IRFs under the benchmark calibration when the IES is bigger than one and agents prefer early resolution of uncertainty. First, a positive shock on λ generates a temporary decline in the current consumption growth and an increase in the SDF, which indicates a higher marginal utility from consumption and a bad state of the world. Second, labor, investments, and Tobin's q in sector G increase relative to sector B. As a result, the green sector appreciates relative to the brown one. This result is consistent with that in the two-period model, again showing that green stocks hedge a disaster shock and offer insurance against global warming.

[30] Appendix C presents a detailed description of how to construct sectoral and market stock returns.

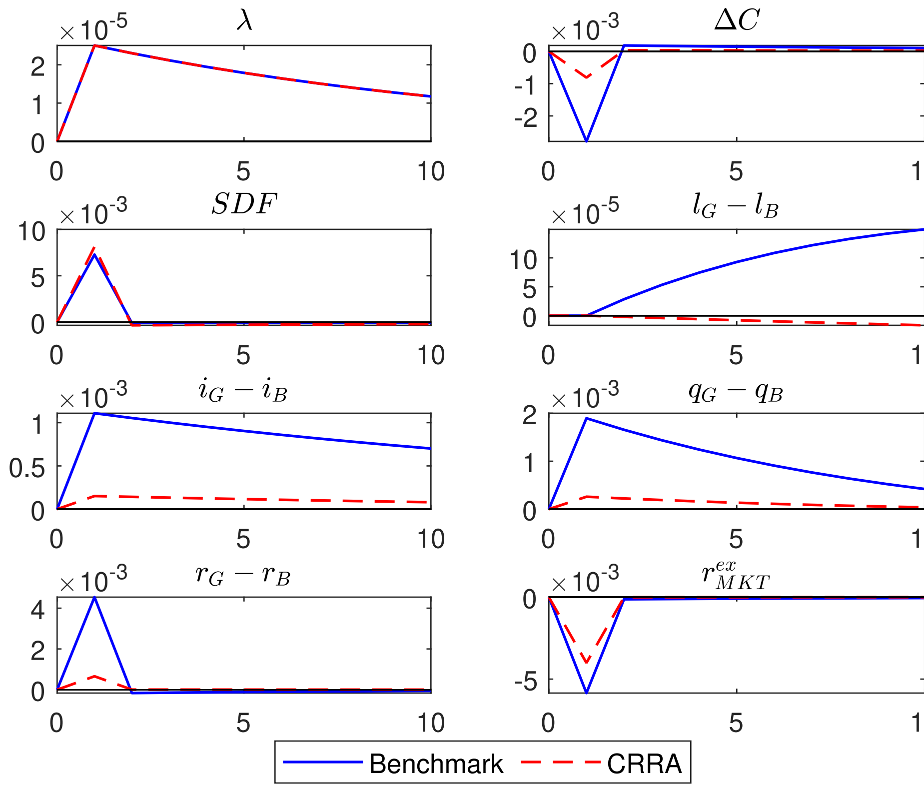

Figure 4: **Impulse response functions to a positive shock on the damage intensity parameter λ_t:** This figure shows the impulse response functions (IRF) of a one-standard-deviation positive shock on the damage intensity λ. The shock happens at $t = 1$. The blue solid lines show the IRF under the benchmark case with recursive preference. The red dashed lines show the IRF under the case with CRRA utility.

Specifically, a one-standard-deviation shock on λ increases the return difference between green versus brown stocks by around 50 b.p. This result explains the lower simulated return of sector G in Table XI. Third, as shown in the last panel of Figure 4, market return decreases significantly after a positive disaster shock. Thus the disaster shock helps explain the market premium, consistent with the rare disaster models (Barro, 2006; Nakamura et al., 2013)

The red dotted line shows the alternative case when agent has CRRA utility (IES being equal to the reciprocal of risk aversion). In this case, the difference between the responses of green versus brown sectors are much less pronounced. This phenomenon means that agents care less about the bad news and are reluctant to reallocate resources. As a result, under the CRRA case, a strategy that longs the green and shorts the brown cannot generate a sufficient hedge against a disaster shock. Therefore, the greenium is less pronounced, consistent with the simulation results in Table

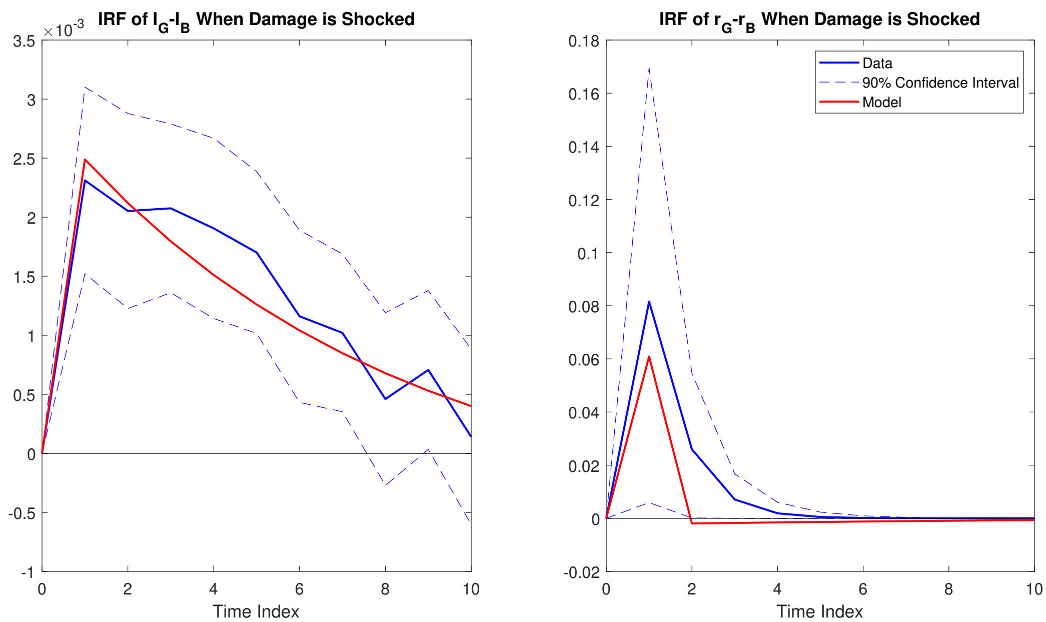

Figure 5: **Impulse response functions to a positive climate damage shock: Model vs. Data** This figure shows the impulse response functions (IRF) of the return and investment differential between green and brown firms to a one-standard-deviation positive shock on the log of real climate damage. The blue solid (dotted) lines show impulse response functions (90% confidence intervals) from the data. Investment is defined by log changes in the total asset. The red solid lines show the model counterpart. All responses are annualized. The shock happens at $t = 1$.

XI.

At last, I implement a quantitative exercise to compare the IRFs implied by the model and those estimated from the data. Our model abstracts away various firm-level idiosyncratic risks and noises that may overwhelm the data. Therefore I focus on the return and investment differentials between green and brown firms, the two key variables that my model tries to capture. Figure 5 shows the result. The blue lines show the empirical IRFs of the investment differential (I_G-I_B) and return differential (R_G-R_B) to a one-standard-deviation positive shock on the log of real climate damage. I find that a positive climate damage shock increases green firms' investment by 0.23% relative to brown firms, and appreciates green stocks by 8% (annualized) relative to brown stocks. These effects are significant at the 10% level. The red lines show the model counterpart, where I impose a climate damage shock with the same magnitude as the data. I find it reassuring that the model generates IRFs consistent with the data, which shows a strong quantitative performance of my model.

D. *Steady-state results*

This subsection reports the SCC, and conducts sensitivity analysis of macroeconomic and climate variables on several key parameters.

Social cost of carbon The SCC measures the present value of the future damages caused when one additional unit of carbon emission is released into the atmosphere. In other words, it captures the marginal rate of transformation between carbon emission and consumption. In environmental economics, the SCC is an essential concept for evaluating the benefits of climate mitigation policies or technologies. A higher SCC indicates higher benefits from implementing these policies or technologies and thus motivates early actions of climate interventions. However, the framework here already presented a first-best optimum, so there is no role played by policies. I interpret SCC in an asset pricing manner: if there is a security with cash flow that exactly offsets the future damage caused by one additional unit of carbon emission (a *climate hedge*), the SCC would be the price that investors are willing to pay for it.

To calculate the SCC for one metric ton of carbon, I implement the following transformation,

$$SCC = -\frac{1}{s}\frac{Q_M}{\tilde{Y}} \cdot Y^{real}, \tag{34}$$

where $\tilde{Y}$ is the model-implied steady-state output, Y^{real} is the real-world output in U.S. dollars, and s is a rescaling factor, indicating the number of tonnes of carbon in one particle per million (ppm) equivalent of CO_2.[31] Finally, Q_M is the steady-state shadow price of emission. The F.O.C. in Appendix C shows that Q_M follows the Euler equation:

$$1 = \mathrm{E}_t\left[\Lambda_{t+1}\frac{\rho_M Q_{M,t+1} - \lambda\tilde{Y}_{t+1}}{Q_{M,t}}\right] \tag{35}$$

where Λ_{t+1} is the SDF. Define $R_{SCC,t+1} = \frac{\rho_M Q_{M,t+1} - \lambda\tilde{Y}_{t+1}}{Q_{M,t}}$ as the return on Q_M.

From equation (34) and (35) we can clearly see that the determinants of the SCC are (i) the depreciation of carbon concentration, ρ_M, (ii) the damage intensity, λ, and (iii) the stochastic discount factor. The first two determine the cash-flow channel, and the third one accounts for the

[31] According to Le Quéré et al. (2018), one part per million of carbon dioxide in the atmosphere corresponds to 2.124 gigatonnes of carbon. Thus $s = 2.124 \times 10^9$.

discount-rate channel.

In my model, the stochastic steady-state $\frac{Q_M}{\hat{Y}}$ is 9.78×10^{-4}. In other words, all else being equal, a one-unit increase in the carbon concentration is equivalent to a 9.78 b.p. decrease in current GDP. Given that the world GDP was 8.77×10^{13} U.S. dollars in 2019 (measured in current U.S. dollars, as reported by the World Bank), then one ppm equivalent CO_2 emission has a present cost of 85.77 billion U.S. dollars. This number means that the SCC is, on average, about 40.38 U.S. dollars per tonne of carbon. In other words, the market price of a climate hedge is 40.38 U.S. dollars. Of course, one should interpret this value with caution or consider this value as a lower bound, as the model only considers the economic cost of climate change while neglecting, for example, its damage to human health.

Risks, endogenous R&D, and green sector This section shows that climate damage is strongly procyclical, which leads to a positive risk premium and drives down the shadow cost of carbon emission, i.e., the SCC. Specifically, I compare the SCC under both stochastic (benchmark) and deterministic (no risks) steady states. The first case accounts for risks (i.e., the covariance between damages and the SDF), and the second only includes first-order moments and no risks whatsoever.

The first and second columns of Table XII show the cases with and without risks, respectively. The SCC under the benchmark case is 27% lower (40.4 vs. 55.6) than the case without risks. Note that the SCC is determined by the present value of future climate damage. The negative covariance between damage and the SDF leads to a positive risk premium in the return of Q_M, illustrated by the second row of the first column. The return that investors used to discount climate damage is $r_{SCC} = 4.71\%$, which indicates a nearly 4% premium given that the risk-free rate is only 0.83%. This is because the cash flow being proportional to the output, climate damage is higher exactly when the economy performs better (hence higher consumption and lower marginal utility). In other words, climate damage is strongly procyclical. Therefore it is highly risky and will be discounted at a positive premium.

Under the deterministic steady state with no risks, the discount rate for climate hedge is the risk-free rate, which is counter-factually high (3.53%). This is due to the lack of a precautionary saving term to drive down the risk-free rate. Nevertheless, the return on SCC is lower due to a

Table XII: **Counterfactual analyses**

	Benchmark	No risks	No Green R&D	No Green energy
SCC	40.38	55.61	40.31	40.40
r_{SCC}	4.71%	3.53%	4.72%	4.71%
Risk-free rate	0.83%	3.53%	0.66%	0.65%
Change in welfare	0.00%	1933%	-48.66%	-58.83%
Share of green energy	62.80%	61.13%	25.43%	0.00%
Temperature	0.95	1.19	1.09	1.16

Note: This table shows the counterfactual analyses. Welfare is measured as the proportional change of utility-over-productivity ratio with respect to the benchmark case. SCC is calculated using world GDP in 2019 and is in units of U.S. dollars. Temperature is in unit of degree Celsius.

zero risk premium, leading to a higher SCC estimate. In sum, the result shown here sheds light on the role of risks in determining the SCC, which is often neglected in previous deterministic IAMs (Nordhaus and Sztorc, 2013). Finally, welfare, measured by utility over productivity ratio, is much higher compared to the benchmark case. This is because agents are particularly averse to long-run risks under recursive preference. Therefore, a higher present value of climate damage does not necessarily mean a lower social welfare: discount rate channel matters.

In another exercise, I investigate the role of endogenous R&D and green energy. Specifically, I add two counterfactual scenarios where endogenous R&D and the green sector are absent, respectively.[32] The third and fourth columns in Table XII show the two cases. Both cases have very similar SCC compared to the benchmark case. This result shows that green R&D and green energy have little impact on SCC. The risk-free rates for the two cases are lower, because agents are less able to smooth intertemporal consumption. As a result, higher consumption risk leads to a more volatile SDF, driving up the premium and suppressing the risk-free rate. Welfare is greatly reduced under the two counterfactual cases. It is 48.7% (58.8%) lower when green R&D (energy) is absent. In addition, the share of green energy, calculated by the share of physical capital in the green sector, decreases when R&D is absent. Finally, equilibrium temperatures are higher under the two counterfactual cases due to more use of fossil fuels. The result shows that the green energy and endogenous R&D represent a vital growth option, improving economic activity and welfare significantly at the equilibrium.

[32]The first case is represented by a re-calibrated model where the share of human capital knowledge ν is equal to zero. Thus R&D plays no role in improving the production efficiency of the green sector. For the second scenario, I set the labor supply in the green sector at zero. In this way, the marginal product of the green sector's physical capital is zero, leading to zero green investment in equilibrium.

The role of damage intensity Damage intensity, λ_t, follows an AR(1) process with an equilibrium value equal to $\bar{\lambda}$. This value is calibrated according to Golosov et al. (2014) and matches the damage magnitude in Nordhaus and Sztorc (2013). It is a key parameter in determining the tightness of the interactions between economic growth and climate change. Given that there is a high uncertainty regarding the true value of this parameter, the economic and environmental effects are worth investigating whenever the value of this parameter changes.

Figure 6 shows the results. The horizontal axis is re-scaled to represent the damage as a proportion of GDP, when the temperature anomaly exceeds two degrees Celsius (the benchmark case is 1.28%). First, an increase in the damage intensity decreases welfare: when the equilibrium damage intensity increases from 0 to $2.5\%/2°C$, welfare decreases 4%. This is due to the increase in equilibrium climate damage. Second, an increase in damage intensity leads to higher marginal costs for investing in the brown sector relative to the green sector. Thus shares of investment, labor, and R&D in the green sector all increase. As a result, temperature decreases in equilibrium. Finally, as the climate-economy interaction becomes tighter, it drives up the risk premium. Therefore, the expected return on climate hedge increases, and SCC is discounted at a higher rate. Still, the cash flow channel dominates the discount rate channel, leading to an increased SCC.

Sensitivity analysis on key parameters This part implements sensitivity analysis on several key parameters. Table XIII shows how model-implied variables change with respect to these parameters. Starting from the subjective discount rate and the IES. When the subjective discount rate is lower (0.95 vs. 0.974 in the benchmark case), the model generates a higher risk-free rate (4.67% vs. 0.83%). The return on SCC is higher than the benchmark case (6.56% vs. 4.71%), resulting in a lower SCC estimate (30.2 vs. 40.4). On the other hand, when the IES is equal to 0.1, which reduces the preference to the CRRA utility, the risk-free rate is counterfactually high (15.91%). This is because the agent does not have enough desire to smooth consumption across time, leading to present-day higher consumption and less saving, thus driving up the risk-free rate. As a result, the climate damage is discounted at a higher rate, and the SCC becomes much lower than the benchmark case (11.8 vs. 40.4). In addition, due to agents' unwillingness to sacrifice current consumption for better future environmental conditions, the shares of investment and R&D in sector G are smaller than the benchmark case.

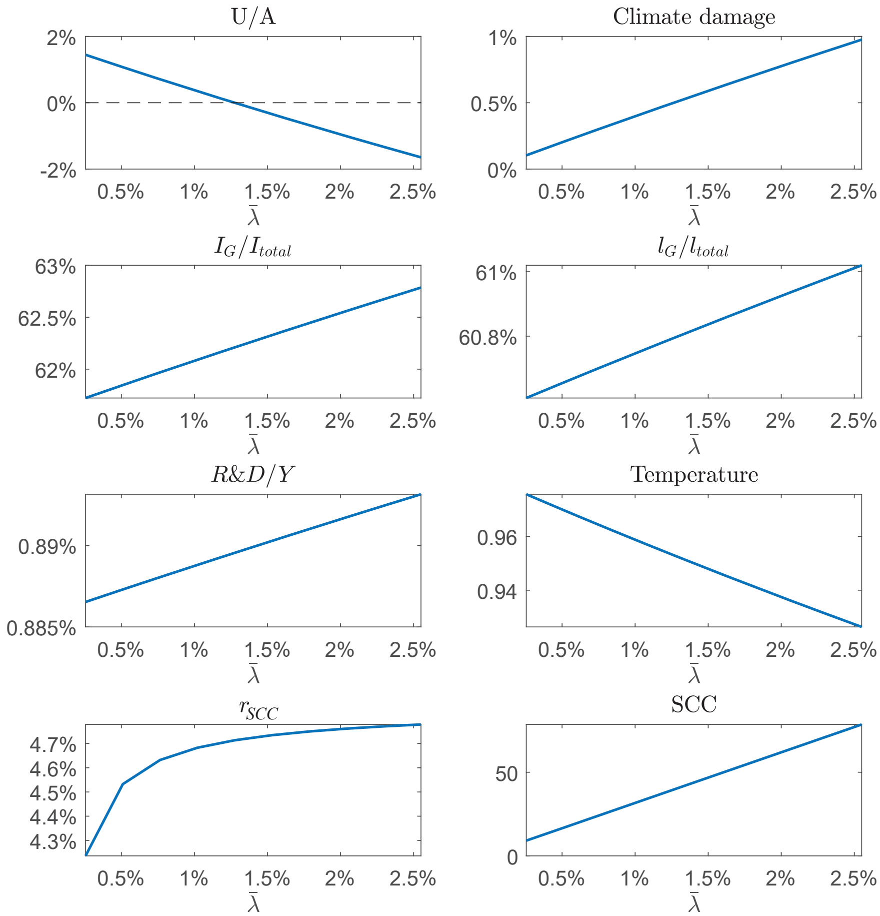

Figure 6: **The role of damage intensity.** The figure shows the stochastic steady-state values under different equilibrium damage intensity $\bar{\lambda}$. The x-axis is re-scaled to show the damage as a proportion of GDP when the temperature anomaly exceeds $2°C$. U/A shows the percentage change in the welfare-over-productivity ratio. SCC is in the unit of U.S. dollars; temperature is in the unit of $°C$.

Another important parameter is the elasticity of substitution between the green and brown sectors in the production function (ε). I compare two cases where ε is either lower (=1.5) or higher (=10) than the benchmark case (=3). The results show that when the degree of substitution is higher, the economy relies much more on the green sector, as the share of green investment, labor and R&D are all higher. This is intuitive: suppose brown and green energy are perfect substitutes; all resources should be directed to green energy since it is free from negative climate feedback. In equilibrium, this leads to a lower temperature (close to zero) and less climate damage. However, the substitution coefficient has little impact on the risk-free rate, discount rate, and the SCC. Thus it mainly affects the equilibrium allocation of resources.

Table XIII: **Sensitivity analysis**

	Benchmark	Subjective discount rate	IES	Substitution		R&D efficiency	
		$\beta = 0.95$	$\psi = 0.1$	$\varepsilon = 1.5$	$\varepsilon = 10$	$\nu = 0.05$	$\nu = 0.1$
SCC	40.38	30.24	11.82	40.65	39.44	40.34	40.43
Return on SCC	4.71%	6.56%	15.91%	4.69%	4.80%	4.72%	4.71%
Risk-free rate	0.83%	4.67%	17.37%	0.78%	0.94%	0.75%	0.95%
Climate damage	0.51%	0.41%	0.18%	0.70%	0.03%	0.55%	0.45%
Temperature	0.95	0.80	0.36	1.24	0.07	1.01	0.86
I_G/I_{total}	62.80%	59.84%	55.49%	45.17%	98.36%	48.64%	76.81%
l_G	61.38%	59.11%	55.32%	44.47%	98.09%	47.58%	75.29%
$R\&D/Y$	0.89%	0.53%	0.20%	0.65%	1.36%	0.47%	1.46%

Note: This table shows the stochastic steady-state values of different cases. SCC is calculated using world GDP in 2019 and is in units of U.S. dollars; temperature is in units of $°C$.

Finally, when decreasing the weight of human knowledge capital in the production (ν), the agent decreases R&D, green investment, and labor, as the marginal product of green investment becomes lower. The temperature is higher. Effectively the discount rate and SCC are quantitatively unchanged.

VII. Conclusion

This paper documents a negative risk premium of green stocks compared to brown stocks. The greenium cannot be explained by various systematic risks and firms' idiosyncratic risks. Further investigation of the sources of risk shows that green stocks appreciate after climate-related disasters relative to brown stocks, thus offering a hedge against climate-change physical risks. The empirical finding is then qualitatively explained in a simple two-period model and quantitatively matched in a MFIAM with time-varying damage intensities, recursive preferences, and investment frictions. This paper chiefly contributes to providing a first benchmark MFIAM that considers elements from both IAM and macro-finance literature, while suggesting implications for climate risks in the stock market.

I study the problem using a first-best approach (a planner's problem) because it offers a handy and transparent way to start analyzing environmental feedback in the macro-finance literature. An important limitation of my approach is that this approach cannot fully reflect externalities.

Nevertheless, I show that the greenium can be rationalized in such an economy. Further extension of this paper should consider a decentralized economy where investments and R&D are distorted (Romer, 1990). It would be interesting to study a second-best distortionary taxation that corrects the externalities and how green/brown firms are exposed to endogenous regulatory changes.

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Appendix A. Additional results

Appendix A.1. Decomposition of ENSCORE

In this section, I use the three category scores of ENSCORE to sort portfolios. This exercise shows which components of ENSCORE are most powerful in explaining the greenium. In other words, this shows which aspect of firms' environmental performance matters most for investors. Recall that ENSCORE is a weighted average of three categories: emission, innovation, and resource. The emission category measures firms' responsibility in emitting greenhouse gases. This score is constructed by metrics such as carbon emission. The innovation score captures firms' ability to develop environmentally friendly products, such as patents to produce green energy or control wastes. Finally, the resource score measures firms' use of renewable energy versus fossil fuel.

I implement the same time-series study as in the main part of the paper. First, I sort firms into quintile portfolios using one of the three category scores of the last year relative to industry peers. Then I regress the excess returns of the quintile portfolios and the low-minus-high portfolio on asset pricing factors. Table A1 shows the results. The abnormal (α) of the low-minus-high portfolio remains positive for all three cases. After controlling for FF5 and FF5 plus the momentum factor, these abnormal returns are all significant. The result here is consistent with those obtained using ENSCORE. Moreover, the greenium seems to be most significant for emission scores. This shows that investors care more about the emission profile when evaluating firms' greenness.

Table A1: **Abnormal return of portfolios according to category scores**

	L	2	3	4	H	L − H
			Panel A. Emission score			
$E[R^{ex}]$	10.59	9.05	9.16	7.48	7.78	2.81**
	(4.03)	(4.18)	(4.16)	(3.62)	(3.25)	(1.23)
CAPM α	2.63	1.05	1.53	0.77	1.10	1.54*
	(1.22)	(1.53)	(1.47)	(1.03)	(0.87)	(1.06)
FF3 α	2.82	1.14	1.95	1.07	1.54	1.28*
	(0.99)	(1.55)	(1.39)	(1.01)	(0.77)	(0.91)
FF5 α	4.74	0.78	2.21	0.82	1.99	2.74**
	(1.15)	(1.69)	(1.47)	(1.1)	(1)	(1.31)
FF5 & MOM α	4.76	0.76	2.27	0.76	1.95	2.81**
	(1.16)	(1.71)	(1.44)	(1.12)	(1.05)	(1.38)
			Panel B. Innovation score			
$E[R^{ex}]$	10.11	10.42	9.04	10.79	8.81	1.30
	(4.46)	(5.36)	(4.36)	(4.37)	(4.16)	(1.13)
CAPM α	2.17	0.68	1.32	3.55	1.57	0.60
	(1.52)	(1.75)	(1.87)	(2.19)	(1.37)	(1.09)
FF3 α	2.39	0.89	1.64	3.70	1.90	0.49
	(1.51)	(1.65)	(1.85)	(2.14)	(1.41)	(1.14)
FF5 α	4.99	2.86	2.17	4.92	3.11	1.88*
	(2.07)	(1.51)	(2.12)	(2.72)	(2.05)	(1.32)
FF5 & MOM α	5.09	3.05	2.33	4.93	3.23	1.86*
	(2.02)	(1.52)	(2.05)	(2.68)	(2.05)	(1.32)
			Panel C. Resource score			
$E[R^{ex}]$	9.81	9.38	9.09	8.11	7.56	2.25*
	(4.29)	(4.52)	(3.52)	(4.02)	(3.18)	(1.44)
CAPM α	1.60	1.29	2.00	0.89	0.94	0.66
	(1.14)	(1.44)	(1.04)	(1.21)	(1.02)	(1.1)
FF3 α	1.74	1.18	2.30	1.18	1.43	0.31
	(0.98)	(1.45)	(1)	(1.25)	(0.81)	(0.96)
FF5 α	3.68	2.58	3.21	0.80	1.70	1.98**
	(1.12)	(1.78)	(1.16)	(1.13)	(0.91)	(1.07)
FF5 & MOM α	3.72	2.66	3.08	0.77	1.68	2.04**
	(1.1)	(1.73)	(1.22)	(1.12)	(0.93)	(1.12)

Note: The table shows the excess returns and abnormal returns (α) of the quintile and low-minus-high portfolios sorted by the three category scores of ENSCORE: emission, innovation, and resource. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_{i,t} = \alpha_i + \beta_i' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum. Returns are value-weighted and annualized. The sample period is 2003-2019. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

Table A2: **Sub-sample investigation of the greenium**

	$E[R^{ex}]$	CAPM α	FF3 α	FF5 α	FF5_MOM α
Full sample	3.83***	2.43**	2.17**	3.91***	3.98***
	(1.39)	(1.18)	(0.98)	(1.22)	(1.25)
2004-2019	3.80***	2.45**	2.46***	4.77***	4.98***
	(1.48)	(1.21)	(0.97)	(1.17)	(1.21)
2005-2019	3.42**	2.19**	2.22**	4.56***	4.71***
	(1.58)	(1.29)	(1.03)	(1.21)	(1.24)
2006-2019	3.71**	2.51**	2.51***	4.51***	4.58***
	(1.67)	(1.34)	(1.07)	(1.33)	(1.36)
2007-2019	4.04**	2.97**	2.71***	4.84***	4.86***
	(1.76)	(1.35)	(1.14)	(1.41)	(1.43)
2008-2019	4.39***	3.37***	2.79**	4.89***	4.88***
	(1.86)	(1.42)	(1.23)	(1.57)	(1.58)
2009-2019	5.98***	4.12**	2.31**	3.56**	3.52***
	(2.1)	(1.99)	(1.37)	(1.55)	(1.5)

Note: The table shows the excess returns and abnormal returns (α) of the low-minus-high portfolio sorted by ENSCORE. The sample period is from year y to 2019. y is shown in the first column of the table. Returns are value-weighted and annualized. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

Appendix A.2. Subsample analysis

In this section, I investigate the greenium in a shrinking window. Specifically, I repeat the same investigation of Table III but using a sample period from some starting year (2003-2009) to the end year (2019) of the sample, which ensures coverage of at least half the sample. This exercise shows (1) whether the greenium is driven by specific sample periods and (2) how the greenium changes when we focus on a shorter and more recent sample. To save space, I only show αs of low-minus-high portfolio for different asset pricing factors. Further results are available upon request.

Table A2 show the results. First, the greenium exists also in a shorter and more recent sample. All the abnormal returns remain significant at 5% level. In addition, the excess return of the low-minus-high portfolio seems to increase when focusing on a more recent sample. This demonstrates an increasing trend that investors are becoming more and more concerned about climate change issues over the last two decades.

In a similar exercise, I investigate the subsample but focus on the group of firms with ENSCORE at the starting years. Specifically, I focus on the sample from year y to 2019 and only use the

Table A3: **Sub-sample investigation of the greenium (fixed firms)**

	$E[R^{ex}]$	CAPM α	FF3 α	FF5 α	FF5_MOM α
2003-2019	2.33*	0.90	0.71	1.73*	1.78*
	(1.66)	(1.68)	(1.43)	(1.34)	(1.35)
2004-2019	2.06	0.67	0.69	2.10*	2.26*
	(1.76)	(1.7)	(1.4)	(1.36)	(1.38)
2005-2019	3.31**	1.98*	2.05**	4.16***	4.41***
	(1.64)	(1.37)	(1.07)	(1.18)	(1.22)
2006-2019	3.12**	1.99*	2.06**	3.66***	3.74***
	(1.61)	(1.4)	(1.13)	(1.33)	(1.35)
2007-2019	3.32**	2.29*	2.20**	3.84***	3.87***
	(1.73)	(1.48)	(1.23)	(1.4)	(1.43)
2008-2019	3.91**	2.83**	2.48**	4.01***	3.98***
	(1.99)	(1.6)	(1.3)	(1.36)	(1.38)
2009-2019	4.94***	3.20**	2.18*	2.91**	3.00**
	(1.81)	(1.81)	(1.41)	(1.39)	(1.39)

Note: The table shows the excess returns and abnormal returns (α) of the low-minus-high portfolio sorted by ENSCORE. The sample period is from year y to year 2019 and focusing on firms with ENSCOREs at year $y-1$. y is shown in the first column of the table. Returns are value-weighted and annualized. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

companies with a score in year $y-1$. This eliminates the endogenous issue that firms strategically time the release of information. Table A3 shows the results. As before, abnormal returns of the low-minus-high portfolio remain positive and, in most cases, significant for different subsamples and asset pricing factor sets.

Finally, I investigate whether greenium exists in a sample with only U.S. firms. Specifically, I run the same factor regressions with quintile portfolios sorted by U.S. firms. For the asset pricing factors I choose those from the U.S. market: CAPM, FF3, FF5, and q5 factor (Hou et al., 2021). The q-factor model is an important workhorse in empirical asset pricing literature, as it subsumes the Fama-French six factors (Hou et al., 2015). Table A4 shows the result. Using only U.S. firms does not qualitatively change the result. In particular, when controlling the q5 factor, the abnormal return of a low-minus-high ENSCORE portfolio is 5.15%, which is higher than that from the global sample.

Appendix A.3. Alternative greenness measures

Berg et al. (2019) show substantial divergences among different ESG ratings. As such, I use

Table A4: **Abnormal return of quintile portfolios in U.S. subsample**

	L	2	3	4	H	L − H
$E[R^{ex}]$	12.73	12.05	10.66	11.22	8.37	4.36**
	(4.55)	(4.58)	(3.92)	(3.64)	(3.26)	(1.88)
CAPM α	2.61	1.79	1.47	2.26	0.07	2.54*
	(1.45)	(1.79)	(1.64)	(1.31)	(0.95)	(1.64)
FF3 α	2.25	1.88	1.36	2.20	0.05	2.20*
	(1.18)	(1.84)	(1.62)	(1.32)	(1)	(1.6)
FF5 α	2.97	0.81	0.62	1.25	-0.40	3.37**
	(1.24)	(1.64)	(1.82)	(1.39)	(1.16)	(1.49)
q5 α	4.33	3.98	2.71	1.76	-0.82	5.15***
	(1.54)	(1.39)	(1.48)	(1.29)	(1.03)	(1.47)

Note: The table shows the excess returns and abnormal returns (α) of the quintile and low-minus-high portfolios using the U.S. subsample. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and q5. Returns are value-weighted and annualized. The sample period is 2003-2019. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

alternative greenness measures to sort portfolios and check whether a greenium still exists. Specifically, I first use the *emission intensity* following Bolton and Kacperczyk (2021a,b). The emission intensity is calculated using firms' carbon emission levels (scope 3) divided by the total asset or revenue.[33] We do not consider the level of carbon emissions because it is innately related to firms' size, thus it may not be representative for firms' greenness (e.g., a big green firm can have higher emissions than a small brown one). Emission intensity is obtained from Refinitiv Eikon.

I follow the same process in section III.B. I first sort firms into quintile portfolios according to their emission intensity of the last year relative to their industry peers. Then I obtain the return on the portfolio of the quintile portfolio and a low-minus-high portfolio. I run regressions of these returns on asset pricing factors, including CAPM, FF3, FF5, and FF5 plus the momentum factor. Table A5 shows the results for carbon intensity. The estimated greenium remains significant, and it is in the right direction, i.e., a portfolio with higher emission intensity has higher abnormal returns.

[33]Scope 3 emissions come from the operations and products of the company but occur from sources not owned or controlled by the company. I consider scope 3 emission because it is the most comprehensive measure of a firm's carbon emissions.

Table A5: **Abnormal return of portfolios according to emission intensity**

	L	2	3	4	H	L − H
			Panel A. Carbon emission/Total asset			
$E[R^{ex}]$	4.70	6.64	7.41	6.85	9.23	-4.53*
	(5.74)	(4.49)	(4.76)	(4.09)	(3.53)	(3.41)
CAPM α	0.07	2.43	3.00	2.71	5.44	-5.38**
	(2.95)	(2.14)	(2.07)	(2.43)	(2.57)	(3.25)
FF3 α	-0.12	2.51	2.94	2.96	5.59	-5.71**
	(2.89)	(2.15)	(2.07)	(2.41)	(2.48)	(3.22)
FF5 α	-0.81	3.11	2.77	2.07	4.75	-5.57**
	(2.85)	(2.5)	(2.13)	(2.64)	(2.39)	(3.02)
FF5 & MOM α	-0.77	3.05	2.77	2.05	4.74	-5.51**
	(2.85)	(2.39)	(2.13)	(2.59)	(2.35)	(2.91)
			Panel B. Carbon emission/Revenue			
$E[R^{ex}]$	4.96	8.07	6.88	7.13	9.06	-4.10*
	(5.27)	(4.48)	(4.72)	(4.25)	(3.53)	(2.99)
CAPM α	0.80	3.43	2.54	2.85	5.32	-4.53*
	(2.68)	(1.82)	(2.32)	(2.25)	(2.58)	(3.02)
FF3 α	0.87	3.39	2.46	3.02	5.50	-4.63*
	(2.67)	(1.71)	(2.32)	(2.25)	(2.51)	(3.03)
FF5 α	0.44	3.59	1.52	2.47	4.78	-4.34**
	(2.45)	(2.21)	(2.41)	(2.51)	(2.41)	(2.61)
FF5 & MOM α	0.41	3.51	1.57	2.46	4.76	-4.34**
	(2.43)	(2.06)	(2.46)	(2.48)	(2.34)	(2.6)

Note: The table shows the excess returns and abnormal returns (α) of the quintile portfolio and a low-minus-high portfolio, sorted by the emission intensity. Emission intensity is measured by carbon emission (scope 3) divided by total asset or revenue. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum. Returns are value-weighted and annualized. The sample period is 2007-2019. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

Second, I use another popular ESG ratings, the MSCI ESG score. This rating score is binary. It evaluates whether a firm fulfills its environmental responsibilities over sixteen positive subcategories or satisfies certain conditions over nine negative subcategories. I follow Engle et al. (2020) to subtract the total score of negative subcategories from that of positive subcategories to get the overall environmental score of each firm. The higher the score is, the more eco-friendly the firm is. I collect MSCI scores from WRDS of a sample period from 1996 - 2016. Table A6 shows the result

Table A6: **Abnormal return of portfolios sorted by MSCI E-score**

	L	H	L − H
$E[R^{ex}]$	10.02	7.73	2.29
	(3.59)	(4.19)	(2.54)
CAPM α	4.21	0.47	3.74*
	(2.45)	(1.82)	(2.45)
FF3 α	3.16	-0.74	3.89*
	(2.54)	(1.44)	(2.68)
FF5 α	1.33	-2.89	4.22*
	(2.44)	(1.53)	(2.59)
FF5&MOM α	1.57	-2.37	3.94*
	(2.37)	(1.61)	(2.6)

Note: The table shows the excess returns and abnormal returns (α) of the low, high, and low-minus-high portfolio sorted by the MSCI E-score. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum. Returns are value-weighted and annualized. The sample period is 1996-2016. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

using MSCI E-scores. The MSCI E-score is an integer ranging from -5 to 5 over the sample period. Each year, I include firms with the highest and second-highest E-scores (e.g., 5 and 4) in a high portfolio. Firms with the lowest and second-lowest E-scores (e.g., -5 and -4) are included in a low portfolio. I also construct a portfolio that longs the low portfolio and shorts the high one. Table A6 shows the factor regression results. The L-H portfolio always delivers a positive return. It is also significant at 10% after controlling for asset pricing factors. The result confirms that greenium exists when using the MSCI E-score.

Third, Faccini et al. (2021) find that firms with the biggest improvement in their ENSCORE have lower expected returns. As such, it is worth investigating whether sorting based on the annual change in ENSCORE, instead of ENSCORE levels, also induces a greenium. Table A7 shows the result. Surprisingly, I find no evidence of greenium when sorted based on the annual changes on ENSCORE. Faccini et al. (2021) construct a proxy of climate transition risk through textual analysis. They find that the portfolio with the lowest exposure (which has a low expected return) to this risk factor has the biggest improvement in ENSCORE. However, when I sort portfolios

Table A7: **Abnormal return of quintile portfolios sorted by annual changes in ENSCORE**

	L	2	3	4	H	L − H
ΔENSCORE	-7.30	-1.11	1.06	5.40	18.26	-25.57
ENSCORE	33.22	32.22	22.71	28.43	40.66	-7.44
$E[R^{ex}]$	7.62	8.76	8.49	7.70	7.02	0.60
	(3.48)	(3.75)	(4.37)	(3.43)	(3.64)	(0.8)
CAPM α	1.55	2.48	1.79	1.60	0.78	0.77
	(1)	(0.74)	(1.35)	(0.79)	(0.88)	(0.82)
FF3 α	1.59	2.50	1.80	1.63	0.82	0.77
	(0.96)	(0.73)	(1.4)	(0.77)	(0.74)	(0.82)
FF5 α	1.76	2.94	1.50	0.73	1.46	0.30
	(1.12)	(0.94)	(1.37)	(0.97)	(0.85)	(0.93)
FF5&MOM α	1.72	2.91	1.43	0.57	1.43	0.29
	(1.15)	(0.98)	(1.33)	(1.12)	(0.86)	(0.95)

Note: The table shows the excess returns and abnormal returns (α) of the quintile and low-minus-high portfolios sorted by annual changes in ENSCORE. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_{i,t} = \alpha_i + \beta_i{}' \cdot F_t + v_{i,t},$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum factor. Returns are value-weighted and annualized. The sample period is 2003-2019. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

directly based on changes in ENSCORE, the return differences between the high and low portfolios are not significant. This indicates that changes in ENSCORE may not fully capture the exposure to transition risk.

Fourth, Berg et al. (2020) find substantial rewritings of Asset4 ESG ratings due to the changes of scoring methodology in April 2020. That is, the data collected before and after April 2020 are different. They suggest researchers using the updated data to verify the result with the initial data. Therefore, I construct a low-minus-high portfolio using the ENSCORE downloaded in February 2020, before the rewritings. Table A8 shows that sorting based on the initial ENSCORE leads to positive abnormal returns of the low-minus-high portfolio. However, the result is only significant for FF5 and FF5 plus the momentum factors. When using equal-weighted return, the result becomes much more significant. The result suggests that a negative greenium exists, although less significantly, when using the initial ENSCORE.

Table A8: **Abnormal return of low-minus-high portfolios sorted by ENSCORE before rewritten**

Factors	Constant	CAPM	FF3	FF5	FF5&MOM
VW	1.87	0.82	0.55	1.86*	2.01*
	(1.51)	(1.45)	(1.31)	(1.33)	(1.36)
EW	3.58***	2.81***	2.52***	2.33**	2.4**
	(1.22)	(1.18)	(1.08)	(1.14)	(1.15)

Note: The table shows the value-weighted (VW) and equal-weighted (EW) excess returns and abnormal returns (α) of the low-minus-high portfolio sorted by ENSCORE downloaded in February 2020, before the rewritings. Abnormal return is obtained using the following time-series regression in monthly frequency:

$$R_t^{LMH} = \alpha + \beta' \cdot F_t + v_t,$$

where F_t is the list of asset pricing factors in the CAPM, FF3, FF5, and FF5 plus momentum factor. Returns are value-weighted and annualized. The sample period is 2003-2019. Newey-West adjusted standard errors are reported in the parenthesis. One, two, and three asterisks indicate that α is positive at 10%, 5%, and 1% significance levels.

Appendix A.4. Price of risk in a wide cross section of testing portfolios

This section tests whether the return predictability of a firm's greenness exists in a broad cross-section of global stock portfolios. This exercise shows that the greenium is priced in a cross-section of global testing portfolios. One problem with this test is that we do not have ENSCORE for the entire cross-section of stocks. To cope with this problem, I construct a BMG factor corresponding to the return of a portfolio that longs the brown stocks and shorts the green ones. This so-called mimicking portfolio captures the relative risk of brown versus green stocks. Suppose a portfolio with positive exposure to this factor also has a higher expected return after controlling other systematic risks, then we can conclude that such a factor is priced in a broad cross-section of stocks and carries a positive price of risk.

For the testing portfolios, I use six sets of global portfolios from Kenneth French's data library.[34] These are two-way sorted by size and book-to-market (B/M), investment (INV), operating profit (OP), momentum, and reversal.

Following Cochrane (2009), I use the two-pass regression to identify the price of risk. Specifically,

[34] The testing portfolio returns are collected from `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. I thank Kenneth French for providing returns on the testing portfolios.

I first run the time series regression of returns on testing portfolios

$$R_t^p = \beta_{0,p} + \beta_{1,p} \cdot F_t + \beta_{BMG,p} \cdot BMG_t + v_{p,t},$$

where R_t^p is the annualized monthly gross return of testing portfolio p, and F_t is the FF5 factor. In a second step, I do the cross-sectional regression of time-series average portfolio returns on the estimated exposure $\hat{\beta}$ from the first step,

$$E[R_t^p] = \lambda_0 + \lambda_1 \cdot \hat{\beta}_{1,p} + \lambda_{BMG} \cdot \hat{\beta}_{BMG,p} + u_p.$$

The price of risk of the BMG factor is given by λ_{BMG}

Table A9 reports the estimated price of risk for the BMG factor. I report the t-statistics using corrected standard errors according to Shanken (1992) and Newey and West (1987). The estimated price of risk of the BMG factor is positive for all cases and, in most cases, significant. These results show that the empirical results in the previous subsections are not driven merely by luck on the sample I selected. The lower expected returns of green stocks also exist in a wide cross-section of testing portfolios where ENSCORE is not available.

Table A9: **Estimation of λ_{BMG}**

Portfolio sets	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMW}	λ_{BMG}
Size & BV/MV (25)	8.58**	1.92	0.89	1.24	2.55	3.55
	(4.34)	(1.69)	(1.75)	(1.29)	(1.72)	(2.29)
Size & INV (25)	8.52**	1.31	8.57***	-0.94	1.31	5.11*
	(4.34)	(1.69)	(2.38)	(1.42)	(1.34)	(2.76)
Size & OP (25)	8.57**	2.24	0.65	2.89***	2.16	6.87***
	(4.34)	(1.69)	(2.13)	(1.07)	(1.96)	(2.43)
Size & BV/MV & INV (32)	8.70*	2.01	-0.07	3.74***	1.05	7.41***
	(4.34)	(1.69)	(1.75)	(1.26)	(1.34)	(1.93)
Size & BV/MV & OP (32)	8.35**	2.15	0.63	3.64***	-1.11	7.84***
	(4.34)	(1.69)	(1.75)	(1.09)	(1.61)	(1.91)
BV/MV & INV & OP (32)	8.67**	1.88	6.61***	3.10***	1.16	0.28
	(4.34)	(1.69)	(1.89)	(1.07)	(1.33)	(1.96)

Note: The table shows the factor risk premium of the BMG factor from following two-pass regressions:

$$
\begin{aligned}
R_t^p &= \beta_{0,p} + \beta_{1,p} \cdot F_t + \beta_{BMG,p} \cdot BMG_t + v_{p,t} \\
E[R_t^p] &= \lambda_0 + \lambda_1 \cdot \hat{\beta}_{1,p} + \lambda_{BMG} \cdot \hat{\beta}_{BMG,p} + u_p
\end{aligned}
$$

where R_t^p is the annualized monthly gross returns of portfolio p in the testing portfolio sets, two-way sorted by size and book-to-market (BV/MV), investment (INV), operating profit (OP), momentum (MOM), and reversal. F_t is FF5 factor. t-statistics uses standard errors adjusted according to Newey and West (1987) and Shanken (1992). One, two, and three asterisks indicate that the coefficient is significant at 10%, 5%, and 1% levels.

Appendix B. Full derivation of the two-period model

This section shows the derivation of optimal investments, utility, SDF, and stock returns in Section IV. Given the assumptions, the optimization problem at $t = 1$ is written as

$$\max_{I_{G,1}, I_{B,1}} u_1 = (1-\beta)\log(C_1) + \beta\Big((\alpha-\lambda)\log(I_{B,1}/\bar{I}) + (1-\alpha)\log(I_{G,1})\Big), \tag{B.1}$$

where $C_1 = Y_1 - I_{G,1} - I_{B,1}$. It exploits the production function and the fact that $\log(1-D) = -D$ when D is small enough (in general, the climate damage is small).

Optimal investments Solving the following F.O.C.

$$-\frac{1-\beta}{C_1} + \frac{\beta(\alpha-\lambda)}{I_{B,1}} = 0 \tag{B.2}$$

$$-\frac{1-\beta}{C_1} + \frac{\beta(1-\alpha)}{I_{G,1}} = 0 \tag{B.3}$$

which, together with the market clear condition, yields the following solutions:

$$I_{B,1} = \frac{\beta(\alpha-\lambda)}{1-\beta\lambda}Y_1 \tag{B.4}$$

$$I_{G,1} = \frac{\beta(1-\alpha)}{1-\beta\lambda}Y_1 \tag{B.5}$$

$$C_1 = \frac{1-\beta}{1-\beta\lambda}Y_1 \tag{B.6}$$

Thus optimal investment is just a fixed proportion of output at time 1. The proportion is positive when the assumption $\alpha > \lambda$ holds. It is evident that $\frac{\partial I_{B,1}}{\partial \lambda} = -\beta\frac{1-\alpha\beta}{(1-\beta\lambda)^2}Y_1 < 0$ and $\frac{\partial I_{B,1}}{\partial \lambda} = \beta^2\frac{1-\alpha}{(1-\beta\lambda)^2}Y_1 > 0$. This indicates that, in equilibrium, the investment in the brown (green) sector is decreasing (increasing) with the climate damage intensity parameter. Finally, we can write the investment in a linear approximation when the damage intensity is a function on the shock ϵ:

$$I_{i,1} = \bar{I}_{i,1} + \theta_i\epsilon, \quad \forall i \in \{G, B\} \tag{B.7}$$

where $\bar{I}_{i,1}$ is the steady-state investment that does not depend on the shock, $\theta_B = -\beta\frac{1-\alpha\beta}{(1-\beta\lambda)^2}\bar{\lambda}'$ and $\theta_G = \beta^2\frac{1-\alpha}{(1-\beta\lambda)^2}\bar{\lambda}'$ with $\bar{\lambda}' = \frac{\partial\lambda}{\partial\epsilon}\Big|_{\epsilon=0}$. If $\bar{\lambda}' > 0$ then $\theta_B < 0$ and $\theta_G > 0$: an environmental shock that increases damage intensity leads to a higher (lower) investment in sector G (B).

Linear approximation of the utility I approximate the time-1 utility as a function of steady-state utility and the shock

$$u_1 = \bar{u}_1 + \theta_u \epsilon$$

where $\bar{u}_1$ is the steady-state utility when the shock is zero. The coefficient θ_u is given by $\frac{\partial u_1}{\partial \epsilon}$ which can be obtained through the Envelope Theorem,

$$\frac{\partial u_1}{\partial \epsilon} = \frac{\partial u_1}{\partial \lambda}\bar{\lambda}' = -\beta \log(\bar{I}_{B,1}/\bar{I})\bar{\lambda}'$$

Stochastic discount factor The SDF at $t = 1$ is expressed as

$$M_1 = \frac{\partial u_0 / \partial C_1}{\partial u_0 / \partial C_0}$$

where u_0 is the utility at time 0,

$$u_0 = (1-\beta)\log C_0 + \frac{\beta}{1-\gamma}\log E_0\left[\exp\left\{u_1(1-\gamma)\right\}\right].$$

Then

$$M_1 = \beta \frac{C_0}{C_1}\frac{\exp\left(u_1(1-\gamma)\right)}{E_0\left[\exp\left(u_1(1-\gamma)\right)\right]}$$

Taking the logarithm

$$m_1 = \log(\beta) + \log(C_0) - \log(C_1) + (1-\gamma)u_1 - \log E_0\left[\exp\left(u_1(1-\gamma)\right)\right]$$

and substituting u_1 and C_1 with the solutions in the previous part we have

$$m_1 = \bar{m}_1 + \beta\left[(\gamma-1)\log\left(\bar{I}_{B,1}/\bar{I}\right) - \frac{1}{1-\beta\lambda}\right]\bar{\lambda}'\epsilon$$

where the $\bar{m}$ is the steady-state SDF which does not depend on the shock.

Stock returns First I introduce the investment adjustment cost, which relates the investment rate to Tobin's q, and also to the stock returns. This adjustment cost does not have a first order effect on the investment decisions derived in the previous subsections. Thus I make use of the solutions derived under no adjustment cost to calculate the stock returns under the adjustment cost.

For $i \in \{G, B\}$,

$$K_{i,t+1} = I_{i,t} - G(I_{i,t}, K_{i,t})$$

where $G(I, K) = I - \frac{a}{1-\xi} I^{1-\xi} K^{\xi}$, and $\frac{1}{\xi}$ captures the elasticity of investment with respect to the Tobin's q, which is given by $Q = \frac{1}{1-G'_I} = \frac{1}{a} \left(\frac{I}{K}\right)^{\xi}$ (Croce, 2014). Investment return is related to the marginal q following Cochrane (1991)

$$R_{i,1} = \frac{-Q_{i,1} G_{K_i,1} + MPK_{i,1}}{Q_{i,0}} = \frac{1}{Q_{i,0}} \left(\frac{\xi}{1-\xi} \frac{I_{i,1}}{K_{i,1}} + \alpha \frac{Y_1}{K_{i,0}} \right), \quad \forall i \in \{G, B\} \tag{B.8}$$

From equation (B.8) we can see that investment return at time 1 is positively related to the investment at time 1 under convex adjustment cost.

Taking the log of equation (B.8) yields,

$$r_{i,1} = \log \left(\frac{\xi}{1-\xi} \frac{I_{i,1}}{K_{i,1}} + \alpha \frac{Y_1}{K_{i,0}} \right) - q_{G,0}$$

Noting that only $I_{i,1}$ is related to the environmental shock ϵ, we can then write the return into a linear approximation as

$$r_{i,1} = \bar{r}_{i,1} + \kappa_i \theta_i \epsilon,$$

where $\kappa_i = \frac{\partial r_{i,1}}{\partial I_{i,1}} > 0$, θ_i is given in equation (B.7). Given that $\theta_B < 0$ and $\theta_G > 0$, I reach the conclusion that a positive environmental shock, which can be translated to an increase in damage intensity, increases (decreases) stock returns in the green (brown) sector.

Appendix C. Solution details of the Macro-finance IAM

Denote $\mathcal{S} = \{H, M, K_B, K_G\}$ as the state variables. I neglect the time subscript t and denote the variables with a prime symbol as those in the next period. The optimization problem can be written in the following optimization problem with constraints:

$$\max_{\substack{C,RD,I_B,I_G,\\ l_B,l_G,\mathcal{S}'}} \quad W\Big(C, U'(\mathcal{S}')\Big) = \left\{(1-\beta)C^{1-\frac{1}{\psi}} + \beta\left(E\left[U'(\mathcal{S}')^{1-\gamma}|\mathcal{S}\right]\right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right\}^{\frac{1}{1-\frac{1}{\psi}}}$$

$$\begin{aligned}
s.t. \quad C &= e^{-\lambda(M-\bar{M})}\left\{\omega\left[K_B^{\alpha}(Al_B)^{1-\alpha}\right]^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega)\left[H^{\nu}\left(K_G^{\alpha}(Al_G)^{1-\alpha}\right)^{1-\nu}\right]^{\frac{\varepsilon-1}{\varepsilon}}\right\}^{\frac{\varepsilon}{\varepsilon-1}} \\
&\quad -I_G - I_B - kRD && \text{(C.1)}\\
K_B' &= (1-\delta_K)K_B + \frac{a_1}{1-\xi}I_B^{1-\xi}K_B^{\xi} + a_0K_B && \text{(C.2)}\\
K_G' &= (1-\delta_K)K_G + \frac{a_1}{1-\xi}I_G^{1-\xi}K_G^{\xi} + a_0K_G && \text{(C.3)}\\
H' &= (1-\delta_H)H + \frac{b}{1-\eta}RD^{1-\eta}H^{\eta} && \text{(C.4)}\\
M' &= (1-\rho_M)\bar{M} + \rho_M M + \zeta\frac{K_B}{A} + \epsilon_M' && \text{(C.5)}\\
1 &= l_B + l_G && \text{(C.6)}
\end{aligned}$$

with the following stochastic processes:

$$\begin{aligned}
\log(A') &= \log(A) + \mu + x_t + \sigma\epsilon_A' && \text{(C.7)}\\
x' &= \rho_x x + \varphi_x\sigma\epsilon_x' && \text{(C.8)}\\
\lambda' &= (1-\rho_\lambda)\bar{\lambda} + \rho_\lambda\lambda + \sigma_\lambda\epsilon_\lambda && \text{(C.9)}
\end{aligned}$$

where

$$\epsilon_A, \epsilon_x, \epsilon_\lambda \sim i.i.d.N(0,1).$$

The Lagrange multipliers for equations (C.1) to (C.5) are denoted by λ_C, λ_B, λ_G, λ_H, and λ_M, respectively. For constraint (C.6), the F.O.C. condition is manually derived. Denote the Lagrange function as $\mathcal{L}$. Then the first order conditions are

$$\frac{\partial \mathcal{L}}{\partial C} = W_1 - \lambda_C = 0 \tag{C.10}$$

$$\frac{\partial \mathcal{L}}{\partial RD} = -\lambda_C k + \lambda_H b \left(\frac{H}{RD}\right)^{\eta} = 0 \tag{C.11}$$

$$\frac{\partial \mathcal{L}}{\partial I_B} = -\lambda_C + \lambda_B a_1 \left(\frac{K_B}{I_B}\right)^{\xi} = 0 \tag{C.12}$$

$$\frac{\partial \mathcal{L}}{\partial I_G} = -\lambda_C + \lambda_G a_1 \left(\frac{K_G}{I_G}\right)^{\xi} = 0 \tag{C.13}$$

$$\frac{\partial \mathcal{L}}{\partial H'} = \sum_{\omega'} W_2' \frac{\partial U'}{\partial H'} - \lambda_H = 0 \tag{C.14}$$

$$\frac{\partial \mathcal{L}}{\partial K_B'} = \sum_{\omega'} W_2' \frac{\partial U'}{\partial K_B'} - \lambda_B = 0 \tag{C.15}$$

$$\frac{\partial \mathcal{L}}{\partial K_G'} = \sum_{\omega'} W_2' \frac{\partial U'}{\partial K_G'} - \lambda_G = 0 \tag{C.16}$$

$$\frac{\partial \mathcal{L}}{\partial M'} = \sum_{\omega'} W_2' \frac{\partial U'}{\partial M'} - \lambda_M = 0 \tag{C.17}$$

where

$$W_1 = \frac{\partial W}{\partial C} \quad W_2' = \left.\frac{\partial W}{\partial U'}\right|_{\omega'}$$

and ω' denotes a state of the world in the next period.

Now we can use the Envelope Theorem to recover $\frac{\partial U'}{\partial H'}$ to $\frac{\partial U'}{\partial M'}$

$$\frac{\partial U'}{\partial H'} = \left(\frac{\partial \mathcal{L}}{\partial H}\right)' = \lambda_H' \left[1 - \delta_H + \frac{b\eta}{1-\eta}\left(\frac{RD'}{H'}\right)^{1-\eta}\right] + \lambda_C' MPK_H' \tag{C.18}$$

$$\frac{\partial U'}{\partial K_B'} = \left(\frac{\partial \mathcal{L}}{\partial K_B}\right)' = \lambda_B' \left[1 - \delta_K + \frac{a_1\xi}{1-\xi}\left(\frac{I_B'}{K_B'}\right)^{1-\xi} + a_0\right] + \lambda_C' MPK_B' + \lambda_M' \frac{\zeta}{A'} \tag{C.19}$$

$$\frac{\partial U'}{\partial K_G'} = \left(\frac{\partial \mathcal{L}}{\partial K_G}\right)' = \lambda_G' \left[1 - \delta_K + \frac{a_1\xi}{1-\xi}\left(\frac{I_G'}{K_G'}\right)^{1-\xi} + a_0\right] + \lambda_C' MPK_G' \tag{C.20}$$

$$\frac{\partial U'}{\partial M'} = \left(\frac{\partial \mathcal{L}}{\partial M}\right)' = \lambda_M' \rho_M - \lambda_C' \lambda \tilde{Y}' \tag{C.21}$$

$$\tag{C.22}$$

where MPK is the marginal production of capital,

$$\begin{aligned}
MPK_B &= \alpha\omega\frac{Y_B}{K_B}\left(\frac{Y}{Y_B}\right)^{\frac{1}{\varepsilon}} e^{-\lambda(M-\bar{M})} \\
MPK_H &= \nu(1-\omega)\frac{Y_G}{H}\left(\frac{Y}{Y_G}\right)^{\frac{1}{\varepsilon}} e^{-\lambda(M-\bar{M})} \\
MPK_G &= (1-\nu)\alpha(1-\omega)\frac{Y_G}{K_G}\left(\frac{Y}{Y_G}\right)^{\frac{1}{\varepsilon}} e^{-\lambda(M-\bar{M})}
\end{aligned}$$

Y ($\tilde{Y}$) is the total output before (after) accounting for climate damages.

Note that the ratio between λ_H, λ_B, λ_G, and λ_C is the marginal rate of substitution between new capital and consumption, i.e., marginal Tobin's q. I thus denote $\frac{\lambda_H}{\lambda_C}, \frac{\lambda_B}{\lambda_C}, \frac{\lambda_G}{\lambda_C}, \frac{\lambda_M}{\lambda_C}$ as Q_H, Q_B, Q_G, Q_M respectively. Then equations (C.10) to (C.17) are written as

$$Q_H = \frac{k}{b}\left(\frac{RD}{H}\right)^{\eta} \tag{C.23}$$

$$Q_B = \frac{1}{a_1}\left(\frac{I_B}{K_B}\right)^{\xi} \tag{C.24}$$

$$Q_G = \frac{1}{a_1}\left(\frac{I_G}{K_G}\right)^{\xi} \tag{C.25}$$

$$Q_H = \sum_{\omega'}\frac{W_2'W_1'}{W_1}\left(Q_H'\left[1-\delta_H+\frac{b\eta}{1-\eta}\left(\frac{RD'}{H'}\right)^{1-\eta}\right]+MPK_H'\right) \tag{C.26}$$

$$Q_B = \sum_{\omega'}\frac{W_2'W_1'}{W_1}\left(Q_B'\left[1-\delta_K+\frac{a_1\xi}{1-\xi}\left(\frac{I_B'}{K_B'}\right)^{1-\xi}+a_0\right]+MPK_B'+\frac{\lambda_M'}{\lambda_C'}\frac{\zeta}{A'}\right) \tag{C.27}$$

$$Q_G = \sum_{\omega'}\frac{W_2'W_1'}{W_1}\left(Q_G'\left[1-\delta_K+\frac{a_1\xi}{1-\xi}\left(\frac{I_G'}{K_G'}\right)^{1-\xi}+a_0\right]+MPK_G'\right) \tag{C.28}$$

$$Q_M = \sum_{\omega'}\frac{W_2'W_1'}{W_1}\left(Q_M'\rho_M-\lambda\tilde{Y}'\right) \tag{C.29}$$

Note that the intertemporal marginal rate of substitution (IMRS) is

$$\frac{W_2'W_1'}{W_1} = \frac{\partial U}{\partial C'}\Big/\frac{\partial U}{\partial C} = \underbrace{\beta\left(\frac{C'}{C}\right)^{-\frac{1}{\psi}}\left(\frac{U'}{\mathbb{E}\left[U'^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma}}_{\Lambda'}\cdot p(\omega')$$

where Λ is the SDF. We can now write the Euler equations (C.26) to (C.29) in the form of asset pricing equations,

$$\mathrm{E}[\Lambda' R_i'] = 1, \quad \forall i \in \{H, B, G, M\},$$

where

$$R_H = \frac{Q_H'\left[1-\delta_H+\frac{b\eta}{1-\eta}\left(\frac{RD'}{H'}\right)^{1-\eta}\right]+MPK_H'}{Q_H} \tag{C.30}$$

$$R_B = \frac{Q_B'\left[1-\delta_K+\frac{a_1\xi}{1-\xi}\left(\frac{I_B'}{K_B'}\right)^{1-\xi}+a_0\right]+MPK_B'+\frac{\lambda_M'}{\lambda_C'}\frac{\zeta}{A'}}{Q_B} \tag{C.31}$$

$$R_G = \frac{Q_G'\left[1-\delta_K+\frac{a_1\xi}{1-\xi}\left(\frac{I_G'}{K_G'}\right)^{1-\xi}+a_0\right]+MPK_G'}{Q_G} \tag{C.32}$$

$$R_M = \frac{Q_M'\rho_M-\lambda\tilde{Y}'}{Q_M} \tag{C.33}$$

The optimality condition for the constraint of labor market clearing is derived by equaling the marginal product of labor in the two sectors:

$$\frac{\partial Y}{\partial l_B} = \frac{\partial Y}{\partial l_G} \quad \Rightarrow \quad \omega\frac{Y_B^{1-\frac{1}{\varepsilon}}}{l_B} = (1-\nu)(1-\omega)\frac{Y_G^{1-\frac{1}{\varepsilon}}}{l_G}. \tag{C.34}$$

This system has fourteen endogenous variables,

$$C, RD, I_B, I_G, l_B, l_G, H, M, K_B, K_G, Q_B, Q_H, Q_G, Q_M.$$

with fourteen equations: six constraints (C.1 - C.6) and eight F.O.C. (C.23 - C.29 and C.34). Thus the model is closed.

Stock returns Stock returns on sector B are related to the return on physical capital, R_B. Since in reality excess stock returns are levered with idiosyncratic risks, the levered excess return in sector B is

$$R_{B,t+1}^{lev} = lev * (R_{B,t+1} - R_{f,t}) + \epsilon_{t+1}^d$$

where lev is the average leverage in the data and R_f is the risk-free rate. $\epsilon_t^d \sim N(0, \sigma_d^2)$ is the dividend payout shocks.

Excess return on sector G is a composite of return on physical capital R_G and return on human knowledge capital R_H weighted by the market values. Namely

$$R^{lev}_{G,t+1} = lev * \left(\frac{Q_{G,t}K_{G,t}R_{G,t+1} + Q_{H,t}H_tR_{H,t+1}}{Q_{G,t}K_{G,t} + Q_{H,t}H_t} - R_{f,t} \right) + \epsilon^d_{t+1}$$

Finally, the market excess return is given by

$$R_{MKT,t+1} = \frac{Q_{B,t}K_{B,t}R^{lev}_{B,t+1} + (Q_{G,t}K_{G,t} + Q_{H,t}H_t)R^{lev}_{G,t+1}}{Q_{B,t}K_{B,t} + Q_{G,t}K_{G,t} + Q_{H,t}H_t}$$