Explaining Greenium in a Macro-Finance Integrated Assessment Model

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ABSTRACT

I investigate how firms' environmental responsibilities ("greenness") affect expected stock returns. Using a comprehensive measure of firm-level greenness, I find that a portfolio that longs the brown stocks and shorts the green ones delivers a significant 3.54% annualized return, which remains significant after controlling for common asset pricing factors. Returns of green stocks increase upon a climate-related natural disaster relative to brown ones, which indicates that green stocks hedge physical climate-change risks and thus carry lower premium. I qualitatively justify the economic rationale behind these findings through a toy model. Finally, I build a macro-finance integrated assessment model (MFIAM) that quantitatively replicates empirical facts on climate variables, economic quantities, and asset prices.

Keywords: Climate finance, macro-finance, asset pricing

JEL classification: G12, Q43, Q5.

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1. Introduction

Recent studies in climate finance find that investors perceive climate risk in the stock market and take action to manage it (Choi, Gao, and Jiang, 2020; Krueger, Sautner, and Starks, 2020). However, the understanding of how climate risk materializes in the stock market is limited in three aspects. First, there is no consensus on the relationship between firm-level environmental responsibilities ("greenness") and stock returns, perhaps due to the lack of an universal measure of greenness and limited data availability. Second, the responses of stock returns and investments of firms with different levels of greenness to exogenous climate-related natural disaster shocks have not been explored. This can shed light on the potential role of green stocks as an insurance against climate change risks and help explain the associated premium. Third, in environmental economics, we have the integrated assessment models (IAM) that capture climate-economy interactions; in macro-finance, we have models that explain asset prices in production economies. Yet, no studies have provided an unified framework to simultaneously incorporate climate risk into both stock market and the real economy.

These aspects are important to facilitate a better understanding of the mechanism through which climate shocks affect the cross-section of stocks, and help guide investors to manage climate risk. I contribute to the growing literature on climate finance by addressing these three issues.

To address the first issue, I use the environmental pillar score (*ENSCORE*) from Refinitiv (formerly known as the Thomson Reuters) as the measure of greenness. The ENSORE covers near four thousand firms globally as of 2019. It provides a comprehensive measure of firms' environmental responsibilities reflecting three main categories: emission, innovation, and resource use. I sort firms with available ENSOREs into quintile portfolios over the longest period possible (2003 to 2019). The sorting is based on the previous year's ENSCORE and relative to the industry peers to get rid of the look-ahead bias and industry effect. I find that portfolio of stocks in the highest quintile (the green one) has a significantly 3.54% (t = 3.48) lower annualized return compared to the portfolio with stocks in the lowest quintile (the brown one). This difference remains significant after controlling for common asset pricing factors such as the CAPM (Sharpe, 1964), the Fama-French three factor model (FF3) (Fama and French, 1993), the Fama-French five factor models (FF5) (Fama and French, 2015), and the q5 factors (Hou, Mo, Xue, and Zhang, 2020). These findings indicate the existence of a negative green premium (“greennium”).

To eliminate the possibility that this difference in expected returns is not driven by firms' idiosyncratic risks. I implement double sortings with respect to the ENSCORE and other firm characteristics, such as the size, book-to-market, investment over asset, revenue over asset, property, plant and equipment (PPE) over asset, and leverage. I find the return difference becomes statistically and economically insignificant among small firms, indicating the greenium only exists within big firms. To further illustrate the predictive power of ENSCORE, I regress firm-level stock returns on their ENSCOREs and various set of control variables using the Fama-Macbeth regression (Fama and MacBeth, 1973). The result shows that, *ceteris paribus*, an increase of ENSCORE from 0 to 100 decreases annual stock return by 3% - 5% in the next year.

Finally, to see whether this result is due to good luck on the sample I choose, I extend the analysis to a wide cross-section of testing portfolios using the two-pass regression and generalized method of moment (GMM). The results show that returns of a factor-mimicking portfolio that longs the brown stocks and shorts the green ones are positively priced on different sets of testing portfolios.

I address the second issue through investigating how stock returns and investments of green and brown firms respond to climate-related natural disasters. I use two major natural disasters during the sample period: hurricane Katrina in 2005 and the 2012 US drought/heatwave. I find that after the hurricane Katrina (2012 US drought), annualized cumulative stock returns of brown firms decreases from 10% to 31% (10% to 15%) over the horizon from one to twelve months compared to the green firms. A similar analysis shows that investment also follows the same pattern after the US drought. The evidences show that green stocks provide an insurance against climate-related disasters, and thus are demanded a lower premium by investors.

I provide a simply, analytically solvable model that qualitatively justify the empirical findings. In a production economy, agents optimally choose investments into two sectors using fossil fuel (F) and non-fossil fuel (N) knowing that the investment in sector F leads to pollution and climate damages. I assume that a natural disaster causes an increase in the marginal damage from pollution. This assumption can be explained by the fact that agents learn from disasters as a signal about the true value of damage intensity. Thus, a shock on natural disaster leads to higher perceived marginal cost of investing in sector F. At the new optimum, resources reallocate towards sector

N, leading to an increase in its value and stock return under convex investment allocation cost. Consequently, sector N provides an insurance to climate-change physical risks and carries a lower premium compared to sector F. This toy model captures the key mechanism through which natural disasters affect the valuation of green/brown stocks while maintaining analytical tractability.

Addressing the third issue requires a model that incorporates climate risk in both stock market and real economy, which can quantitatively replicates the economic quantities, climate variables and asset prices. A commonly used theoretical approach in environmental economics is the integrated assessment models (IAM), which integrates climate processes and damage mapping into standard macroeconomic models (Nordhaus, 1992). Yet, traditional IAM cannot price climate risks in the stock market. To bridge the gap, I provide an unified study that links IAM and production-based asset pricing models in the macro-finance literature, i.e., a macro-finance IAM (MFIAM).

The model is a production economy with aggregate output produced from sector F and N under a constant elasticity of substitution (CES) framework. Production in sector F generates greenhouse gases (GHG) and leads to climate damages on the aggregate output. Investment in sector N is costlier due to higher extraction cost and lower transformation efficiency on the non-fossil fuel. This additional cost can be reduced by accumulating the *human knowledge capital* through intentional R&D. Productivity growth follows the long-run risks (LRR) dynamics (Bansal and Yaron, 2004; Croce, 2014). Finally, agents have Epstein-Zin (EZ) preferences (Epstein and Zin, 1989; Weil, 1990). These preferences generalize the constant relative risk aversion (CRRA) preferences and are useful to capture aversions towards long-run climate risks (Bansal, Kiku, and Ochoa, 2016a).[1] Further details about EZ preferences are given later in this section.

The model provides rich implications of investment flows and stock valuations. I provide a novel and comprehensive examination of the responses of both economic quantities and asset prices to exogenous shocks that degrade environmental conditions (i.e., shocks that increase climate damage intensity). Specifically, I find that a positive 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 N, indicating that our economy relies more

[1] My 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. I borrow the insights from previous studies to explain asset prices under production economies (Jermann, 1998; Croce, 2014). This enables me to shed light on the dynamics of cross-sector investment allocations and stock returns.

on green energy; (iii) causes Tobin's Q in sector N (F) to increase (decrease) due to reallocation adjustment costs, meaning that sector N becomes more valuable. As a result, excess stock return in sector N increases while that in sector F decreases. These findings imply that sector F is riskier, since it depreciates when state of world becomes bad. Therefore, brown stock carries a higher risk premium compared to green stocks, consistent with the empirical evidences.

My main results also shed light on which factors matter in quantifying climate risk in the real economy, or the social cost of carbon (SCC).[2] I find that the presence of renewable energy and endogenous R&D is of first-order importance. My model implies a SCC of \$59.3 per metric ton of carbon (tC). This value is moderate compared to those from models without renewable energy and induced technological change (ITC).[3] To explain this discrepancy, I compare the SCC in my benchmark model with those from re-calibrated models where endogenous R&D and renewable energy are absent. Not surprisingly, neglecting these elements significantly increases the estimates of SCC. This finding indicates that IAMs aimed at quantifying climate risks and seeking least-cost carbon policies should take into account the roles of renewable energy and ITC, consistent with the recent literature (see, among others, Goulder and Schneider (1999); Gerlagh and Van der Zwaan (2003); Popp (2006); Golosov, Hassler, Krusell, and Tsyvinski (2014), and Acemoglu, Aghion, Bursztyn, and Hemous (2012)). Additionally, through sensitivity analysis, I find that (i) carbon intensity, (ii) intertemporal elasticity of substitution (IES), (iii) elasticity of substitution between two energy sources, and (iv) damage intensity are also important determinants of the SCC estimates.

Traditional IAMs usually adopt the constant relative risk aversion (CRRA) preferences due to its mathematical convenience. However, under CRRA preference, climate risk estimates are highly sensitive to the choices of discount rate and risk aversions (Nordhaus, 2014). The reason is, CRRA specification embeds the assumption that agents' risk aversion is reciprocally related to their IES. Therefore, a high level of risk aversion implies an unwillingless to substitute across time and a counterfactual high risk-free discount rate (Daniel, Litterman, and Wagner, 2016). This leads to a highly under-estimated cost of carbon since climate damage materializes in the distant future and is greatly deferred. Recent literature realizes the importance of extending CRRA preferences to the more generalized recursive preferences (Daniel et al., 2016; Bansal et al., 2016a,b; Ackerman,

[2]The SCC measures the present value of the damage caused by a marginal increase in the carbon emissions, expressed in the unit of current consumption.

[3]For example, \$100/tC in Bansal, Ochoa, and Kiku (2016b) and \$37/tCO_2 (\$135.7/tC) in Nordhaus (2019).

Stanton, and Bueno, 2013; Lemoine and Rudik, 2017). These preferences separate the risk aversion from the IES. In line with the long-run risks literature in coping with the equity premium puzzle, I specify that the IES is bigger than the reciprocal of the risk aversion so that agents prefer early resolution of uncertainty and dislike bad news about long-run productivity growth. I find that the SCC is significantly underestimated under the CRRA utility with discount rates and risk aversions implied by the equity risk premium, consistent with Daniel et al. (2016) and Bansal et al. (2016a). On the contrary, EZ preferences with a preference of early resolution indicates a sizable SCC under reasonable level of discount rate and risk aversion.

The analysis provided in this paper is a social planner's problem which solves the first-best allocation of investments and labor across sectors. To make it clear, this paper doesn't investigate the role of the government and second-best policies in a decentralized economy where investments and R&D are distorted by monopolistic firms, as is presented in the endogenous growth models (Romer, 1990). I left it for future researches. The main focus of this paper is to provide a first benchmark MFIAM that takes into account elements from recent climate economics literature, while capable of extracting implications of climate risks in the stock market.

The rest of the paper is organized as follows. In the next section I present a review of related literature. Section 3 provides a concise but informative empirical analysis on the risk premia of green versus non-green stocks. Section 4 illustrates the economic intuition of the full model through a simplified two-period model. Sections 5 presents the MFIAM and solves the optimization problem. Section 6 discusses the quantitative results. The last section concludes.

2. Literature review

First, this paper contributes to the growing literature in the field of climate finance. For example, Bansal et al. (2016a) find that long-run temperature risk has a significantly negative effect on global equity valuation; Engle, Giglio, Kelly, Lee, and Stroebel (2020) show that a mimicking portfolio constructed by equities with different environmental performances can successfully hedge against innovations in climate change news. These studies documented that financial market already internalizes climate risks. Regarding the relationship between stock return and environmental responsibility, however, literature is inconclusive. 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 (2020); Hsu, Li, and Tsou (2020)), the other finds that the opposite holds (see, for example, Guenster, Bauer, Derwall, and Koedijk (2011); Cai and He (2014); In, Park, and Monk (2017)). The mixed results may be driven by a lack of universal greenness measure and limited data availability. To cope with this issue, I use a comprehensive measure of firm-level responsibility, ENSCORE, with an average of over two thousand firms from 2003 to 2019. In line with the first strand of literature, I find a negative equity premium of being green after controlling for common asset pricing factors. In addition, I theoretically explain the risk associated with this premium through the MFIAM. This has not been investigated in the previous studies.

Literature mainly explains the green premium through three channels: non-pecuniary utility from holding green, environmental policy uncertainty, and climate physical risks. For example, Pastor, Stambaugh, and Taylor (2019) argue that green stock has lower expected return because investors derive non-pecuniary utility from holding it. However, the empirical evidence on whether investors indeed have such tastes is scarce. On the other hand, Hsu et al. (2020) find that green stock carries low premium because it is positively exposed to environmental policy shocks (policies that restrain emission) which are negatively priced. It's however unclear whether an environmental policy is a good or a 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. At last, several papers investigate the potential of green stock as a hedge against climate physical risks (see, among others, Choi et al. (2020); Engle et al. (2020)). Yet none of these studies addressed the mechanism through which green stock rises upon climate-related disasters.

Second, this paper is also related to the literature that identifies climate risks in the real economy through IAMs, pioneered by the seminal work in Nordhaus (1992) with his DICE model. Other examples of IAMs, to list a few, include WITCH (Bosetti, Carraro, Galeotti, Massetti, and Tavoni, 2006), MERGE (Manne, Mendelsohn, and Richels, 1995), DEMETER (Van der Zwaan, Gerlagh, Schrattenholzer, et al., 2002), and ENTICE-BR (Popp, 2006). My model provide a first "handy" model that bridges the broad literature on IAM and production-based asset pricing in macro-finance. The model simultaneously matches the asset prices and investment flows across green and brown sectors.

Finally, this paper is related to the literature that discusses the role of renewable energy and ITC in IAMs. An early work in this field is Goulder and Schneider (1999). They study the implication of ITC for making CO_2 abatement policies, and find that the crowding-out effect limits the role ITC can play. Nevertheless, Van der Zwaan et al. (2002), Gerlagh and Van der Zwaan (2003) and Popp (2006) conclude that development on non-fossil technology is the key for sustainable long-run growth. More recent works include Acemoglu et al. (2012); Acemoglu, Akcigit, Hanley, and Kerr (2016); Golosov et al. (2014); Hillebrand and Hillebrand (2019). For example, Acemoglu et al. (2012) introduce directed technical change in a growth economy with aggregate output produced from "dirty" and "clean" inputs. They conclude that a carbon tax with research subsidies help the economy shift to the clean sector. All these papers assume CRRA preferences. I extend their framework into recursive preferences and show that the intertemporal elasticity of substitution matters for the assessment of carbon tax.

3. Empirical evidence

This section compares the expected returns between green and brown stocks, and calculates the risk premia after controlling for various common asset pricing factors. To this end, I first sort companies according to their greenness levels. I implement the sorting by using the environmental pillar score from the Refinitiv (formerly known as Thomson Reuters) Asset4 ESG ("Environmental", "Social", and "Governance") scores.[4] The ENSCORE covers three major categories in terms 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 number of firms with available ENSCORE is expanding since the year 2002 (from 925 in 2002 to 3927 in 2019). Before that, there are not sufficient observations. To get rid of the small sample bias, I thus focus on the period starting from 2002.

In each June since 2003, I sort firms into quintile portfolios using their ENSCORE of the last year relative to their industry peers according to the Fama-French 49 industries classifications. Thus I have specific cutoff points for each industry in each year. Through this way I eliminate

[4] Refinitiv Asset4 ESG score covers around 70% of the world cap with over 450 ESG metrics, of which 186 most comparable measures are summarized into 10 category scores (e.g., emission, human rights, management, etc.) and three pillar scores (environmental, social, and governance). The information is mainly collected from firms' annual reports, corporate social report (CRS), company websites, etc. There are over 9000 firms in the Asset4 universe as of July 2020. See `https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/esg-scores-methodology.pdf` for more details.

the look-ahead bias and industry effects. I also exclude firms in the finance industry following Hsu et al. (2020) and small firms, i.e., firms with market value 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.

In the rest of this section, I provide several evidences of the existence of a green premium. Specifically, I first regress portfolio returns on common asset pricing factors to see whether the return differences across portfolios are driven by priced systematic risks. Then I implement the double sorting and Fama-macbeth regression to confirm that the predictive power of ENSCORE on stock return doesn't depend on firms' idiosyncratic risks. Third, I extend the analysis to a wide cross-section of test portfolios using a factor-mimicking portfolio approach. Finally I document the source of risk through event studies on major natural disasters.

3.1. Portfolio characteristics

Table 1 shows the time-series average of the cross-section mean of firm characteristics in each quintile portfolio and a market portfolio constructed by all NYSE common listed stocks. The last column reports the differences of these characteristics between the lowest quintile portfolio and the highest one. The characteristics include ENSCORE, market value, book-to-market ratio, investment over asset,[5] revenue over asset, R&D over asset, PPE over asset, and leverage. The sample period is from 2002 to 2019. Except for market value, all characteristics are in an annual frequency.

First of all, I find that, even though the sample and the market portfolio come from different sources, most of their characteristics don't differ too much. This can alleviate the concern of self-selection issue. Second, within the quintile portfolios, firms differ in term of some characteristics. Specifically, greener firms tend to be bigger in size, slightly smaller in R&D and PPE over asset, and slightly bigger in leverage. In the later part, I use time-series on asset pricing factors, double sorting, and Fama-Macbeth regression to make sure that those differences don't account for the return predictability of ENSCORE.

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

Table 1: **Portfolio summary statistics**

	Population	Sample					
		L	2	3	4	H	L - H
ENSCORE	-	8.5	22.3	37.9	54.3	73.8	65.3*
MV (billion $)	9.3	6.6	8.9	11.8	15.1	24.0	17.4*
BV/MV (%)	60.5	58.9	58.9	60.1	62.0	61.8	3.0
I/A (%)	13.0	10.8	9.4	9.6	8.9	6.5	-4.4
REV/A (%)	83.7	85.9	89.0	88.6	89.8	85.2	-0.7
R&D/A (%)	2.6	3.5	3.3	3.2	3.0	2.9	-0.5*
PPE/A (%)	30.5	33.8	34.2	33.5	32.7	32.6	-1.2*
Lev (%)	31.4	38.1	38.1	39.2	40.0	40.8	2.6*
# of firms	2278	403	394	397	398	397	

*N*ote: The table shows time-series average of cross-section mean of firm characteristics in each of the quintile portfolios, and the market portfilio. The last column shows the difference between the lowest quintile portfolio and the highest one. The market portfolio uses all NYSE common listed stocks with data collected from Compustat. * indicates that the difference is significant at 5%

3.2. Factor regressions

Table 2 reports the annualized value-weighted returns of the quintile portfolios. The portfolio with the highest ENSCORE (the green portfolio) has a significant 3.54% lower 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 portfolio returns on standard factor models such as the CAPM (Sharpe, 1964), FF3 (Fama and French, 1993), FF5 (Fama and French, 2015) and q5 factors (Hou et al., 2020) to get the abnormal returns (α),

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

where F_t is the list of factors listed above, $R_{i,t}$ are the returns of the quintile portfolios i at month t. The αs are reported in the panel A to D in table 2. The last column of this table also shows the αs of the strategy that longs the brown portfolio and shorts the green portfolio (i.e., the low-minus-high portfolio).

After controlling for these factors, the abnormal returns of the low-minus-high portfolio remains significantly positive. The α is 2.54% (t=2.82) for the CAPM, 2.52% (t=2.65) for the FF3, 3.02% (t=2.87) for the FF5, and 4.20% (t=4.02) for the q5 factor models. The results show that portfolios with higher ENSCORE indeed carry higher expected returns, after controlling for various of asset

Table 2: **Factor regressions**

	L	2	3	4	H	L - H
$E[R^{ex}]$	15.21	14.95	13.19	12.75	11.67	3.54
t	(3.91)	(4.12)	(3.86)	(3.99)	(3.59)	(3.48)
SR	0.30	0.31	0.28	0.27	0.26	0.19
			Panel A. CAPM			
α	6.90	6.98	5.54	5.10	4.35	2.54
t	(5.09)	(5.22)	(3.87)	(5.44)	(4.13)	(2.82)
			Panel B. FF3			
α	6.80	6.84	5.39	4.96	4.28	2.52
t	(4.99)	(4.83)	(3.71)	(5.33)	(3.92)	(2.65)
			Panel C. FF5			
α	7.33	7.31	5.70	5.46	4.32	3.02
t	(4.93)	(5.26)	(3.88)	(4.81)	(3.66)	(2.87)
			Panel D. q5			
α	8.54	7.72	6.38	5.32	4.34	4.20
t	(6.84)	(6.35)	(4.84)	(5.05)	(4.35)	(4.02)

*N*ote: 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 asst pricing factors in the CAPM, FF3, FF5, and q5. Returns are value-weighted and annualzied. Newey-West adjusted t-statistics are reported in the parenthesis.

pricing factors that account for systematic risks. In the next subsection, I investigate whether this return predictability remains after controlling for firm characteristics.

3.3. Double sorting and Fama-Macbeth regression

Since firm characteristics of green and brown portfolios differ from each other in several aspects as shown in table 1. I implement two exercises to see whether these differences account for the return difference. In the first exercise, I double-sort the stocks using ENSCORE and another firm characteristics. For example, in each year, I first sort firms into *big* and *small* groups according to their market value of the last year relative to their industry peers.[6] Second, within the big and small groups I sort firms into quintile portfolios according to their last year's ENSCORE relative to their industry peers. Thus I create ten portfolios. I then compare the annualized returns of these portfolios to see whether the lower expected return of green portfolio exists in both big and small

[6] 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 are classified as "small" and vice versa.

firms. I also do the same double sorting for other characteristics.

Table 3 shows the results. Except for the market value, all other firm characteristics do not affect the positive return obtained from a low-minus-high portfolio. In terms of market value, the green premium do not seem to exist in small firms. A possible explanation of this phenomenon is that investors may not consider small firms as a major contributor to climate change, so that the risks associated to climate externality do not exist in small brown firms.

Table 3: **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	16.80	16.77	17.70	15.75	17.22	-0.42	L	14.19	14.46	12.89	12.29	11.00	3.20
t	4.41	4.09	4.76	4.05	4.31	-0.41	t	4.10	4.29	3.92	3.87	3.76	2.96
H	14.37	14.23	11.82	11.77	10.99	3.38	H	16.55	16.21	13.03	14.95	11.44	5.11
t	3.94	4.15	3.60	3.65	3.46	3.63	t	4.08	3.64	3.48	4.02	3.03	3.72
			Panel C. I/A							Panel D. REV/A			
L	14.25	13.44	12.34	12.68	10.67	3.58	L	14.85	14.09	14.26	12.88	11.00	3.85
t	3.47	3.79	3.50	3.68	3.18	2.85	t	3.59	4.07	4.01	3.92	3.44	2.79
H	15.85	16.43	13.69	13.68	12.56	3.29	H	16.04	14.84	12.95	13.30	11.83	4.21
t	4.33	4.15	3.90	4.29	3.96	2.71	t	4.15	3.80	3.78	3.88	3.80	3.15
			Panel E. R&D/A							Panel F. PPE/A			
L	13.48	13.27	13.69	12.87	11.01	2.46	L	14.97	13.68	13.44	11.98	10.67	4.31
t	3.54	3.61	4.40	3.63	3.27	1.49	t	3.64	3.60	3.78	3.77	3.18	3.22
H	17.94	13.59	10.79	12.38	11.86	6.08	H	14.78	15.43	14.97	13.15	12.80	1.98
t	4.23	4.18	2.96	3.51	3.30	4.27	t	3.87	4.44	4.25	3.79	4.20	1.60
			Panel G. Lev										
L	14.55	13.92	12.11	11.60	11.03	3.52							
t	4.07	3.60	3.79	3.58	3.54	3.50							
H	16.32	15.14	14.75	12.69	12.56	3.76							
t	4.05	3.96	4.11	3.71	3.90	2.67							

*N*ote: The table shows portfolios returns after double sorting according to the ENSCORE and another firm characteristics. 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, and leverage. Then within each portfolio I further sort firms into quintile portfolios according to the ENSCORE. The sortings are all based on the last year's value and relative to the industry peers.

In a second exercise, I run the Fama-Macbeth regressions of firm-level stock returns on their ENSCOREs and other characteristics of the last year, 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. This process consists of two step. In the first step, I run the cross-sectional regression at each month to get the estimated slopes $\hat{\beta}_t$; in a second step, I take the average of the slopes over the whole sample period. I only include stocks with size bigger than the median of their industry peers, since the green premium doesn't exist among small firms. Table 4 shows the results. An increase of the ENSCORE from 0 to 100 decreases a firm's annualized stock return of next year by 3% to 5% under various subsets of control variables. This result is consistent with the negative green premium documented in the previous subsection.

Table 4: **Fama-Macbeth regression on ENSCORE and other firm characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ENSCORE	-0.05	-0.03	-0.04	-0.03	-0.04	-0.04	-0.04	-0.04
t	-3.54	-1.85	-2.10	-1.99	-2.08	-1.94	-1.83	-1.89
MV		-0.11	-0.10	-0.10	-0.09	-0.09	-0.09	-0.09
t		-4.91	-4.71	-4.69	-4.58	-3.80	-4.00	-3.83
BV/MV			2.34	2.34	2.54	1.88	1.86	2.62
t			1.72	1.70	1.80	0.94	0.92	1.29
I/A				1.07	1.05	4.15	4.20	4.22
t				0.81	0.79	2.10	2.13	2.07
REV/A					0.80	0.54	0.55	0.91
t					1.33	0.60	0.61	1.00
R&D/A						18.24	16.98	22.62
t						1.09	1.01	1.29
PPE/A							-4.11	-3.51
t							-1.36	-1.15
Lev								0.05
t								2.07
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.15	0.16	0.16	0.17	0.17	0.20	0.21	0.21
Obs.	253021	252903	242910	240618	240485	133934	133934	129695

*N*ote: The table shows the results of the Fama-Macbeth regression

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

Specifically, I first run cross-section regression for each month. Then I take average of the estimated slope. t-statistics are obtained from the average slope divided by their Newey-West adjusted standard errors. The sample is based on stocks with size bigger than the median of their industry peers.

In sum, these two exercises provide valid evidence that the risk premium of green vs. brown stocks cannot be attributed to firms' idiosyncratic risks.

3.4. Price of risk in a wide cross section of test portfolios

In this subsection, I test whether the return predictability of firm's greenness exists in a wide cross section of stock portfolios, or it's only priced in the sample that I selected. One problem for this test is that we don't have ENSCORE for the entire cross-section of stocks. To cope with this problem, I construct a factor corresponding to the return of a portfolio that longs the brown stocks and shorts the green ones. This so-called mimicking portfolio capture the relative risk of brown vs. green stocks. If a portfolio with a positive exposure to this factor also has a higher expected return after control for other systematic risks, then we can conclude that such a factor is priced in a wide cross section of stocks and carries a positive price of risk.

For the test portfolios, I use eight sets of portfolios from French Kenneth's data library.[7] Six of them are two-way sorted on Size and book-to-market (B/M), investment (INV), operating profit (OP), momentum, and reversal. The other two are based on the 38 and 49 industry classifications.

To construct the factor-mimicking portfolio return, I follow Fama and French (2015) using the following method to get rid of the noise from other systematic risks,

$$\begin{aligned}
BMG_{size} &= Big\,Brown - Big\,Green \\
BMG_{B/M} &= 1/2(Value\,Brown + Growth\,Brown) \\
&\quad -1/2(Value\,Green + Growth\,Green) \\
BMG &= 1/2(BMG_{size} + BMG_{B/M})
\end{aligned}$$

where the $Big\,Brown$ is the portfolio with big size and lowest ENSCORE in the double sorting of the previous subsection. Others are similarly defined. BMG is the Brown-minus-Green factor that we need to price.

I use two different methods to implement the estimation: the two-pass regression and the GMM. In the two-pass regression, I first run the time series regression of returns on test portfolios

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

[7]The test portfolios 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 test portfolios.

where R_t^p is the annualized monthly gross return of testing portfolio p, F_t is the asset pricing factors from the CAPM, FF3, FF5, and q5. In a second step, I do the cross-sectional regression of time-series average portfolio return 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}

For the GMM estimation, I use the following moment condition,

$$E[R_1^p(1 - b \cdot \tilde{F}_t)] = a$$

where $\tilde{F}_t = [F_t, BMG_t]$. An implicit assumption in this specification is that the SDF $M_t = \frac{1}{a} - \frac{b}{a}\tilde{F}_t$. Then the vector of risk premium is given by Cochrane (2009).

$$\lambda = E[\tilde{F}_t' \tilde{F}_t] \cdot b$$

Table 5 reports the estimated price of risk for the BMG factor. For the two-pass regression I report the t-statistics using corrected standard errors according to Shanken (1992) and Newey and West (1987). In most of the cases, the estimated price of risk of the BMG factor are positive and significant. These results show that the empirical results in the previous subsections are not driven by merely luck on the sample I selected, and the lower expected returns of green stocks also exist in a wide cross section of test portfolios where ENSCORE is not available.

3.5. Source of risk

I conclude this section by investigating the potential role of greens stock as an insurance against climate-related natural disasters. First, I find two major natural disasters during the sample period: Hurricane Katrina and the 2012 US drought. These two disasters are identified as the most devastating hurricane and drought/heatwave by the National Oceanic and Atmosphere Admistration (NOAA) during the period 2002-2019.[8] I implement an event study to see how the stock returns

[8] See `https://www.ncdc.noaa.gov/billions/events/US/2003-2019`, the hurricane Katrina causes an economic cost of 170 billion US dollars and 1833 deaths; the 2012 US drought/heatwave causes 34.2 billion US dollars and 123 direct deaths.

Table 5: **Estimation of λ_{BMG}**

Portfolio sets	Two-pass				GMM			
	CAPM	FF3	FF5	q5	CAPM	FF3	FF5	q5
Size & BV/MV (25)	4.09	3.50	7.33	2.69	5.91	7.03	4.73	2.98
t	2.47	1.75	2.69	1.41	2.78	2.42	1.95	1.03
Size & INV (25)	3.86	3.25	3.75	4.16	3.04	3.82	4.29	5.03
t	2.57	1.95	1.62	1.62	1.57	1.83	1.90	1.57
Size & OP (25)	4.66	3.11	-1.12	2.56	5.33	4.24	-0.44	4.69
t	3.09	1.88	-0.50	1.35	3.42	1.62	-0.14	1.45
Size & MOM (25)	8.59	4.32	1.24	6.72	13.42	8.26	1.48	9.67
t	3.67	1.73	0.44	2.10	5.62	3.05	0.57	4.65
Size & ST reversal (25)	4.23	5.39	7.72	9.25	10.96	9.37	15.34	11.17
t	1.86	2.20	2.63	2.69	3.76	3.10	4.59	5.28
Size & LT reversal (25)	3.08	-0.26	0.95	4.31	5.24	3.28	3.15	4.68
t	2.50	-0.15	0.52	1.94	3.05	1.25	1.33	1.97
38 Industries	1.81	2.25	2.08	2.56	4.11	5.35	5.40	6.62
t	1.44	1.74	1.54	1.92	2.76	3.46	3.18	4.50
49 Industries	3.82	4.08	3.15	3.97	4.73	6.48	7.37	6.15
t	3.30	3.42	2.50	2.95	3.41	4.56	4.59	4.62

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 test portfolio sets, two-way sorted by size and book-to-market (BV/MV), investment (INV), operating profit (OP), momentum (MOM), and reversal. F_t includes pricing factors in the CAPM, FF3, FF5, and q5. The GMM estimation uses the following moment condition:

$$E[R_1^p(1 - b \cdot \tilde{F}_t)] = a.$$

t-statistics uses standard errors adjusted according to Newey and West (1987) and Shanken (1992).

react to such disasters,

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

where t is the month where the disaster happens (for the 2012 US drought, t is set to be the last month of 2012); $R^i_{t \to t+M}$ is the (annualized) cumulative return from month t to month $t+M$ of firm i; $Brown_i$ 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. The variable of interest is β. A negative β indicates that brown stocks depreciate upon a natural disaster relative to green stocks. Thus, green stocks could offer insurance against climate change, which explains the lower premium documented in the previous part.

Table 6 shows that the estimated β are significantly negative for the horizon from one month to one year for both events. Specifically, compared to green stocks, annualized cumulative returns of brown stocks decrease 10% to 31% (10% to 15%) after the hurtricane Katrina (2012 US drought/heatwave). The results confirm the role of green stocks as a hedge against climate-related natural shocks.

Table 6: **Event study on stock returns**

M	1m	2 m	3m	6m	12m
		Panel A. Hurricane Katrina			
β	-0.31	-0.19	-0.16	-0.17	-0.10
t	-2.31	-2.19	-2.34	-3.38	-3.07
Adj. R^2	0.00	0.01	0.13	0.20	0.16
Obs.	272	272	272	272	272
		Panel B. 2012 US drought			
β	-0.12	-0.08	-0.15	-0.14	-0.10
t	-1.63	-1.62	-3.25	-4.02	-4.42
Adj. R^2	0.13	0.17	0.28	0.26	0.25
Obs.	969	969	969	969	969

*N*ote: The table shows the results for the event study

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

where $R_{i,t\to t+M}$ is the annualized cumulative return of firm i from month t (when the event happens) to month t+M. $Brown_i$ 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 of the previous year. t-statistics using Newey-West adjusted standard errors are reported.

Finally, I examine the dynamics of investment flows across brown/green firms upon natural disasters. Specifically, I do the same event study on investments focusing on the 2012 US drought/heat wave, since the investment data is at the annual frequency,

$$\Delta(I/A)_t = \alpha + \beta \cdot Brown_i + \gamma X_{i,t-1} + \epsilon_i$$

where t is the year 2012. $\Delta(I/A)_t$ is the change of the investment-over-asset from year $t-1$ to year t. The investment is defined in two ways: (1) change in total assets(ΔA), and (2) change in PPE

(ΔPPE). The control variable $X_{i,t}$ includes industry dummies, revenue over asset, and leverage.

Table 7 shows that during the 2012 US drought, investment-over-asset ratio of brown firms decrease a significant 6.8% (2.1%) when investment is defined as change in total asset (PPE) relative to green stocks. This indicates that upon climate-related disasters, investments flow from brown sector to green sector. Under a convex investment allocation cost, this could lead a increase in the value of green sector and thus a higher realized returns. In the next section, I provide a simple, analytically solvable model to qualitative explain the empirical findings in this section.

Table 7: **Event study on investment**

	$I \equiv \Delta A$	$I \equiv \Delta PPE$
β	-0.068	-0.021
t	-2.94	-1.89
Adj. R^2	0.03	0.04
Obs.	934	932

*N*ote: The table shows the results for the event study

$$\Delta(I/A)_t = \alpha + \beta \cdot Brown_i + \gamma X_{i,t-1} + \epsilon_i$$

where $\Delta(I/A)_t$ the change of the investment-over-asset from year $t-1$ to year t. The investment is defined in two ways: (1) change in total assets, and (2) change in PPE. The control variable $X_{i,t}$ includes industry dummies, revenue over asset, and leverage. t-statistics using Newey-West adjusted standard errors are reported.

4. A toy model

In this section I present a simple two-period model to qualitatively explain the empirical results in previous section. At $t = 0$, a representative agent invests in a production sector using fossil fuel (sector F) and a production sector using non-fossil fuel (sector N). At $t = 1$, agent observes an exogenous natural disaster shock ϵ and again makes investment decisions on the two sectors. At $t = 2$ agent consumes all goods and the economy is closed. The climate damage is introduced as a mapping from time-1 investment in sector F and the shock to the time-2 output.

Agents have the EZ preferences. For mathematical tractability, I assume the IES=1 and take the logarithm of the utility, then at time t

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

where u_{t+1} is the continuation utility at time $t+1$, β and γ are the subjective discount factor and relative risk aversion, respectively.

This model may be unrealistic and oversimplified in terms of the climate-economy interactions from the standard IAM literature. However, the focus of this section is to provide a glimpse into the mechanism through which green stocks rise upon climate-related disasters while maintaining analytical tractability. The next section provides a fully-specified model to quantitatively rationalize the data.

In the rest of this section, I show how investment and stock returns at *time 1* respond to the shock, and what is the key assumption that makes the model matching the data qualitatively.

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

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

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 processes. In addition, I include the climate damage D

$$C_2 = Y_2 = \Big(1 - D(I_{F,1}, \epsilon)\Big) I_{F,1}^{\alpha} I_{N,1}^{1-\alpha}, \tag{2}$$

where $\alpha \in (0,1)$ is the weight of sector F in the production function; $I_{F,1}$ ($I_{N,1}$) is the time-1 investments in sector F (N); $\epsilon \sim N(0,\sigma^2)$ is the shock of natural disaster. D is the climate damage, which depends on both the investment in sector F and the natural disaster shock. I assume that $D_1' > 0$, $D_2' > 0$, and $D_{12}' > 0$. The last assumption is essential to make the model consistent with the data and generate a lower premium for the green stocks. It says that the marginal climate damage caused by pollution i.e., production activities using fossil fuel, is increasing with the shock of natural disasters. I assume the following functional form for the climate damage $D(\cdot,\cdot)$,

$$D(I_{F,1}, \epsilon) = \lambda(\epsilon)\log(I_{F,1}), \quad \lambda' > 0 \tag{3}$$

An explanation for this setting is that the damage intensity parameter λ is itself uncertain. Thus 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 the perceived value of λ is an increasing function on the shock ϵ.

The assumption of full capital depreciation simplifies the mathematics and generate linear solutions. In the last part of this section where I derive the stock returns for both sectors, I introduce a convex investment adjustment cost. The convex adjustment cost is a standard assumption in the macro-finance literature (Cochrane, 1991; Jermann, 1998). It relates investments to Tobin's q (the marginal rate of transformation between new capital and consumption) as well as stock returns.

Optimization I solve the social planner's problem at time 1

$$\max_{I_{N,1}, I_{F,1}} \quad u_1 = (1-\beta)\log C_1 + \beta \log C_2 \tag{4}$$

subject to the constraints in equation 2, 3 and the market clear condition $Y_1 = I_{F,1} + I_{N,1} + C_1$.

Optimal investments Solving the F.O.C. in the optimization problem in equation 4 gives the solution to the investments and consumption. These are linear functions of the state variable Y_1, where the coefficients depend on the damage intensity λ

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

$$I_{N,1} = \frac{\beta(1-\alpha)}{1-\beta\lambda} Y_1 \tag{6}$$

where $\frac{\partial I_{B,1}}{\partial \lambda} < 0$ and $\frac{\partial I_{G,1}}{\partial \lambda} > 0$. Thus, a natural disaster shock (a positive ϵ), which can be translated into an increase in the damage intensity λ, will lead to a higher (lower) investment in the sector N (F). 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 depress the use of fossil fuel. This leads to a lower investment in sector F.

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

Finally, we can write the investments in a linear approximation as a function of the steady-state investments and the shock

$$I_{F,1} = \bar{I}_{F,1} + \theta_F \epsilon \tag{7}$$

$$I_{N,1} = \bar{I}_{N,1} + \theta_N \epsilon \tag{8}$$

where $\bar{I}_{F,1}$ ($\bar{I}_{N,1}$) is the steady-state investment that doesn't depend on the shock, $\theta_F = -\beta \frac{1-\alpha\beta}{(1-\beta\lambda)^2} \bar{\lambda}'$ and $\theta_N = \beta^2 \frac{1-\alpha}{(1-\beta\lambda)^2} \bar{\lambda}'$ with $\bar{\lambda}' = \frac{\partial \lambda}{\partial \epsilon}\Big|_{\epsilon=0}$.

Linear approximation of the utility Using the Envelop theorem, the partial derivative of utility to the shock is given by

$$\frac{\partial u_1}{\partial \epsilon} = \frac{\partial u_1}{\partial \lambda} \bar{\lambda}' = -\beta \log I_{F,1} \bar{\lambda}' < 0 \tag{9}$$

Thus, utility decreases when there is a positive shock on the natural disaster.

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

$$M_1 = \frac{\partial u_0 / \partial C_1}{\partial u_0 / \partial C_0} = \beta \frac{C_0}{C_1} \frac{\exp\left(u_1(1-\gamma)\right)}{E_0\left[\exp\left(u_1(1-\gamma)\right)\right]} \tag{10}$$

Taking the logarithm to equation 10 and apply a linear approximation,

$$m_2 = \bar{m}_2 + \theta_m \epsilon \tag{11}$$

where the $\bar{m}_2$ is the steady-state SDF and $\theta_m = \beta \left[(\gamma - 1) \log I_{F,1} - \frac{1}{1-\beta\lambda} \right] \bar{\lambda}'$.

The sign of θ_m depends on two terms. The first term is caused by the disutility due to the shock and leads to an increase in the SDF. The second one comes from the increased consumption of the time-1 consumption since agents refrain investment in sector F. How the SDF changes depends on the interaction of these two terms.

Proposition 2. *When agent is risk averse enough, so that $\gamma > 1 + \frac{1}{(1-\beta\lambda)\log I_{F,1}}$, a positive shock increases the SDF, leading to a bad state of the world.*

Stock returns In this section, I introduce *investment adjustment cost*, an essential concept that enables a macroeconomic model to generate time-varying capital gains. The goal is to relate stock returns to the investments and see how returns respond to carbon emission shocks. Specifically, I change the assumption on the capital accumulation process to the following (still maintaining the assumption on full depreciation)

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

where $G(I, K)$ reflects a convex adjustment cost, satisfying $G'_I > 0, G'_K < 0$ and $G'_{II} > 0$. The stock returns are recovered from the Euler equation of the social optimization problem (Cochrane, 1991) (I neglect index i for simplicity)

$$R_{t+1} = \frac{-Q_{t+1}G'_{K,t+1} + MPK_{t+1}}{Q_t} \tag{12}$$

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 $G(I, K) = I - aI^{\xi}K^{1-\xi}$ following Jermann (1998) and Croce (2014), where $0 < \xi < 1$.

Following the Campbell-Shiller approximation, the log return for sector i can be expressed as

$$r_{i,1} = \bar{r}_{i,1} + \kappa_i\theta_i\epsilon, \forall i \in \{F, N\} \tag{13}$$

where $\kappa_i = \frac{\exp(\bar{pd}_{i,1})}{1+\exp(\bar{pd}_{i,1})}$ with $\bar{pd}_{i,1}$ being the steady-state price-dividend ratio of sector i; $\bar{r}_{i,1}$ is the steady-state log stock return at time 1. θ_F and θ_N are given in equation 7 and 8.

Note that κ_F and κ_N are both positive, $\theta_F < 0$ and $\theta_N > 0$. Then,

Proposition 3. *A positive shock on the natural disaster increases the stock return in sector N and* *decreases that in sector F.*

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

$$E_0[r_{i,1}^{ex}] = -\kappa_i\theta_i\theta_m\sigma^2 - \frac{1}{2}\kappa_i^2\theta_i^2\sigma^2, \quad \forall i \in \{F, N\}$$

when agent is risk averse enough, so that the condition on *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., $\kappa_F\theta_F < 0$, sector F carries a positive risk premium. Whereas sector N carries a negative risk premium due to the positive exposure, i.e., $\kappa_N\theta_N > 0$. In summary, sector N provides an insurance against global warming and thus carries a lower risk premium, consistent with the data.

5. The macro-finance integrated assessment model

This section replicates the empirical findings in a fully-specified, infinite horizon model that unifies the standard IAM and production-based asset pricing models in the Macro-finance literature, which I called the MFIAM. The model is based on, but differs significantly from the long-run risks temperature 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 fuel. Second, I include investment adjustment cost, which explicitly relates investment decisions to stock returns. Third, I specify that a time-varying damage intensity parameter that depends on the shock of natural disasters. These model setups enable me to elicit moments of macroeconomic variables and stock market returns and match them with the empirical facts. In the following part of this section, I describe the economic sector, the climate change dynamics, preferences, and the welfare optimization problem, respectively.

5.1. Economic sector

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

$$Y_t = \left(\omega Y_{F,t}^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega) Y_{N,t}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{14}$$

where Y_F (Y_N) is the output from sector F (N). ω is the fraction of final output from sector F. ε is the elasticity of substitution between the two sectors. When $\varepsilon > 1$ ($\varepsilon < 1$), outputs in the two sectors are substitutes (complement). A benchmark value of ε indicates $\varepsilon > 1$ (Acemoglu et al., 2012; Van der Zwaan et al., 2002), suggesting that fossil fuel and non-fossil fuel are usually substitutes.[9]

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

$$Y_{i,t} = K_{i,t}^{\alpha} (A_t l_{i,t})^{1-\alpha}, \quad \forall i \in \{F, N\} \tag{15}$$

where $K_{i,t}$ and $l_{i,t}$ are the capital stock and labor input at sector i, A_t is the TFP.

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., quantity of machines that extract, transport and convert energy sources into final products. As in Van der Zwaan et al. (2002), raw energy inputs in each sectors are proportional to the level of corresponding capital stocks. This approach has two advantages: first, costs of energy extraction and conversion are usually hard to quantify. I convert this cost to the depreciation of capital and investments. Cost difference between fossil and non-fossil fuel is thus captured by the different investment efficiencies. Second, through this approach I explicitly derive the investment of the two sectors and thus shed light on the cross-sector stock returns.

Capital accumulation For sector F,

$$K_{F,t+1} = (1-\delta_K) K_{F,t} + I_{F,t} - G_t(I_{F,t}, K_{F,t}) \tag{16}$$

where δ_K is the rate of depreciation of the capital, $I_{F,t}$ is the investment in sector F at time t. $G_t(I_{F,t}, K_{F,t})$ introduces adjustment cost for capital accumulation. I assume a convex adjustment

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

cost following Jermann (1998) and Croce (2014),

$$G_t(I_{F,t}, K_{F,t}) = I_{F,t} - \left(\frac{a_1}{1-\xi} I_{F,t}^{1-\xi} K_{F,t}^{\xi} + a_0 K_{F,t} \right), \tag{17}$$

where $0 < \xi < 1$, a_1 and a_0 is chosen to satisfy the restriction that $G = \frac{\partial G}{\partial I_F} = 0$ at steady state.

The capital accumulation for sector N is quite similar, except that there is an additional cost reflecting the lack of human knowledge and under-development of the infrastructure on non-fossil fuel.

$$K_{N,t+1} = (1 - \delta_K) K_{N,t} + I_{N,t} - G_t(I_{N,t}, K_{N,t}) - N_t(I_{N,t}, H_t) \tag{18}$$

I assume that the additional cost $N_t(I_{N,t}, H_t)$ follows the same functional form as the adjustment cost, but depends on the investment and the human knowledge capital on non-fossil fuel H_t,

$$N_t(I_{N,t}, H_t) = I_{N,t} - \left(\frac{b_1}{1-\eta} I_{N,t}^{1-\eta} H_t^{\eta} + b_0 H_t \right), \tag{19}$$

where $0 < \eta < 1$, b_1 and b_0 is chosen to satisfy the restriction that $N = \frac{\partial N}{\partial I_N} = 0$ at steady state. Note that $N'_H < 0$, thus higher human knowledge capital improves the investment efficiency on non-fossil fuel sector.[10] In addition, $N''_H > 0$. It indicates that the marginal benefit of expanding human knowledge is decreasing. This is the common specification that ensures there is an optimal level of human knowledge (Popp, 2006).

Research & developement The human knowledge capital is accumulated through R&D,

$$H_{t+1} = (1 - \delta_H) H_t + h(R_{N,t}, H_t), \tag{20}$$

where δ_H is the depreciation on the human knowledge capital, $R_{N,t}$ is the R&D investment directed to the sector N. $h(R_{N,t}, H_t)$ is called 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,

$$h(R_{N,t}, H_t) = R_{N,t}^{\phi} H_t^{1-\phi} \tag{21}$$

[10]This reflects the findings of new materials that improve transition efficiency on renewable energy, or new technology that lower the cost of building the facilities that extract renewable energy.

where ϕ is between 0 and 1. This setting bears two standard assumptions in the literature about technological change: (1) a diminishing return to research in accumulating human knowledge, and (2) positive externality of human knowledge.[11]

Sector stock returns Stock returns are derived from the Euler equation by solving the first order conditions of the intertemporal optimization problem,

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

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

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

$$\log(A_t) = \log(A_{t-1}) + \mu + x_t + \sigma\epsilon_{A,t} \tag{22}$$

$$x_t = \rho_x x_{t-1} + \varphi_x \sigma \epsilon_{x,t} \tag{23}$$

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 assumed to be *i.i.d.* standard Gaussian.

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

$$\tilde{Y}_t = \exp(-\gamma_t(M_t - \bar{M}))Y_t \tag{24}$$

where $\tilde{Y}_t$ is the output after accounting for the climate damage. M_t and $\bar{M}$ is the atmospheric carbon concentration at time t and at the pre-industrial era. γ_t is the damage intensity parameter. It governs the marginal cost of pollution, i.e., the additional damage caused by one unit increase

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

in carbon concentration. I assume the following AR(1) process for γ_t:

$$\gamma_t = (1 - \rho_\gamma)\bar{\gamma} + \rho_\gamma \gamma_{t-1} + \epsilon_{\gamma,t} \tag{25}$$

where $\epsilon_{\gamma,t} \sim N(0, \sigma_r^2)$ is a shock that affects the perceived value of γ. This could be a natural disaster that causes people revise upward their belief of the climate damage intensity.

Labor market clear Labor market clearing condition requires that the total labor demand be less than the total labor supply,

$$l_{F,t} + l_{N,t} \leq 1 \tag{26}$$

where the total labor supply is normalized to 1.

Consumption Consumption is given by

$$C_t = \tilde{Y}_t - I_{F,t} - I_{N,t} - kR_{N,t} \tag{27}$$

As discussed in studies about the research externality (Nordhaus, 2010b; Popp, 2006), the opportunity cost of research on renewable energy is multiple times of its dollar cost. The parameter k reflects this opportunity cost.

5.2. Climate-change dynamics

The climate-change dynamics follows closely the DICE model (Nordhaus, 1992).[12]

$$T_{t+1} = (1 - \rho_T)\bar{T} + \rho_T T_t + \chi \log\left(\frac{M_{t+1}}{\bar{M}}\right) \tag{28}$$

$$M_{t+1} = (1 - \rho_M)\bar{M} + \rho_M M_t + E_t \tag{29}$$

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 equilibrium level of T_t and M_t under no anthropogenic CO_2 emission. The mapping from carbon concentration to temperature is represented by the

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

radiative forcing term $\log\left(\frac{M_{t+1}}{M}\right)$, according to the Arrhenius's greenhouse law (Arrhenius, 1896). E_t is the endogenous carbon emission caused by human activities. I assume E_t depends on the *standardized capital* in sector F:

$$E_t = \lambda \frac{K_{F,t}}{A_t} \tag{30}$$

where λ is the carbon intensity.[13] The idea behind this specification is that E_t depends on the combustion of fossil fuel and thus are determined by the capital stock in sector F. In addition, as the 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 the productivity. This 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.

5.3. *Preferences*

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

$$U_t = \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{31}$$

where U_t is the continuation utility at time t; δ is the discount rate, γ is the relative risk aversion, and ψ is the IES. When $\psi = 1/\gamma$, the utility function collapse to the CRRA utility, which is commonly used in standard IAMs (Nordhaus, 2010a; Pindyck, 2012).

5.4. *Optimization problem*

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

$$\max_{\substack{C_t, R_{N,t}, I_{F,t}, I_{N,t}, \\ l_{F,t}, l_{N,t}, \mathcal{S}_{t+1}}} \left\{ (1-\delta) C_t^{1-\frac{1}{\psi}} + \delta \left(E_t \left[U_{t+1}(\mathcal{S}_{t+1})^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{32}$$

[13] DICE model introduces the de-carbonization process (i.e., 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 is decreasing at 1.6 percent every year over the last six decades. This is actually consistent with my specification on a constant λ. Note that $E_t = \frac{\lambda}{A_t} K_{F,t}$, thus the emission-output ratio decreases as productivity increases.

subject to the dynamics and constraints from equation 14 to 30. 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.

5.5. Social cost of carbon

One of the most important concept that is widely reported in the climate change literature is the social cost of carbon (SCC). SCC measures the present value of the damage caused by one additional unit of CO_2 emission expressed in the units of consumption. My model provides an straightforward way to estimate the SCC by using the envelop 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 the consumption.

6. Quantitative results

This section shows the quantitative results of the MFIAM. I first describe the calibration and the simulation results. Then I estimate the IRFs to shocks that alter the damage intensity, i.e., ϵ_γ. Finally I do the sensitivity analysis of the key parameters on the steady-state results.

6.1. Calibration

I collect data on global temperature anomaly, carbon concentration, anthropogenic CO_2 emission, world real GDP and consumption per capita for calibration. Parameters on the climate dynamics are estimated through regressions using the data in an yearly frequency. Whereas parameters on the economic dynamics are from the literature. See table 8.

6.2. Simulation

Figure 1 shows simulations of three series: (1) GDP growth rate; (2) temperature, and (3) carbon concentration. I compare the simulated series with those from data. The figure shows that

Table 8: **Calibration**

Description	Parameter		
Panel A: Data-driven calibration			
		Estimate	SE
Elasticity of CO_2 emission	λ	2.00	0.6
Autocorrelation of CO_2 concentration	ρ_M	0.98	0.002
Autocorrelation of temperature	ρ_T	0.17	0.130
Sensitivity of temperature to CO_2 concentration	χ	3.088	0.496
Equilibrium temperature	$\bar{T}$	-0.46	0.081
Equilibrium CO_2 concentration	$\bar{M}$	279.48	0.06
Panel B: Literature-driven calibration			
		Value	Reference
Fraction of fossil fuel in the production	ω	0.59	Golosov *et al*. (2014)
Elasticity between two sectors	ε	3	Acemoglu *et al*. (2012)
Capital depreciation rate	δ_K	0.06	Croce (2014)
Share of capital in production	α	0.34	Croce (2014)
Adjustment cost parameter	ξ	0.14	Croce (2014)
Subjective discount factor	β	0.95	Croce (2014)
Risk aversion	γ	10	Croce (2014)
IES	ψ	2	Croce (2014)
Unconditional mean of TFP growth	μ	1.8%	Croce (2014)
Volatility of TFP growth short-run fluctuation	σ	0.034	Croce (2014)
Equilibrium damage intensity	$\bar{\gamma}$	5.05×10^{-5}	Golosov et al. (2014)
Autocorrelation of expected growth of TFP	ρ_x	0.8	Croce (2014)
Scale factor of long-run volatility	φ_x	0.1	Croce (2014)
Opportunity cost of renewable R&D	k	4	Popp (2006), Nordhaus (2010b)
R&D parameters	η	0.4	Popp (2006)
R&D parameters	ϕ	0.55	Popp (2006)
Depreciation of human knowledge capital	δ_H	0.1	Popp (2006)

*N*ote: This table show the calibration. In panel A, ρ_M is estimated through Eq. (29); ρ_T, $\bar{T}$, χ, and σ_T are estimated through Eq. (28). $\bar{M}$ equals to the average carbon concentration over the period from AD 1 to 1750. λ is calibrated to match the trend of carbon concentration in the data.

calibrated parameters lie in a reasonable areas that ensure the model to replicate the real-world observed data.

Table 9 presents the simulated moments of macroeconomic, environmental variables and asset market returns. The simulated moments under the benchmark calibration resemble the volatilities of macroeconomic variables (growth rate of total output, consumption, and investments) and environmental variables (growth rate of the temperature and carbon concentration) in the data. In terms of the asset returns, the model quantitatively captures the higher risk premium of sector F observed in the data. A zero-cost strategy that longs the renewable energy and short the fossil fuel portfolio delivers a expected annualized return of 3.54% with a standard error of 1.04%. The model simulated return is 3.29%, which lies in the confidence interval of the data. The model-implied standard deviation of excess returns are quite low compared to the data. This may be

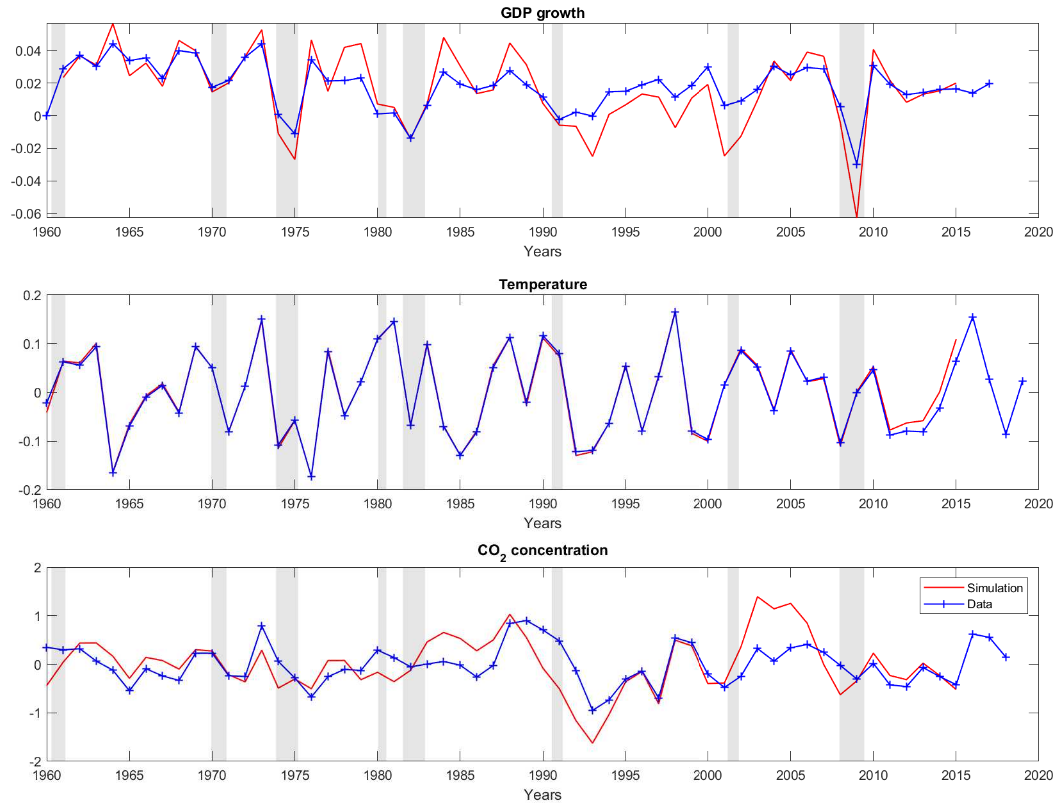

Fig. 1. **Model simulation and data:** I simulated 60 time steps of the model as in the data. All the shocks are extracted from the data and fitted in to dynare++ to get the simulation. Shocks on climate dynamics are extracted using Eq. 28 and 29. Short-run and long-run productivity shocks are extracted 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 short- and long-run shocks. Temperature and CO_2 concentration are detrended. Shaded areas indicate the NBER based recessions for U.S.

due to the other systematic risks that are not captured in this model. In addition, I constructed the model-implied market return by averaging the stock returns of the two sectors weighted by the their market values. This also replicates the market return in the data quite well (7.29% in the model and 6.68% in the data). Finally, the model matches the low risk-free rate observed in the data.

I implement the simulation under the another case where agents have CRRA preferences instead of recursive ones. Under such cases, moments on economic quantities and asset prices don't align with the data. For example, the investments become excessively volatile. The difference between

Table 9: **Simulated moments and data**

Moments	Data		Model	
	Estimate	SE	Benchmark	IES=$1/\gamma$ (CRRA)
$\sigma(\Delta y)$ (%)	2.43	(0.32)	3.13	2.47
$\sigma(\Delta c)/\sigma(\Delta y)$	0.85	(0.02)	1.00	1.10
$\sigma(\Delta i_F)/\sigma(\Delta y)$	1.96	(1.70)	1.49	4.27
$\sigma(\Delta i_N)/\sigma(\Delta y)$	1.40	(0.88)	1.07	5.32
AR1(Δc)	0.48	(0.00)	0.14	0.13
$\sigma(\Delta T)$ ($°C$)	0.12	(0.01)	0.12	0.00
$\sigma(\Delta M)$ (ppm)	0.64	(0.07)	1.14	0.18
$E(R_F - R_N)$ (%)	3.54	(1.04)	3.29	0.16
$\sigma(R_F - R_N)$ (%)	17.27	(1.33)	6.02	1.02
$E(R^{ex}_{MKT})$ (%)	6.68	(1.94)	7.29	-1.53
$\sigma(R^{ex}_{MKT})$ (%)	17.20	(1.50)	6.29	11.58
$E(r_f)$ (%)	0.85	(0.52)	1.81	19.03
$\sigma(r_f)$ (%)	2.12	(0.28)	0.85	8.50

*N*ote: Δy is output growth rate; Δc is consumption growth rate; ΔT is temperature increment; ΔM is carbon concentration increment; R^{ex}_{MKT} is stock market return; Δi_F (Δi_N) and R^{ex}_F (R^{ex}_N) are investment growth rate and stock return in sector F (N). I simulate the model under the benchmark calibration and a case that the IES equal to $1/\gamma$, which corresponding to the case with CRRA utilities. For both cases. I simulate for 500 steps for 1,000 repetition. In addition, I drop the inital 10% of simulation periods as burn–ins. Excess returns have a leverage of two in the simulation. Data on Δy, Δc, ΔT, ΔM, R^{ex}_{MKT}, and r_f is from 1960-2018. Growth rates of investment in the two sectors (Δi_F and Δi_N) in data are defined as the growth rate of physical capitals (PPE) of firms in the top and bottom decile portfolios constructed in section 3. $E(\cdot)$, $\sigma(\cdot)$ and $AR1(\cdot)$ are mean, standard deviation, and first-order autocorrelation, respectively. Numbers in the parenthesis are Newey-West adjusted standard errors obtained through GMM. All statistics in annual term.

green and brown stocks becomes less pronounced. Finally, the most obvious discrepancies between a CRRA model 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.

6.3. Impulse response functions

I estimate the IRFs to a positive shock on the climate damage intensity parameter γ. This could be a exogenous natural disaster that revise upward people's belief on 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 2.

The blue solid lines in figure 2 shows the IRFs under the benchmark calibration, when the IES is bigger than one and agents prefers early resolution of uncertainty. First, a positive shock

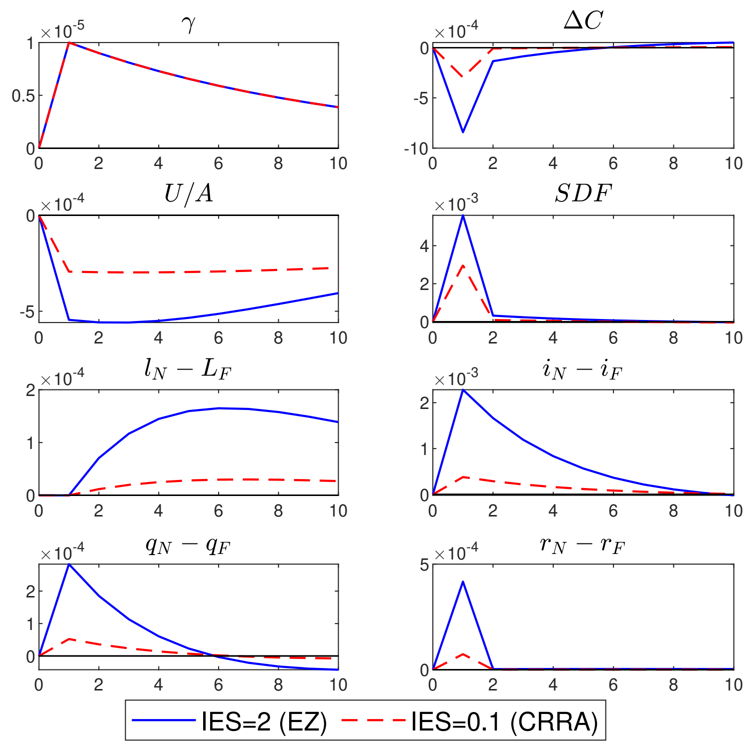

Fig. 2. **Impulse response functions to a positive shock on the damage intensity parameter γ_t:** The shock happens at $t = 1$.

on γ generates a temporal decline in the current consumption and a persistent decline on the welfare-over-productivity ratio. Second, SDF increases which indicates a higher marginal utility from consumption and a bad state of world. Third, labor, investments, Tobin-q, and returns in the sector N increase relative to the sector F, This is consistent with the results in two-period model, again showing that green stocks appreciate after a bad shock, and offer an insurance against global warming. This explains the lower simulated return of sector N in table 9.

The red dotted line shows the other case when agents are indifferent to the time of resolution of uncertainty (IES equal to the reciprocal of risk aversion), or the case with CRRA preference. Under this case, all the IRFs are still in the right direction, although the effects are greatly attenuated. As a result, the CRRA case cannot generate a sufficient difference between and green and brown stocks and leads to a much smaller green premium.

6.4. Steady-state results

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

Social cost of carbon Estimated SSC in this model is about 0.0022 of the total consumption. The world real consumption is 5.82×10^{13} U.S. dollars in 2017. Thus 1 ppm equivalent CO_2 emission (which is 2.124 billion ton of carbon) has a cost of 125.9 billion dollars. This means that the SCC is, on average, about 59.3 U.S. dollars per metric ton of carbon.[14] Compared with those in Bansal et al. (2016b) (104 U.S. dollars per ton of carbon) and Nordhaus (2019) (135.7 U.S. dollars per ton of carbon), the estimate here is smaller. This is mainly due to the introduction of the renewable energy sector.

Why would the introduction of clean energy decrease the SCC estimate? First, note that an exogenous increase in the carbon emission can only be offset by reducing capital stock in sector F. In an economy with only fossil fuel, this reduction causes a full cost on current output and consumption. Instead, in an economy with clean energy in the production function, reduction in capital stock of sector F can only partially impact the output and consumption. The negative effect is smaller when the share of fossil fuel in the production function is smaller. Second, investments and R&D endogenously change to accommodate climate shock and minimize the welfare cost. Consequently, adopting renewable energy with endogenous R&D makes our economy less sensitive to exogenous climate shocks.

Carbon intensity The carbon intensity, λ, is a key parameter that determines the tightness of interaction between economic growth and climate change. Thus its economic and environmental effects are worth investigating. The red solid lines in Fig. 3 show the effects of λ under the benchmark case (i.e., with renewable energy and R&D). First, An increase in the carbon intensity decreases the welfare and consumption growth at steady state. This is due to the increase in climate damage caused by a higher steady-state temperature anomaly, which increases from 2.2 degrees to 3.1 degrees.

[14] Note that the SCC is itself uncertain due to stochastic nature of climate change and the economic damage. The SCC reported should be considered as an average.

Second, as λ increases, marginal cost of burning fossil fuel increases. Thus, investment and labor reallocates toward sector N. On the other hand, as the economy becomes more relied on renewable energy, R&D aimed at improving investment efficiency becomes more profitable. As a result, R&D over aggregate output increases. This indicates an increase in the investment efficiency in sector N. Finally, SCC increases on carbon intensity. This is driven by a higher economic damage due to the increase in the temperature anomaly (see the red line in the last panel of Fig. 3).

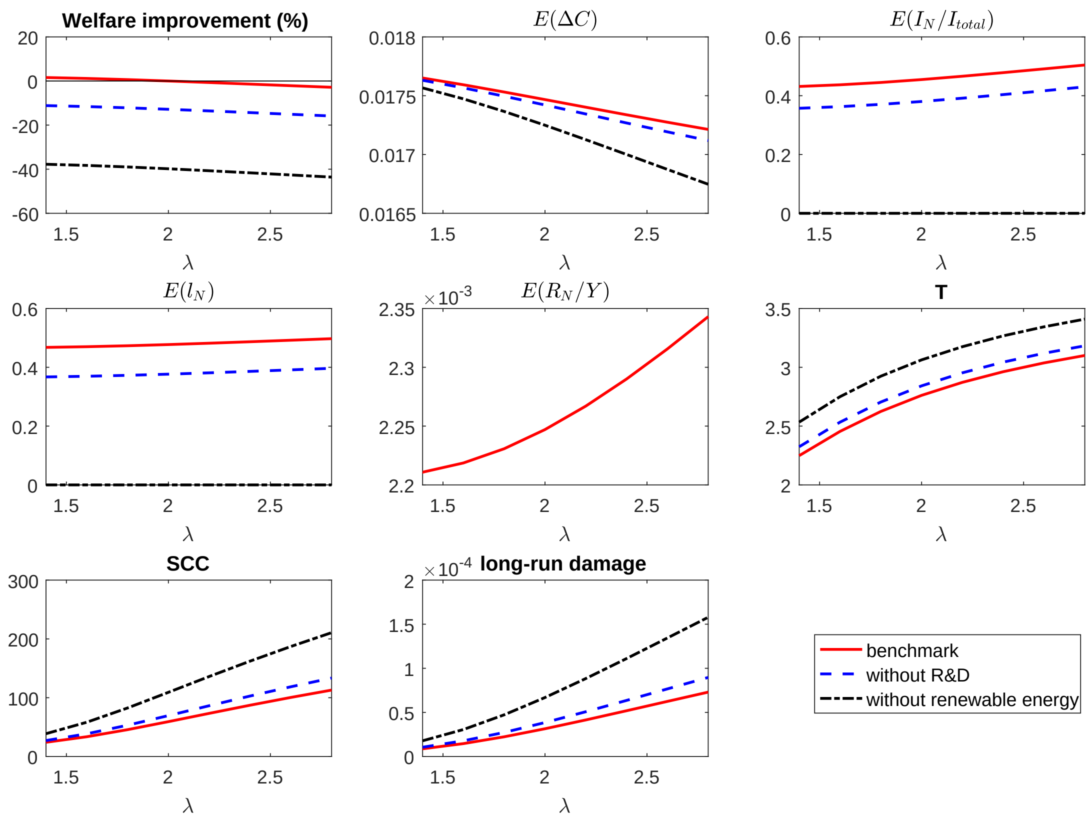

Fig. 3. **The effects of carbon intensity and induced technological change:** The figure shows the stochastic steady-state values under different λ. The red lines represent the benchmark case where renewable energy and R&D are present; the blue dashed lines are the case where R&D is absent; the black dash-dotted lines are the case where both renewable energy and R&D are absent. "Welfare improvement" shows the change in the welfare-over-productivity ratio. SCC is in unit of U.S. dollars; temperature is in unit of $^\circ C$.

The role of endogenous R&D and renewable energy The blue dashed lines in Figure 3 show the effects of λ under no endogenous R&D.[15] Compared to the benchmark model, first,

[15] I implement this exercise by changing the parameters in Eq. 19 (i.e, the additional investment cost on renewable energy N_t). Specifically, by setting $\eta = 0$ and $b_0 = 0$, human capital knowledge doesn't enter the formula of efficiency

welfare-over-productivity ratio is 15% smaller. Second, investment share and labor in sector N is 8% and 10% lower, respectively. This is intuitive since there is no R&D to improve and motivate investment in sector N. Finally, SCC is higher, meaning that neglecting endogenous R&D causes overestimation of the economic cost of climate shocks.

Under the case with no renewable energy (black dash-dotted line), welfare decreases furthermore (about 40%). Steady-state temperature is 0.3 degrees higher, and consumption growth rate is much lower than the benchmark case. At last, SCC is substantially overestimated, it reaches 200 U.S. dollars when $\lambda = 3$. These results highlight that the inclusion of carbon-free technology is of first-order importance to precisely estimate the SCC.

Sensitivity analysis on key parameters Table 10 shows the quantitative results on the sensitivity of several key parameters in my model. Starting from the IES. I discuss the cases when IES<1, meaning that agent is less willing to sacrifice current consumption for a better environmental condition. Thus, in equilibrium the share of investment and R&D in sector N are smaller compared to the benchmark case. Furthermore, SCC in this case is significantly underestimated (only 30.3 U.S. dollars).

Another important parameter is the elasticity of substitution between fossil and non-fossil fuel (ε). I show that when the degree of substitution is high, the economy will rely more on the fossil fuel under no policy intervention. This is intuitive: if two inputs are close substitutes, production will rely more on the input that is cheaper, i.e., the fossil fuel. This is consistent with the implication in Acemoglu et al. (2012), that when clean and dirty inputs are highly substitutable, economy will quickly shift to dirty sector and eventually lead to a climate degradation without policy interventions.

Finally, when decreasing the elasticity of efficiency cost to the human knowledge capital, i.e., η, the investment cost of renewable energy decreases. As a result, agent increase investment and labor in sector N, as renewable energy is cheaper. However, the marginal benefit of R&D also decrease. Thus agents decrease the R&D. Welfare and SCC are quantitatively unchanged.

cost N_t. In such case, R&D plays no role in the welfare optimization problem. The equilibrium value of R&D thus becomes zero. In addition, to reflect the cost difference between two sectors, I set $b_1 = 0.5$. It means that the cost of investment in sector N is fixed at two times of that in sector F. This is a conservative estimates compared to Van der Zwaan et al. (2002).

Table 10: **Sensitivity analysis**

	Benchmark	IES	Substitution		Investment efficiency	
		$\psi = 0.9$	$\varepsilon = 2$	$\varepsilon = 10$	$\eta = 0.2$	$\eta = 0.8$
Welfare improvement	0.00%	-1.89%	-5.79%	0.81%	6.73E-05	-0.01%
ΔC	1.75%	1.75%	1.70%	1.76%	1.75%	1.75%
$\frac{I_N}{I_{total}}$	45.5%	43.4%	53.5%	34.0%	49.2%	42.0%
l_N	47.7%	46.8%	50.6%	37.0%	49.5%	46.1%
$\frac{R_N}{Y}$	0.22%	0.20%	0.24%	0.18%	0.12%	0.31%
Temperature	2.76	2.64	3.25	2.45	2.75	2.78
SCC	59.3	30.3	149.0	33.6	57.8	60.7
Climate damage	0.0031%	0.0023%	0.0105%	0.0015%	0.0030%	0.0033%

*N*ote: This table shows the stochastic steady-state values of different cases. Welfare is measured as the welfare-over-productivity ratio. SCC is in unit of U.S. dollars; temperature is in unit of $^{\circ}C$.

7. Conclusion

This paper documents a lower risk premium of green stocks compared to brown stocks. The greenium cannot be explained by various of systematic risks and firms' idiosyncratic risks, and is priced in a wide cross section of testing portfolios. Further investigation on the source 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 MAFIAM with time-varying damage intensities.

Further extension of this paper should take into account the exhaustibility of fossil fuel. As in Acemoglu et al. (2012), extraction cost increases as the world reserve of fossil fuel decreases. This leads to a increasing cost of using fossil fuel and accelerates the transition from fossil fuel to renewable energy. Another extension is to build a multi-region model which takes into account heterogeneity on technical progresses, vulnerabilities from climate damages, and so on. Finally, this paper only investigated the social planner's problem. It would be interesting to extend the model to a decentralized economy with market distortion of R&D and endogenous growth.

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