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Abstract

My first paper studies how firms' environmental performances affect cross-sectional expected stock returns and investments. 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.

The second paper is a joint work with Shasha Li, a former colleague at Bocconi University who is now an assistant professor at the Halle Institute for Economic Research. We study how the attention allocation of green-motivated investors changes information asymmetry in financial markets and thus affects firms' financing costs. To guide our empirical analysis, we propose a model where an investor with green taste endogenously allocates attention to market or firm-specific shocks. We find that more green-motivated investors tend to give more attention to green firm-level information instead of market-level information. Thus higher green taste leads to less category learning behavior and reduces the information asymmetry. Furthermore, it suggests that higher green taste results in lower leverage and lower cost of capital of green firms.

The last paper is a proposal that applies the information theory on climate change. I study how a better information about climate evolution and feedback in the future affects current actions to mitigate carbon emissions. This proposal improves previous studies on the precautionary principal, by extending the traditional method to rank information structures by Blackwell (1966) to a less strict but more versatile method by Lehmann (1988). This study could help policymaker better decide the timing of climate mitigation when facing decreased future uncertainty.

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Chapter 1

Explaining Greenium in a Macro-Finance Integrated Assessment Model

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 finance, macro-finance, asset pricing
JEL classification: G12, Q43, Q5.

1.1 Introduction

Climate change has been accelerating over the last decades. As shown in Figure 1.1, 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.

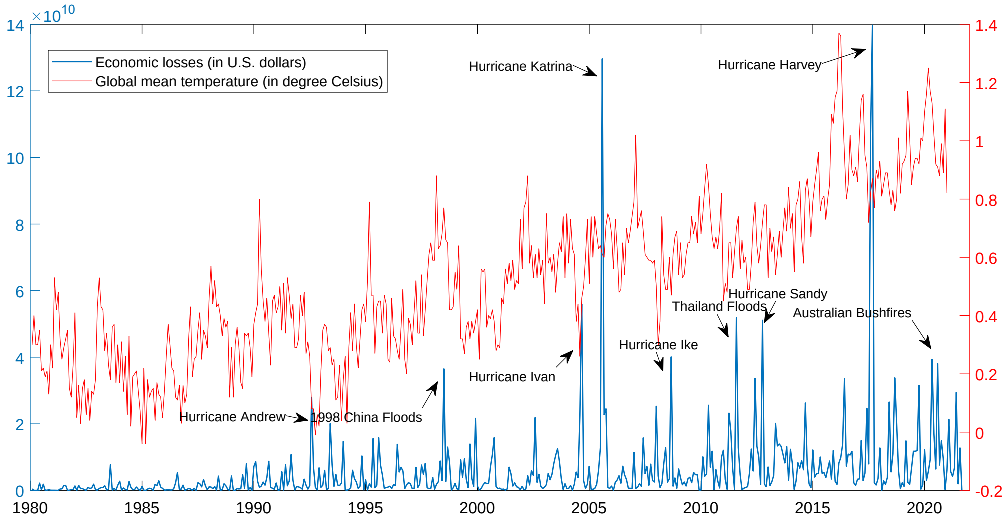

Figure 1.1: **Global temperature anormaly and economic losses due to climate disasters, 1980-2021**: Economic losses are monthly aggregated across more than 10,000 individual disasters related to climate change. Data collected from the International Disaster Database

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

[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.

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 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 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 1.1, 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]

[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.

[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

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 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

endogenous policy response to natural disasters and consider both transition risk and physical risk in a decentralized economy.

[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.

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, consistent with my empirical evidence.

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 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 1.2, I discuss my contribution to related literature. Section 1.3 provides a concise but informative empirical analysis of the greenium and how green and brown firms respond to climate disaster shocks. Section 1.4 illustrates the economic intuition of the mechanism through a simplified two-period model. In Section 1.5, I present the MFIAM and solve the social planner's optimization problem. Section 1.6 discusses the quantitative results. Section 1.7 summarizes my

[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).

findings.

1.2 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 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.

1.3 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.

[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.

[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.

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.

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

[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.

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.

1.3.1 Portfolio characteristics

Table 1.1 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 1.1 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 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

[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).

[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`.

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 1.1, 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 1.2 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.

1.3.2 Factor regressions

The first row of Table 1.3 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

Table 1.1: **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 1.2: **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

brown portfolio). To see whether this return difference is driven by priced systematic risks, I apply time-series regression of these 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 1.3. 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).

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 1.2 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.

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[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`.

Table 1.3: **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.

1.3.3 Double sorting and Fama-Macbeth regression

Since the firm characteristics of green versus brown portfolios differ in several aspects as shown in Table 1.1, 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,

[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.

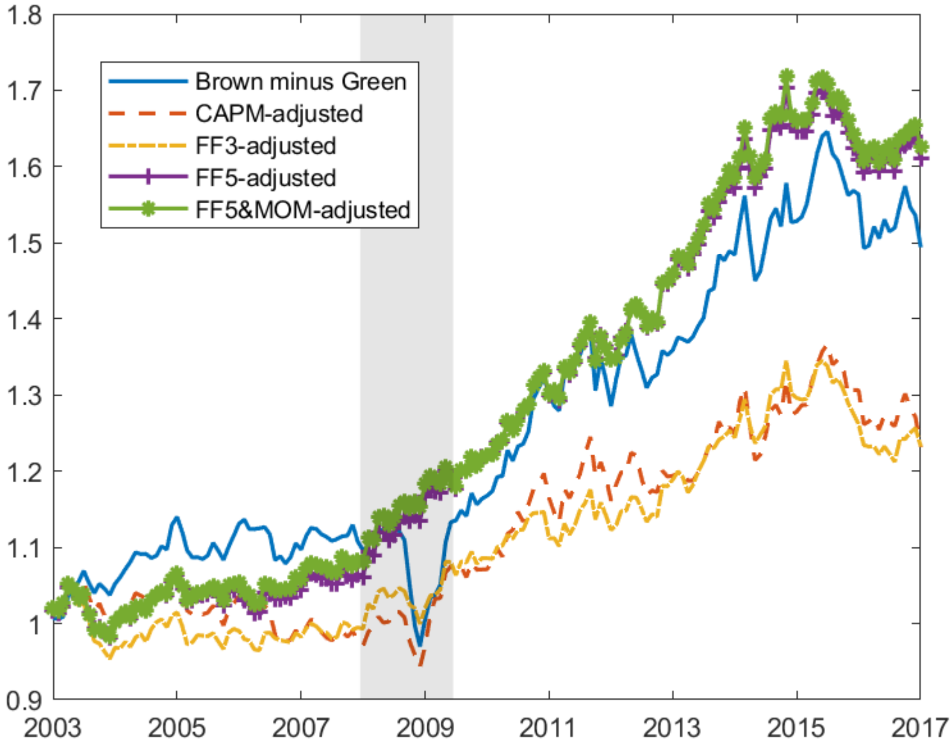

Figure 1.2: **Risk adjusted cumulative returns**

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 1.4 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

Table 1.4: **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.

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 1.5 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, 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.

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.

1.3.4 Green stock hedges physical risks

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

Table 1.5: **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.

disasters that are related to climate change.[17] I then construct a monthly index of climate

[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.

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

$$AR_{i,t} = \alpha_i + (\beta_1 + \beta_2 \cdot ENSCORE_{i,t-12}) \cdot logdamage_t + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{1.1}$$

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.

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.,

$$AR_{i,t} = \alpha_i + (\beta_1 + \beta_2 \cdot Quintile_{i,t-12}) \cdot logdamage_t + \gamma X_{i,t-1} + \epsilon_{i,t} \tag{1.2}$$

Column 1 and 2 of Table 1.6 present the result from the equations (1.1) and (1.2), respectively. The result shows that the CAPM-adjusted return of a firm with zero EN-

During my sample period, there are 5,892 disaster event, where more than 85% are storms and floods.

Table 1.6: **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.

SCORE (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 1.6 show that the result is robust when using raw return as dependent variable and adding market return as a control. In Figure 1.2, 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 reallocation) caused by climate shocks. Specifically, I replace the dependent variable in regressions (1.1) and (1.2) by firm-level investment. I follow literature to define investment by log changes in the (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

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

Table 1.7: **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.

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 1.7 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

[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.

and the greenness, consistent with result in column 1. Finally, the result is robust with other measures of investment. In sum, the evidence presented in Table 1.7 clearly shows a reallocation of investment from brown firms to green firms when facing a positive climate damage shocks.

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

[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 1.8: **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.

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 1.8 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 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 1.9 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

Table 1.9: **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.

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 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.

1.4 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,

$$u_1 = (1 - \beta) \log(C_1) + \beta \log(C_2). \tag{1.3}$$

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

$$C_2 = Y_2 = \Big(1 - D(I_{B,1}, \epsilon)\Big) I_{B,1}^{\alpha} I_{G,1}^{1-\alpha}, \tag{1.4}$$

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 $D(\cdot, \cdot)$:

$$D(I_{B,1}, \epsilon) = \begin{cases} \lambda(\epsilon) \log(I_{B,1}/\bar{I}), & I_{B,1} > \bar{I} \\ 0, & I_{B,1} \leq \bar{I} \end{cases} \tag{1.5}$$

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

$$\max_{I_{G,1},I_{B,1}} \quad u_1 = (1-\beta)\log C_1 + \beta \log C_2, \tag{1.6}$$

subject to the constraints in equations (1.4), (1.5), 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 (1.6) 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,

$$I_{B,1} = \frac{\beta(\alpha-\lambda)}{1-\beta\lambda} Y_1, \tag{1.7}$$

$$I_{G,1} = \frac{\beta(1-\alpha)}{1-\beta\lambda} Y_1. \tag{1.8}$$

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,

$$I_{B,1} = \bar{I}_{B,1} + \theta_B \epsilon, \tag{1.9}$$

$$I_{G,1} = \bar{I}_{G,1} + \theta_G \epsilon, \tag{1.10}$$

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

$$\frac{\partial u_1}{\partial \epsilon} = \frac{\partial u_1}{\partial \lambda}\bar{\lambda}' = -\beta \log(I_{B,1}/\bar{I})\bar{\lambda}' < 0. \tag{1.11}$$

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

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

$$M_1 = \frac{\partial u_0/\partial C_1}{\partial u_0/\partial C_0} = \beta \frac{C_0}{C_1} \frac{\exp\left(u_1(1-\gamma)\right)}{E_0\left[\exp\left(u_1(1-\gamma)\right)\right]} \tag{1.12}$$

Taking the logarithm to equation (1.12) and applying a linear approximation,

$$m_1 = \bar{m}_1 + \theta_m \epsilon, \tag{1.13}$$

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 (1.7) and (1.8) remain good linear approximations.

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

$$R_{t+1} = \frac{-Q_{t+1}G'_{K,t+1} + MPK_{t+1}}{Q_t}, \tag{1.14}$$

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

$$r_{i,1} = \bar{r}_{i,1} + \kappa_i \theta_i \epsilon, \quad \forall i \in \{B, G\}, \tag{1.15}$$

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 (1.9) and (1.10). 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.

1.5 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.

1.5.1 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).

$$Y_t = \left(\omega Y_{B,t}^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega) Y_{G,t}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1.16}$$

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:

$$Y_{B,t} = K_{B,t}^{\alpha}(A_t l_{B,t})^{1-\alpha}, \tag{1.17}$$

where K_t and l_t are the capital stock and labor input, A_t is productivity. Output in sector G is determined by both physical and intangible capital (human knowledge):

$$Y_{G,t} = H_t^{\nu}\left(K_{G,t}^{\alpha}(A_t l_{B,t})^{1-\alpha}\right)^{1-\nu}, \tag{1.18}$$

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

[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.

[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).

derive the investment flows between two production sectors, thus shedding light on the cross-sector stock returns.

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

$$K_{i,t+1} = (1 - \delta_K)K_{i,t} + I_{i,t} - G_t(I_{i,t}, K_{i,t}), \tag{1.19}$$

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 1.4, I assume a convex adjustment cost following Jermann (1998) and Croce (2014):

$$G_t(I_{i,t}, K_{i,t}) = I_{i,t} - \left(\frac{a_1}{1-\xi} I_{i,t}^{1-\xi} K_{i,t}^{\xi} + a_0 K_{i,t} \right), \tag{1.20}$$

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,

$$H_{t+1} = (1 - \delta_H)H_t + h(RD_t, H_t), \tag{1.21}$$

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:

$$h(RD_t, H_t) = \frac{b}{1-\eta} RD_t^{1-\eta} H_t^{\eta}, \tag{1.22}$$

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). Specifically,

$$\log(A_t) = \log(A_{t-1}) + \mu + x_t + \sigma\epsilon_{A,t}, \tag{1.23}$$

$$x_t = \rho_x x_{t-1} + \varphi_x \sigma \epsilon_{x,t}, \tag{1.24}$$

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,

$$\tilde{Y}_t = \exp\left(-\lambda_t(M_t - \bar{M})\right) Y_t, \tag{1.25}$$

[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).

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:

$$\lambda_t = (1 - \rho_\lambda)\bar{\lambda} + \rho_\lambda \lambda_{t-1} + \sigma_\lambda \epsilon_{\lambda,t}, \tag{1.26}$$

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,

$$l_{B,t} + l_{G,t} \leq 1. \tag{1.27}$$

The market clearing condition for consumption is given by

$$C_t = \tilde{Y}_t - I_{B,t} - I_{G,t} - k \cdot RD_t. \tag{1.28}$$

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.

1.5.2 Climate-change dynamics

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

$$T_{t+1} = (1-\rho_T)\bar{T} + \rho_T T_t + \chi \log\left(\frac{M_{t+1}}{\bar{M}}\right) + \sigma_T \epsilon_{T,t+1} \tag{1.29}$$

$$M_{t+1} = (1-\rho_M)\bar{M} + \rho_M M_t + E_t + \sigma_M \epsilon_{M,t+1} \tag{1.30}$$

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:

$$E_t = \zeta \frac{K_{B,t}}{A_t}, \tag{1.31}$$

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

[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.

of CO_2 emission and temperature at equilibrium, where capital is growing at the same speed of productivity.

1.5.3 Preferences

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

$$U_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{1.32}$$

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).

1.5.4 Optimization problem

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

$$\max_{\substack{C_t, RD_t, I_{B,t}, I_{G,t}, \\ l_{B,t}, l_{G,t}, \mathcal{S}_{t+1}}} \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}(\mathcal{S}_{t+1})^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}} \tag{1.33}$$

subject to the dynamics and constraints from equation (1.16) to (1.31). 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.

1.5.5 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,

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

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.

1.6 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.

1.6.1 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 1.10.

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 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 (1.29) and (1.30). $\bar{T}$ 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

[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 $\theta = 0.0028388$.

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 1.10 shows the point estimates.

1.6.2 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 (1.29) and (1.30). The shock on damage intensity is set as random noise. Figure 1.3 shows simulations of three series: (1) 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 both cases, I simulate the model for 60 time steps with

[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 1.10: **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

1,000 repetitions, consistent with the data length.

Table 1.11 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 au-

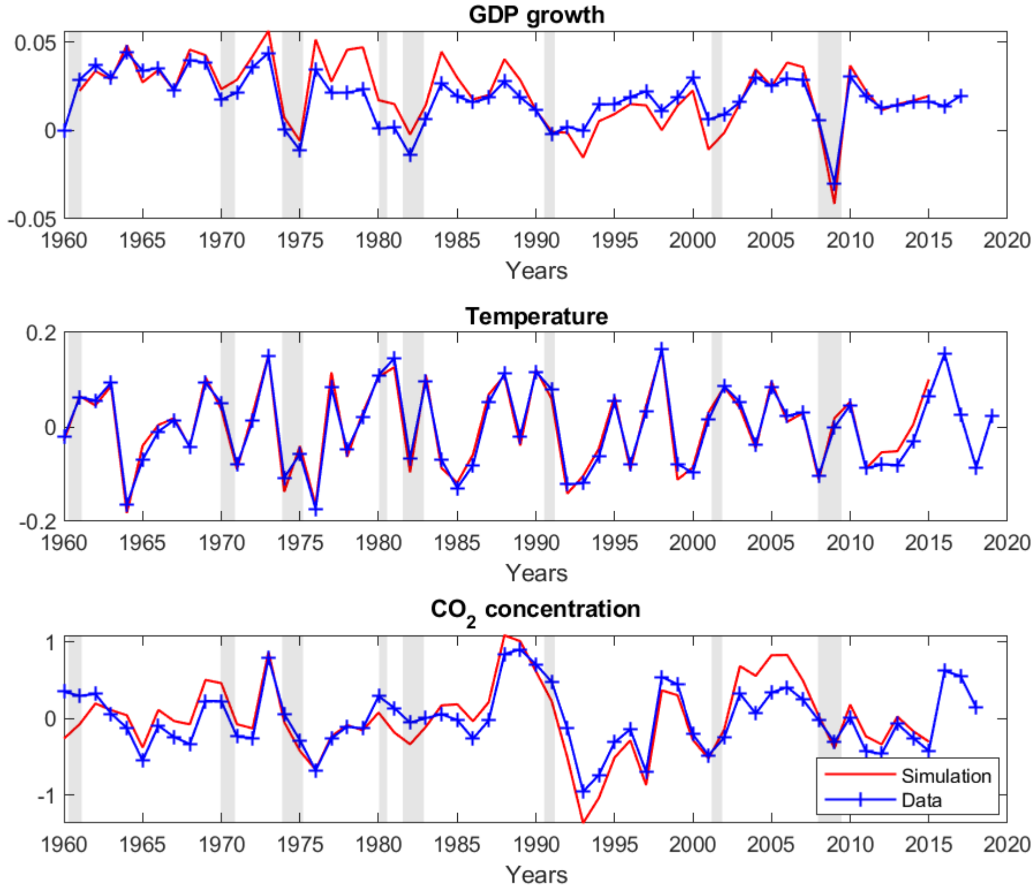

Figure 1.3: **Model simulation and data:** I simulated 60 time steps of the model as in the data. All the shocks are extracted from the data and are fed to dynare++ to get the simulation. Shocks on climate dynamics are extracted using equations (1.29) and (1.30). Short-run and long-run productivity shocks 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.

tocorrelations in the output, consumption, 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.

1.6.3 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 1.4.

The solid blue lines in Figure 1.4 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

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

Table 1.11: **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 1.3, 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.

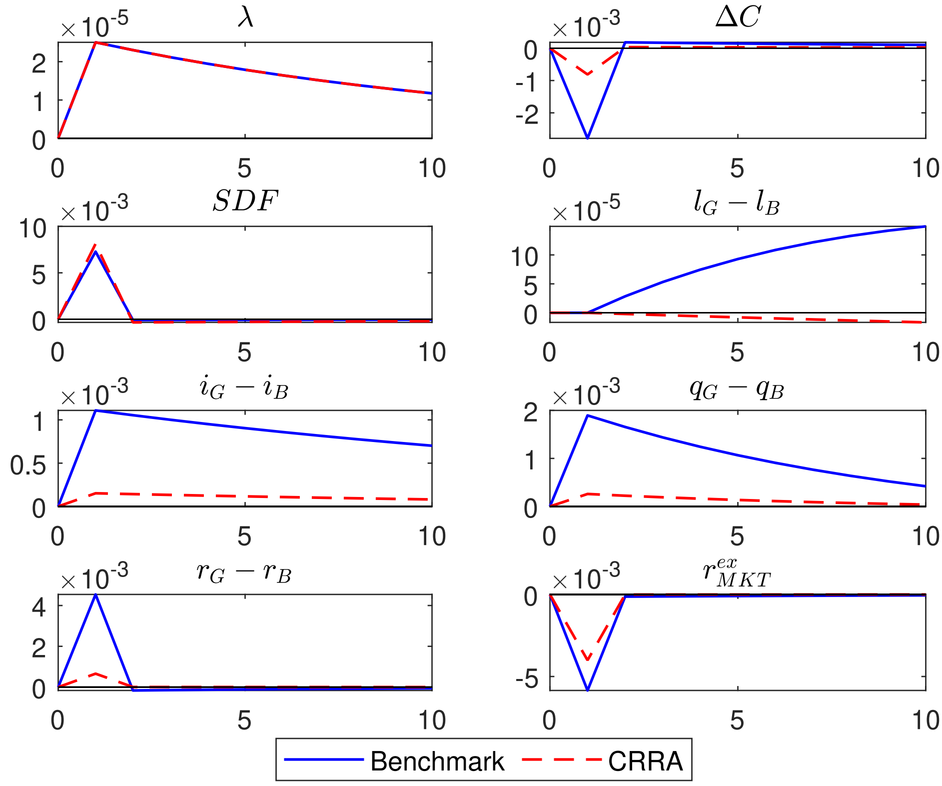

Figure 1.4: **Impulse response functions to a positive shock on the damage intensity parameter λ_t:** This figure shows the impulse response functions (IRF) of a one-standard-deviation positive shock on the damage intensity λ. The shock happens at $t = 1$. The blue solid lines show the IRF under the benchmark case with recursive preference. The red dashed lines show the IRF under the case with CRRA utility.

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. 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 1.11. Third, as shown in the last panel of Figure 1.4, 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 1.11.

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 1.5 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.

1.6.4 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

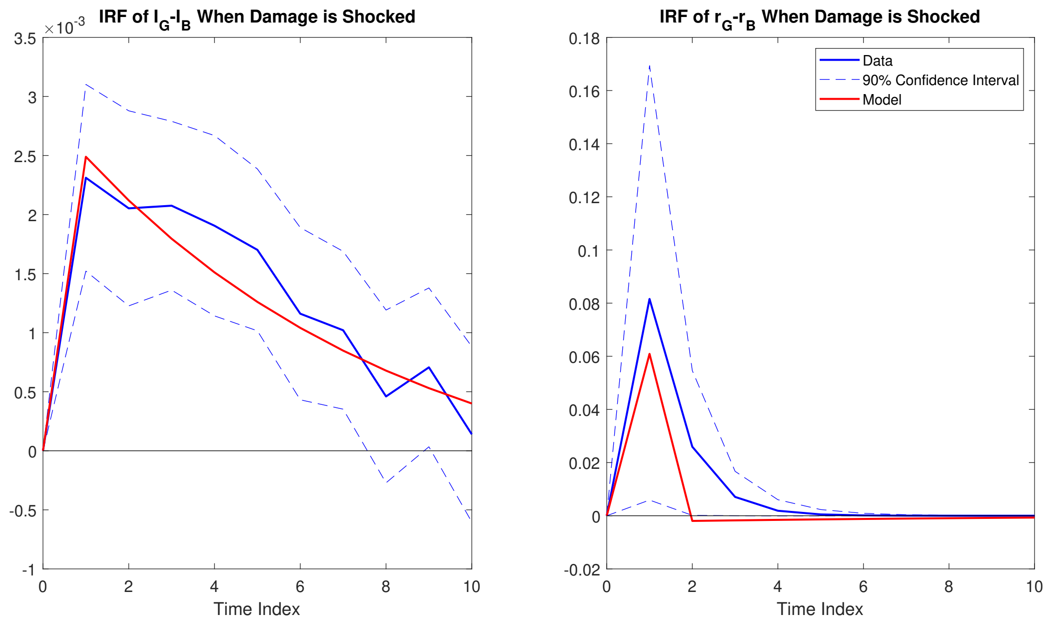

Figure 1.5: **Impulse response functions to a positive climate damage shock: Model vs. Data** This figure shows the impulse response functions (IRF) of the return and investment differential between green and brown firms to a one-standard-deviation positive shock on the log of real climate damage. The 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 $t = 1$.

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,

$$SCC = -\frac{1}{s}\frac{Q_M}{\tilde{Y}} \cdot Y^{real}, \tag{1.34}$$

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:

$$1 = \mathrm{E}_t\left[\Lambda_{t+1}\frac{\rho_M Q_{M,t+1} - \lambda\tilde{Y}_{t+1}}{Q_{M,t}}\right] \tag{1.35}$$

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 (1.34) and (1.35) 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 discount-rate channel.

In my model, the stochastic steady-state $\frac{Q_M}{\tilde{Y}}$ 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.

[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 $s = 2.124 \times 10^9$.

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 1.12 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 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.

Table 1.12: **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.

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 1.12 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 1.6 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 1.13 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

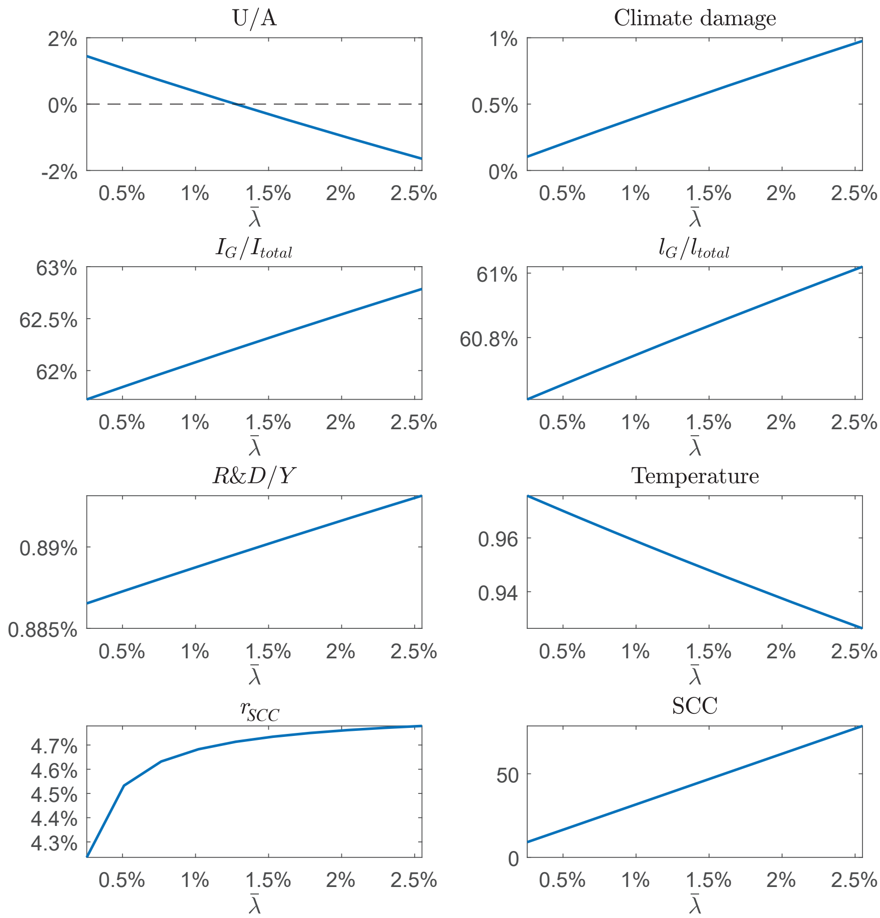

Figure 1.6: **The role of damage intensity.** The figure shows the stochastic steady-state values under different equilibrium damage intensity $\bar{\lambda}$. The x-axis is re-scaled to show the damage as a proportion of GDP when the temperature anomaly exceeds $2°C$. U/A shows the percentage change in the welfare-over-productivity ratio. SCC is in the unit of U.S. dollars; temperature is in the unit of $°C$.

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.

Table 1.13: **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 $^\circ C$.

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.

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.

1.7 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.

1.8 Appendices

1.8.1 Additional results

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.

Subsample analysis

In this section, I investigate the greenium in a shrinking window. Specifically, I repeat the same investigation of Table 1.3 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

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.

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 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: **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.

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.

Alternative greenness measures

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

[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.

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 1.3.2. 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.

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 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

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.

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

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.

lowest exposure (which has a low expected return) to this risk factor has the biggest improvement in ENSCORE. However, when I sort portfolios 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

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.

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.

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

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.

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

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

[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.

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.

1.8.2 Full derivation of the two-period model

This section shows the derivation of optimal investments, utility, SDF, and stock returns in Section 1.4. 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,

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

Then

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

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

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

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)

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

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.

1.8.3 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:

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

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

with the following stochastic processes:

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

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

$$R^{lev}_{B,t+1} = lev * (R_{B,t+1} - R_{f,t}) + \epsilon^d_{t+1}$$

where lev is the average leverage in the data and R_f is the risk-free rate. $\epsilon^d_t \sim N(0, \sigma^2_d)$ 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

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

Finally, the market excess return is given by

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

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, 2012, The environment and directed technical change, *American Economic Review* 102, 131–66.

Ackerman, Frank, Elizabeth A Stanton, and Ramón Bueno, 2013, Epstein–zin utility in dice: Is risk aversion irrelevant to climate policy?, *Environmental and Resource Economics* 56, 73–84.

Addoum, Jawad M, David T Ng, and Ariel Ortiz-Bobea, 2020, Temperature shocks and establishment sales, *The Review of Financial Studies* 33, 1331–1366.

Arrhenius, Svante, 1896, On the influence of carbonic acid in the air upon the temperature of the ground, *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science* 41, 237–276.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016a, Price of long-run temperature shifts in capital markets, Technical report, National Bureau of Economic Research.

Bansal, Ravi, Marcelo Ochoa, and Dana Kiku, 2016b, Climate change and growth risks, Technical report, National Bureau of Economic Research.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *The Journal of Finance* 59, 1481–1509.

Barnett, Michael, 2017, Climate change and uncertainty: An asset pricing perspective, Working paper.

Barro, Robert J, 2006, Rare disasters and asset markets in the twentieth century, *The Quarterly Journal of Economics* 121, 823–866.

Berg, Florian, Kornelia Fabisik, and Zacharias Sautner, 2020, Rewriting history II: The (un) predictable past of ESG ratings, *European Corporate Governance Institute Working Paper* .

Berg, Florian, Julian F Koelbel, and Roberto Rigobon, 2019, Aggregate confusion: The divergence of ESG ratings, Working paper, Available at SSRN 3438533.

Bolton, Patrick, and Marcin Kacperczyk, 2021a, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2021b, Global pricing of carbon-transition risk, Technical report, National Bureau of Economic Research.

Bosetti, Valentina, Carlo Carraro, Marzio Galeotti, Emanuele Massetti, and Massimo Tavoni, 2006, A world induced technical change hybrid model, *The Energy Journal* Special Issue# 2.

Cai, Li, and Chaohua He, 2014, Corporate environmental responsibility and equity prices, *Journal of Business Ethics* 125, 617–635.

Chava, Sudheer, 2014, Environmental externalities and cost of capital, *Management Science* 60, 2223–2247.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to global warming, *The Review of Financial Studies* 33, 1112–1145.

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

Cochrane, John H, 2009, *Asset pricing: Revised edition* (Princeton University Press).

Colacito, Ric, Bridget Hoffmann, and Toan Phan, 2018, Temperatures and growth: A panel analysis of the united states, *Journal of Money, Credit, and Banking* 51, 2019.

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

Dai, Aiguo, Kevin E Trenberth, and Taotao Qian, 2004, A global dataset of palmer drought severity index for 1870–2002: Relationship with soil moisture and effects of surface warming, *Journal of Hydrometeorology* 5, 1117–1130.

Daniel, Kent D, Robert B Litterman, and Gernot Wagner, 2016, Applying asset pricing theory to calibrate the price of climate risk, Technical report, National Bureau of Economic Research.

Dietz, Simon, Christian Gollier, and Louise Kessler, 2018, The climate beta, *Journal of Environmental Economics and Management* 87, 258–274.

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

Epstein, Larry G, and Stanley E Zin, 1989, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.

Faccini, Renato, Rastin Matin, and George S Skiadopoulos, 2021, Dissecting climate risks: Are they reflected in stock prices?, *Available at SSRN 3795964* .

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

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Gibson, Matthew, Jamie T Mullins, and Alison Hill, 2017, Climate change, flood risk, and property values: Evidence from New York City, Technical report, Working Paper.

Giglio, Stefano, Bryan T Kelly, and Johannes Stroebel, 2020, Climate finance, Technical report, National Bureau of Economic Research.

Gollier, Christian, 2021, The cost-efficiency carbon pricing puzzle, Technical report, CEPR Discussion Paper No. DP15919.

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

Guenster, Nadja, Rob Bauer, Jeroen Derwall, and Kees Koedijk, 2011, The economic value of corporate eco-efficiency, *European Financial Management* 17, 679–704.

Hayashi, Fumio, 1982, Tobin's marginal q and average q: A neoclassical interpretation, *Econometrica: Journal of the Econometric Society* 213–224.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu, 2019, Climate risks and market efficiency, *Journal of Econometrics* 208, 265–281.

Hong, Harrison, Neng Wang, and Jinqiang Yang, 2020, Mitigating disaster risks in the age of climate change, Technical report, National Bureau of Economic Research.

Hong, Harrison, Neng Wang, and Jinqiang Yang, 2021, Welfare consequences of sustainable finance, Technical report, National Bureau of Economic Research.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *The Review of Financial Studies* 28, 650–705.

Hsu, Po-Hsuan, Kai Li, and Chi-Yang Tsou, 2020, The pollution premium, Working paper, Available at SSRN 3578215.

Huynh, Thanh, and Ying Xia, 2021, Panic selling when disaster strikes: Evidence in the bond and stock markets, *Management Science, Forthcoming* .

In, Soh Young, Ki Young Park, and Ashby Monk, 2017, Is 'being green' rewarded in the market? An empirical investigation of decarbonization risk and stock returns, *International Association for Energy Economics (Singapore Issue)* 46, 48.

IRENA, 2015, A background paper to "renewable energy in manufacturing", Technical report, Abu Dhabi.

Jaccard, Ivan, Ghassane Benmir, and Gauthier Vermandel, 2020, Green asset pricing, ECB working paper.

Jensen, Svenn, and Christian P Traeger, 2014, Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings, *European Economic Review* 69, 104–125.

Jermann, Urban J, 1998, Asset pricing in production economies, *Journal of Monetary Economics* 41, 257–275.

Le Quéré, Corinne, et al., 2018, Global carbon budget 2018, *Earth System Science Data* 10, 2141–2194.

Lemoine, Derek, 2021, The climate risk premium: how uncertainty affects the social cost of carbon, *Journal of the Association of Environmental and Resource Economists* 8, 27–57.

Lemoine, Derek, and Ivan Rudik, 2017, Managing climate change under uncertainty: Recursive integrated assessment at an inflection point, *Annual Review of Resource Economics* 9, 117–142.

Lev, Baruch, and S Ramu Thiagarajan, 1993, Fundamental information analysis, *Journal of Accounting research* 31, 190–215.

Manne, Alan, Robert Mendelsohn, and Richard Richels, 1995, MERGE: A model for evaluating regional and global effects of GHG reduction policies, *Energy Policy* 23, 17–34.

Miroshnychenko, Ivan, Roberto Barontini, and Francesco Testa, 2017, Green practices and financial performance: A global outlook, *Journal of Cleaner Production* 147, 340–351.

Nakamura, Emi, Jón Steinsson, Robert Barro, and José Ursúa, 2013, Crises and recoveries in an empirical model of consumption disasters, *American Economic Journal: Macroeconomics* 5, 35–74.

Newey, Whitney K, and Kenneth D West, 1987, Hypothesis testing with efficient method of moments estimation, *International Economic Review* 28, 777–787.

Nordhaus, William, 2019, Climate change: The ultimate challenge for economics, *American Economic Review* 109, 1991–2014.

Nordhaus, William, and Paul Sztorc, 2013, DICE 2013R: Introduction and User's Manual, available at http://www.econ.yale.edu/ nordhaus/homepage/.

Nordhaus, William D, 1992, An optimal transition path for controlling greenhouse gases, *Science* 258, 1315–1319.

Nordhaus, William D, 2002, Modeling induced innovation in climate-change policy, *Technological change and the environment* 9, 259–290.

Nordhaus, William D, 2010, Economic aspects of global warming in a post-Copenhagen environment, *Proceedings of the National Academy of Sciences* 107, 11721–11726.

Ortega, Francesc, and Süleyman Taspınar, 2018, Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market, *Journal of Urban Economics* 106, 81–100.

Palmer, Wayne C, 1965, *Meteorological drought*, volume 30 (US Department of Commerce, Weather Bureau).

Pastor, Lubos, Robert F Stambaugh, and Lucian A Taylor, 2019, Sustainable investing in equilibrium, Technical report, National Bureau of Economic Research.

Pindyck, Robert S, 2012, Uncertain outcomes and climate change policy, *Journal of Environmental Economics and Management* 63, 289–303.

Popp, David, 2004, ENTICE: endogenous technological change in the dice model of global warming, *Journal of Environmental Economics and Management* 48, 742–768.

Popp, David, 2006, ENTICE-BR: The effects of backstop technology R&D on climate policy models, *Energy Economics* 28, 188–222.

Romer, Paul M, 1990, Endogenous technological change, *Journal of Political Economy* 98, S71–S102.

Shanken, Jay, 1992, On the estimation of beta-pricing models, *The Review of Financial Studies* 5, 1–33.

Sharpe, William F, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *The Journal of Finance* 19, 425–442.

Tarmuji, Indarawati, Ruhanita Maelah, and Nor Habibah Tarmuji, 2016, The impact of environmental, social and governance practices (ESG) on economic performance: Evidence from ESG score, *International Journal of Trade, Economics and Finance* 7, 67.

Thomas, Jacob K, and Huai Zhang, 2002, Inventory changes and future returns, *Review of Accounting Studies* 7, 163–187.

Van der Zwaan, Bob CC, Reyer Gerlagh, Leo Schrattenholzer, et al., 2002, Endogenous technological change in climate change modelling, *Energy Economics* 24, 1–19.

Weil, Philippe, 1990, Nonexpected utility in macroeconomics, *The Quarterly Journal of Economics* 105, 29–42.

Zhang, Lu, 2005, The value premium, *The Journal of Finance* 60, 67–103.

Chapter 2

Green Investing, Information Asymmetry, and Category Learning

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ABSTRACT

We investigate how the attention allocation of green-motivated investors changes information asymmetry in financial markets and thus affects firms' financing costs. To guide our empirical analysis, we propose a model where an investor with green taste endogenously allocates attention to market or firm-specific shocks. We find that more green-motivated investors tend to give more attention to green firm-level information instead of market-level information. Thus higher green taste leads to less category learning behavior and reduces the information asymmetry. Furthermore, it suggests that higher green taste results in lower leverage and lower cost of capital of green firms.

Keywords: Climate Finance, Information Asymmetry, Category Learning

JEL classification: D82, G11.

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2.1 Introduction

Information processing is costly, and human attention is a limited cognitive resource. As such, rational investor needs to optimally allocate limited attention to various sources of information to resolve uncertainty optimally. The attention allocation will then affect the information asymmetry in the financial market. In addition, in recent years sustainable investments using environmental, social, and government (ESG) investing strategies, especially green investments, has been growing dynamically[3]. Despite the natural link between investors' attention and a firm's information asymmetry, few studies investigated how the relationship between these two terms interacts with the rising green preference.

In this paper, we aim to answer how investors' taste for green investing and limited attention affects information asymmetry of firms with different "greenness". Specifically, we investigate the impact of greater public attention on environmental issues, measured by the Google Search Volume (GSV) on the keyword "Climate Change", on green firms' information asymmetry.

To guide the empirical analysis, we propose a model based on Kacperczyk et al. (2016) and incorporate green preference into the framework. A representative investor chooses to invest into a group of risky assets where she derives non-pecuniary benefit from holding green assets, i.e., a "green taste" following Pástor et al. (2020) and Pedersen et al. (2020).[4] Investors have to make two kinds of decisions, asset allocation, and attention allocation. Because the investor faces attention constraints, she has to allocate attention to firm-level or market-level information optimally.

The model predicts that higher green taste induces investors to learn more about the

[3]According to the 2020 Report on US Sustainable and Impact Investing Trends released by the US SIF foundation, there's a rising popularity of sustainable investments among institutional and private investors and the total US-domiciled assets under management using ESG investing criteria grew from $12.0 trillion in the beginning of 2018 to $17.1 trillion in the beginning of 2020.

[4]We consider green taste of a representative investor as an analog of GSV in the data. The rationale is, a higher GSV indicates more investors become green-motivated (Pedersen et al., 2020). In a model with a representative investor, this is equivalent to an increase in the green taste.

green firm. Specifically, the investor puts more attention on learning the shock that is specific to the green asset. This is not surprising given that investors now care more about holding green, and reducing the uncertainty related to the green asset is more rewarding. As a result, the information asymmetry of green firms decreases. Given that the total amount of attention is limited, less attention is allocated to the brown firms, leading to a higher information asymmetry of brown firms. In addition, increased learning on green firms leads to a lower price co-movement between green stock and the market, which explains the reduction of category learning (Peng and Xiong, 2006). Finally, the model also implies a reduction in the cost of equity capital for green firms when climate attention is greater.

To test the predictions from the model, we follow Bharath et al. (2009) to extract the first principal component of seven information asymmetry measures to get our major measure on information asymmetry. These seven measures are based on component of bid-ask spread due to adverse selection (Roll, 1984; George et al., 1991); return momentum/reversal (Llorente et al., 2002; Pástor and Stambaugh, 2003); illiquidity (Amihud et al., 1997; Amihud, 2002); and probability of informed trading (Easley et al., 1996). To define the greenness of firms, we apply the environmental pillar score (ENSCORE) from the Refinitive Asset4 ESG database. We calculate the correlation between individual stock return and the market return as a measure of firm-level category learning (Huang et al., 2019). Finally, we retrieve the Google Search Volume (GSV) of keyword *Climate Change* as the measure of green taste.[5] Our sample covers more than 2,500 U.S. firms that span from 2004 (when GSV is first available) to 2020 on a quarterly frequency.

Consistent with the model predictions, our main empirical results show that an increase in the growth rate of GSV on climate change decreases green firms' information asymmetry relative to the brown ones. To better estimate the causal effects, we use temperature as the instrumental variable for growth rate of GSV on the keyword *cli-*

[5]We follow the literature to use this keyword. The result also holds using alternative keywords such as "Global Warming".

mate change. We find a one-standard-deviation increase in the GSV growth rate decrease 27.8% of information asymmetry for green firms compared to brown ones. In addition, we find that the same increase in GSV decreases category learning of green firms by 5.6% compared to brown firms.

As documented in the previous literature, lower category learning benefits both the stock market and the real economy. For example, Durnev et al. (2003) shows that stock prices are less informative in industries with more synchronous returns (i.e., higher category learning). Wurgler (2000) shows that capital allocation is less efficient in countries with higher stock return comovement. An example that a high degree of category learning can hurt effective information spread is the Internet Bubble during the early 2000. Firms earned significant positive returns just by changing their name to dot.com (Cooper et al., 2001). In other words, investors treat a special group of firms as a single category and completely ignore information about the firm's fundamentals. Our results indicate that green taste affects attention allocation and thus affects information asymmetry.

Why does information asymmetry matter? A lower information asymmetry means less uncertainty about the firm's fundamental and more transparent future cash flow from the investor's perspective. Less uncertainty benefits investors, given that they are usually risk-averse. From the standpoint of firm managers, a lower information asymmetry means a lower cost of equity since the market penalizes stocks with less transparent fundamentals, i.e., equity is information-sensitive. Thus information asymmetry will affect firms' capital structure decisions, an idea first illustrated by the pecking order theory (Myers, 1984). Consistent with Easley and O'hara (2004), we find that information asymmetry significantly affects the cost of equity capital. A high-minus-low portfolio based on firms sorted by our information asymmetry measure delivers a positive abnormal return of 1.06% after controlling for CAPM. In addition, we test the pecking order theory by regressing firms' leverage on information asymmetry and find significant positive effects. The fact that our result replicates that from previous literature (Bharath et al., 2009) validates our measure of information asymmetry. The informational channel of pecking order theory also implies that when the public's green taste is higher (greater GSV on "climate change"), firms with high ENSCORE is less likely to choose debt as a financing source due to lower information asymmetry.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 presents our model. Sections 4 and 5 are data construction and empirical analysis. The last section concludes.

2.2 Literature Review

First, this paper contributes to the literature on the consequences of investors' ESG preferences in financial markets (Pedersen et al., 2020; Pástor et al., 2020; Goldstein et al., 2021). A growing body of research has discussed the impact of ESG on firms' financial performance. Previous studies show that ESG could raise (Hong and Kacperczyk, 2009; Baker et al., 2018) or lower the implied return (Edmans, 2011). Pedersen et al. (2020) model ESG in a way that ESG affects both the investor's preference and firm fundamentals, bridging the gap between the opposite findings. In our paper, investors also gain non-pecuniary utility from holding green assets but differently face endogenous information acquisition with attention constraint. This interaction between taste and attention allocation sheds light on how public attention on climate change affects firms' information asymmetry and category learning.

Second, our paper is related to the literature on endogenous information acquisition and investor's limited attention. The rational inattention model by Sims (2003) introduced information processing capacity into standard control problems in the field of macroeconomics. Van Nieuwerburgh and Veldkamp (2010) build a framework to solve jointly for investment and information choices. They find that allowing endogenous information acquisition leads an investor to hold concentrated portfolios. Kacperczyk et al.

(2016) investigate how mutual fund managers change attention allocation with respect to the business cycle, which predicts patterns of portfolio investments and returns. Other papers in this field include Peng (2005), Peng and Xiong (2006), and Peress (2010). Our model differs from previous studies in two aspects. First, we introduce a taste parameter in the investor's portfolio choice problem and examine how information acquisition changes with the taste. Second, we innovate by introducing a convex cost of information processing, such that the more attention allocated, the more difficult it is to reduce noise further. This approach is not only more intuitive but also generates interior optimal attention allocation. Peng and Xiong (2006) find that investors exhibit category learning behavior with limited attention. Our result shows that this phenomenon is lessened with a higher taste.

Third, this paper contributes to the relationship between asymmetric information and capital structure by emphasizing the attention allocation channel. There are several approaches to estimate the information disparity between outside investors and firm manager (or insider traders), including the bid-ask spread component due to adverse selection (George et al., 1991), return reversal or momentum (Llorente et al., 2002; Pástor and Stambaugh, 2003), illiquidity (Amihud et al., 1997; Amihud, 2002), and probability of informed trading (Easley et al., 1996; Easley and O'hara, 2004). Bharath et al. (2009) take the first principal component of all these measures and find information asymmetry indeed plays a significant role in determining the capital structure as implied by pecking order theory. We contribute to the literature by providing a rigorous examination of the relationship between investor attention and information asymmetry with empirical and theoretical evidence. To our knowledge, this issue remains largely unexplored (Gao et al., 2018; Ding and Hou, 2015; Sankaraguruswamy et al., 2013).

2.3 Model: Green Investing and Attention Allocation

To show how green taste affects attention allocation and information asymmetry, we present a theoretical framework based on Kacperczyk et al. (2016) and Van Nieuwerburgh and Veldkamp (2010). The model has three periods $t = 0, 1, 2$. At $t = 0$, a representative investor chooses to allocate her attention across different assets. Allocated attention reduces the variance (or, in other words, improves the precision) of the asset fundamentals. At $t = 1$, the investor chooses the portfolio of risky and riskless assets. At $t = 2$, asset payoffs are realized. The decision problem of the investor is a two-step optimization. In the first step (at $t = 1$), she chooses the portfolio to maximize expected utility conditional on her information set. In the second step (at $t = 0$), she optimally allocates attention across assets to maximize the unconditional expected utility.

2.3.1 Setup

Assets There are one riskless and three risky assets. The riskless asset (bond) is normalized to have unit return and infinity supply. Risky assets (stocks) have net positive supplies, which are normalized to one. Stock $i \in 1, 2, 3$ has a random payoff f_i with the following factor structure:

$$
\begin{aligned}
f_1 &= \mu_1 + \tilde{m} + \tilde{z}_1 \\
f_2 &= \mu_2 + \tilde{m} + \tilde{z}_2 \\
f_3 &= \mu_3 + \tilde{m}
\end{aligned}
$$

where $\tilde{m}$ is an aggregate shock to all stocks. $\tilde{z}_i$ is firm-specific shock to stock i. We interpret asset 3 as a composite asset (the market) and asset 1 (2) as the green (brown) stock, These shocks are independent of each other and follow normal distributions with zero means and variance-covariance matrix

$$\Sigma = \begin{bmatrix} \frac{1}{\tau_{z,1}} & 0 & 0 \\ 0 & \frac{1}{\tau_{z,2}} & 0 \\ 0 & 0 & \frac{1}{\tau_m} \end{bmatrix},$$

where $\tau_{z,1}$, $\tau_{z,2}$ and τ_m are the inverse of variances of the shocks $\tilde{z}_1$, and $\tilde{z}_2$, and $\tilde{m}$ respectively. These parameters denote the precision of investor's prior to these shocks. We can write the payoff vector in the following matrix form: $f = \mu + \Gamma\tilde{f}$, where $f = [f_1, f_2, f_3]'$, $\mu = [\mu_1, \mu_2, \mu_3]'$, $\tilde{f} = [\tilde{z}_1, \tilde{z}_2, \tilde{m}]'$, and $\Gamma = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$.

Preference Following Kacperczyk et al. (2016) we assume the investor has a mean-variance utility over the final wealth at $t = 2$. In addition, following the literature on green finance (Pástor et al., 2020; Pedersen et al., 2020) we assume investors derive non-pecuniary utility form holding green stock.

Let W_0 and W as the initial and final wealth. We use E_0 and V_0 to denote the mean and variance conditional on the prior beliefs, and E_1 and V_1 to denote the mean and variance conditional on information obtained through attention allocation. Thus, at $t = 1$, the investor chooses the holding of stocks, X, to maximized the expected utility

$$U_1 = E_1[W] - \frac{\gamma}{2} V_1[W] + X'b$$

where γ is the risk aversion coefficient. The budget constraint is $W = W_0 + X'(f - p)$, where X and p are the 3×1 vector of stock holdings and prices. b is the 3×1 vector of non-pecuniary benefit from the stock holdings. For simplicity, we assume b has a positive number g at the first element and zeros otherwise. This number g measures the representative investor's "green taste".

At $t = 0$, the investor choose attention allocations, κ, across stocks to maximize her unconditional expected utility, $E_0[U_1]$. The following part describes how learning affects the precision of fundamental shocks.

Learning The investor can attentively learn each stock, but the total amount of attention is limited (Peng and Xiong, 2006). Learning improves the precision of stock payoffs through a Bayesian way. Specifically, the investor receives signals of the fundamental shocks from learning,

$$\begin{aligned} s_m &= \tilde{m} + \varepsilon_m, \quad \varepsilon_m \sim N\left(0, \frac{1}{\rho(\kappa_m)}\right) \\ s_{z,1} &= \tilde{z}_1 + \varepsilon_{z,1}, \quad \varepsilon_{z,1} \sim N\left(0, \frac{1}{\rho(\kappa_{z,1})}\right) \\ s_{z,2} &= \tilde{z}_2 + \varepsilon_{z,2}, \quad \varepsilon_{z,2} \sim N\left(0, \frac{1}{\rho(\kappa_{z,2})}\right), \end{aligned}$$

where the signal noises ε_m, $\varepsilon_{z,1}$, and $\varepsilon_{z,1}$ are independent. The noisiness of signals depend on the attention κ_m, $\kappa_{z,1}$, and $\kappa_{z,2}$ that investor allocated to each shock. $\rho(\cdot)$ is the learning function, which determines how much precision improvement can be obtained for a given amount of attention. In general, $\rho(\cdot)$ is an increasing function, indicating that the more attention allocated to a shock, the more precise the signal becomes. Given the signal structure, the posterior mean and variance of the market shock will be

$$\hat{\mu}_m \equiv E[\tilde{m}|s_m] = \frac{\rho(\kappa_m) \cdot s_m}{\tau_m + \rho(\kappa_m)}, \quad \hat{\Sigma}_m \equiv \frac{1}{\tau_m + \rho(\kappa_m)}$$

The posterior means ($\hat{\mu}_{z,1}$ and $\hat{\mu}_{z,2}$) and variances ($\hat{\Sigma}_{z,1}$ and$\hat{\Sigma}_{z,2}$) of the two firm-specific shocks are similarly defined. We get $\hat{\mu} \equiv E_1\left(\tilde{f}\right) = [\hat{\mu}_{z,1}, \hat{\mu}_{z,2}, \hat{\mu}_m]'$ and $\hat{\Sigma} \equiv V_1\left(\tilde{f}\right) = diag\left(\left[\hat{\Sigma}_{z,1}, \hat{\Sigma}_{z,2}, \hat{\Sigma}_m\right]\right)$, where *diag* is the function that converts a vector to a diagonal matrix. From the time-0 perspective, $\hat{\Sigma}$ is deterministic depending on the attention allocation; $\hat{\mu}$ is normally distributed with zero mean and variance-covariance matrix $V_0[\hat{\mu}] = \Sigma - \hat{\Sigma}$ according to the law of total variance.

The investor's learning capacity is subject to the attention constraint as follows

$$\kappa_m + \kappa_{z,1} + \kappa_{z,2} \leq K, \quad \kappa_m, \kappa_{z,1}, \kappa_{z,2} \geq 0 \tag{C.1}$$

where K is the exogenous total attention span of the investor. The non-negativity constraint ensures that the investor cannot reduce the prior precision of the shocks, i.e., she cannot "unlearn" what she already knows.

Clearly, the optimal allocation of attention depends on the functional form of $\rho(\cdot)$. Previous studies usually assume either a linear learning strategy, where ρ is a linear function, or an entropy-based learning strategy, where ρ is an exponential function. In this paper, we assume that the learning function is concave. This approach is intuitive in the sense that the marginal return of learning should be decreasing. That is, more attention is needed to gain one additional unit of precision when the signal is already very precise. This setting is equivalent to introducing a convex learning cost, as in Peress (2010) and Goldstein and Yang (2015). Moreover, decreasing return is necessary to generate an interior solution where the investor allocates nonzero attention to each shock, which is more likely for real investors. Under linear or entropy-based learning function, increasing return induces the investor to allocate attention to only one shocks (Van Nieuwerburgh and Veldkamp, 2010).

To generate closed-form solutions, we assume a square root learning function $\rho(x) = \sqrt{x}$. The conclusion will hold for any increasing concave function.

2.3.2 The equilibrium

First we solve for the optimal portfolio allocation at $t = 1$ as follows:

$$\max_{X} \quad E_1[W] - \tfrac{\gamma}{2} V_1[W] + X'b$$
$$s.t. \quad W = W_0 + X'(f - p)$$

The solution is given by

$$X = \frac{1}{\gamma} V_1(f)^{-1} \left(E_1(f) - p + b\right)$$

which is the standard solution in a Grossman-Stiglitz economy (Grossman and Stiglitz, 1980) taking into account the taste. In equilibrium, the market-clearing condition is $X = I$, where I is a 3×1 vector of ones. Thus the price is given by

$$p = E_1(f) + b - \gamma V_1(f) \cdot I \tag{C.2}$$

At $t = 0$, the investor chooses attention vector κ to maximize time-0 expected utility, taking price and green taste as endogenously given. Appendix A shows that the time-0 expected utility can be written as a linear function on the posterior precision on the three factors

$$U_0 = W_0 + \frac{1}{2\gamma} \left[\sum_{i=1}^{3} \hat{\Sigma}_{ii}^{-1} \left(\Sigma_{ii} + \theta_i^2 \right) - 3 \right] \tag{C.3}$$

where $\theta = \begin{bmatrix} \mu_1 - p_1 + g - \mu_3 + p_3 \\ \mu_2 - p_2 - \mu + p_3 \\ \mu_3 - p_3 \end{bmatrix}$, which is the synthetic expected excess payoffs for the three factors. The optimization problem is to maximize Equation (C.3) subject to the constraint in Equation (C.1). Given that the objective function is increasing and concave and the budget constraint is linear, the solution will equalize the marginal benefit of $\kappa_m, \kappa_{z,1}, \kappa_{z,2}$ while making the constraint binding.

Proposition 4. *There is one unique interior solution to the investor's attention allocation problem, where attention to the factor i (i = 1: market factor, i = 2, 3: firm-specific factor) equals*

$$\kappa_i = \frac{\left(\Sigma_{ii} + \theta_i^2\right)^2}{\sum_{j=1}^{3}\left(\Sigma_{jj} + \theta_j^2\right)^2} K$$

From proposition 4, we find that the investor will allocate attention to the factors that she knows less (with higher prior variance). This is because learning has a decreasing return, so it is optimal to devote more attention with less prior knowledge. In addition, the investor will allocate more attention to factors with higher expected excess payoffs, which is intuitive since increasing the precision of highly profitable stock is more rewarding. At last, we find that when the investor has a higher green taste g, this increases the synthetic excess payoff of the specific factor of the green firm, which is θ_1. As a result, she allocates more attention to that factor.

Corollary 1. *An increase in the green taste increases an investor's attention to the specific shock of the green firm, and decreases attention to the market shock and firm-specific shock of the brown firm.*

2.3.3 Information asymmetry, price co-movement, and cost of equity capital

Information asymmetry We measure the information asymmetry of a firm as the fraction of the investor's posterior variance divided by the prior variance on the firm's fundamentals $IA_i = \frac{V_1(f_i)}{V_0(f_i)}$ for $i = 1, 2, 3$. This value is bounded between zero and one. If it is close to one, it implies almost a zero learning about the firm and a high information asymmetry; if the fraction is close to zero, it means investor know the fundamental with very high precision, thus inducing a smaller discrepancy between the investor's information and the manager, who presumably knows exactly the fundamental value. Thus, if an investor process more information of a firm, her posterior about the fundamental will become more precise, and the firm experience less information asymmetry. In sum,

$$IA = \left[\frac{\frac{1}{\tau_m+\sqrt{\kappa_m}} + \frac{1}{\tau_{z,1}+\sqrt{\kappa_{z,1}}}}{\frac{1}{\tau_m} + \frac{1}{\tau_{z,1}}}, \frac{\frac{1}{\tau_m+\sqrt{\kappa_m}} + \frac{1}{\tau_{z,2}+\sqrt{\kappa_{z,2}}}}{\frac{1}{\tau_m} + \frac{1}{\tau_{z,2}}}, \frac{\tau_m}{\tau_m + \sqrt{\kappa_m}} \right]'$$

When there is an increase in the green taste, g, $\kappa_{z,1}$ increases, and κ_m and $\kappa_{z,2}$ decrease. This leads to a decrease in the information asymmetry of green firms.

Proposition 5. *An increase in the green taste decreases the green firm's information asymmetry and increases that of the brown firm and the market.*

Price co-movement According to the Equation (C.2), we can calculate the variance-covariance matrix of the price vector as

$$V_0(p) = V_0\left(E_1(f)\right) = \Gamma V_0\left(\hat{\mu}\right)\Gamma' = \Gamma\left(\Sigma - \hat{\Sigma}\right)\Gamma'$$

Substituting the expressions of these variables into the expression, we get the correlation between prices of green stock and the market

$$Corr(p_1, p_3) = \sqrt{\frac{\Sigma_{33} - \hat{\Sigma}_{33}}{\Sigma_{11} - \hat{\Sigma}_{11} + \Sigma_{33} - \hat{\Sigma}_{33}}} = \sqrt{\frac{\frac{1}{\tau_m} - \frac{1}{\tau_m+\sqrt{\kappa_m}}}{\frac{1}{\tau_m} - \frac{1}{\tau_m+\sqrt{\kappa_m}} + \frac{1}{\tau_{z,1}} - \frac{1}{\tau_{z,1}+\sqrt{\kappa_{z,1}}}}}$$

According to proposition 2. An increase in the green taste increases the denominator inside the square root, i.e., the green firm gains greater reduction in the variance, and decrease the numerator inside the square root, i.e., market gain less variance reduction. Thus an increase in green taste will reduce the price correlation between the green firm and the market. On the contrary, the correlation between the brown firm and the market increases. Intuitively, this is because investors learn more about the firm-specific shock of the green firm, so that its price reflects more information of that shock, and co-moves less with the market.

Cost of equity capital We define the cost of capital as the unconditional expected value of the payoff minus the price $E_0(f-p)$. Thus

$$CoC = E_0\left[f - E_1(f) - b + \gamma V_1(f) \cdot I\right] = -b + \gamma \Gamma \hat{\Sigma} \Gamma' \cdot I$$

The cost of capital of the green firm is given by

$$CoC_1 = -g + \gamma \left(\frac{3}{\tau_m + \sqrt{\kappa_m}} + \frac{1}{\tau_{z,1} + \sqrt{\kappa_{z,1}}} \right)$$

An increase in the green taste affects the cost of equity capital of green firm through two channels: a price channel and a variance channel. In the price channel, increased taste leads to higher demand for the stock, which increases price in equilibrium. Thus this channel serves to decrease the cost of capital. In terms of the variance channel, higher green taste shifts attention towards the green firm, making its fundamental less noisy. As a result, this increases the demand and reduces equilibrium price. In sum, the two channels both work to decrease the cost of capital of the green firm when green taste increases, consistent with the empirical result.

2.4 Data and empirical methods

Our main sample of empirical analysis consists of LA4CTYUS firms, U.S. firms included in Refinitiv Asset4 database, for which we could get ESG scores between 2004 to 2020. We exclude financial firms (SIC codes 6000-6999). We also remove the firms with the underlying stock price lower than 5 dollars to avoid the impact of penny stocks. The final sample consists of 2844 U.S. firms. We obtain the data of firm financials from COMPUSTAT North America Fundamentals Quarterly database.

2.4.1 Data Construction

Firm-level greenness indicator We use the environmental pillar score (Datastream code: ENSCORE) from the Refinitiv (formerly known as Thomson Reuters) Asset4 ESG universe. This database covers around 70% of the world cap with over 450 ESG metrics, of which 186 most comparable measures are summarized 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, i.e., firms' annual reports, corporate social report (CRS), company websites, etc.[6] 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. We collect all information of ENSCORE from Refinitiv Eikon, focusing on the U.S. universe from 2004 to 2020. Examples of green firms with high ENSCORE include Tesla and Amazon.

Green taste We collect the Google Search Volume (GSV) on the keyword *Climate Change* as a measure of the investor's green preference. GSV measure is based on real-time search activities for the keywords on the Google search engine. It is scaled from 0 to 100. The key advantage of GSV is its flexibility in terms of both frequencies (from 8 minutes to one month) and granularity (from city- to country-level). It's thus becoming a popular measure of investors' attention in the literature (Da et al., 2011; Ding and Hou, 2015; Bank et al., 2011; Aouadi et al., 2013; Choi et al., 2020). In our context, differently we interpret the GSV index as the measure of investors' green preference. We use the GSV in the United States as we focus on American firms. Furthermore, we take *Climate Change* as the green keyword according to Djerf-Pierre (2012) and construct the green taste measure with the GSV on this keyword. Djerf-Pierre (2012) found that the

[6]See `https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/esg-scores-methodology.pdf` for more details.

environmental issue category that has the greatest significant positive correlation with other environmental issues is *Climate Change* and *Global Warming*. Thus we also use *Global Warming* for the robustness test. In precise, we use the quarterly growth rate of GSV on *Climate Change* as the measure of green taste. Figure C.1 plots monthly aggregate Google Trends search frequency for both "climate change" and "global warming" starting from 2014 January.

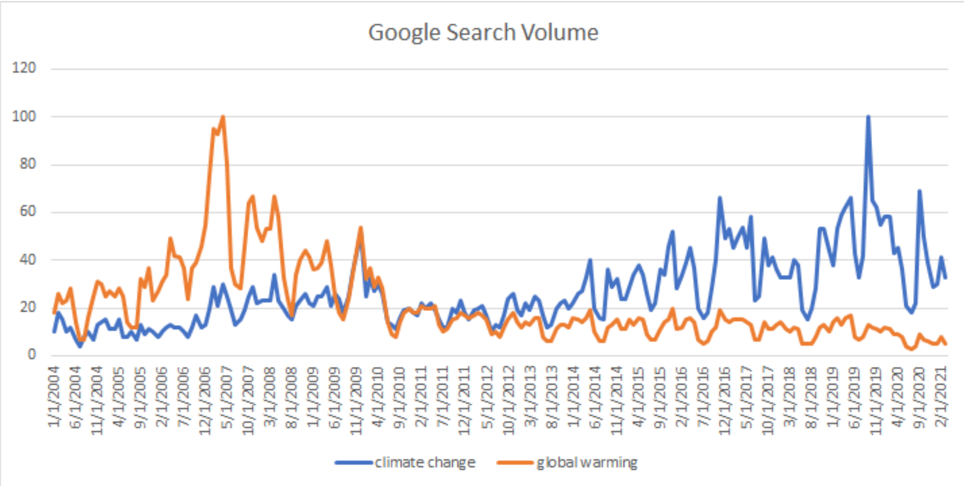


Figure C.1: Google Search Volume

Asymmetric Information In this paper, we follow Bharath et al. (2009) to construct the measures of asymmetric information. We take the first component of seven measures of information asymmetry and liquidity from the most well-known studies in the field of market microstructure, corporate finance, and asset pricing as the main measure of asymmetric information. These measures are based on (1) the adverse selection component of the quoted and effective bid-ask spread, AD and RAD (George et al., 1991; Roll, 1984); (2) stock's volume return dynamics, $C2$ (Llorente et al., 2002); (3) probability of informed trading, PIN (Easley et al., 1996); (4) price impact, ILL and LR (Amihud, 2002; Amihud et al., 1997); and (5) interaction between stock return and order flow, GAM (Pástor and Stambaugh, 2003). Appendix B shows the detailed construction of these measures and explains how these measures capture the information asymmetry. We take the first principal component of these measures as our main measure of information asymmetry, denoted as ASY. An increase in our measure ASY represents an increase in information asymmetry.

Firm Financials Following Ferris et al. (2018) we construct the measures of quarterly firm financials using the data from COMPUSTAT Fundamentals Quarterly database. We are interested in the capital structure of the firms and its determinants. For the capital structure, we use market leverage, which is calculated as total debt divided by market value of total assets [7]. Total debt is the sum of short-term debt $DLCq$ and the long-term debt $DLTTq$, and the market value of total assets is total debt plus market value of equity ($PRCCq \times CSHPRq$) plus preferred stock $PSTKq$ (or $PSTKRq$ if missing) minus deferred taxes and investment tax credit $TXDITCq$. Quarterly sales ($sales_q$) is scaled in million dollars and represents the gross sales reduced by cash or trade discounts, returned sales and allowances to customers. Tangibility is quarterly Property Plant and Equipment Net (PPENTq) divided by the book value of total assets (ATq). And Profitability is calculated by operating income before depreciation divided by the book value of total assets ($OIBDPq/ATq$).

Summary Statistics We also obtain the closing price and markets value of firms at the beginning of each quarter from Refinitiv Datastream. Table 1 reports the summary statistics of the firm characteristics and the information asymmetric variables constructed over the sample period from 2004Q1 to 2020Q4.

[7] We also check alternative capital structure measures such as book leverage.

Table 1: Summary Statistics

Panel A. Firm Characteristics

	count	Mean	p50	SD
market value (million dollars)	17522	12057.87	1557.997	58232.3
closing price	17754	185.0698	28.705	4464.139
ENSCORE	9684	.2577533	.1488	.2808584
mktlev	15194	.2270489	.162395	.2316988
qratio	15194	2.162429	1.419565	3.532211
tangibility	18950	.2612459	.1697085	.2517568
sales_q (million dollars)	19819	1553.13	289.418	5108.115
profitability_q	18623	-.0473825	.026711	3.855605

Panel B. Information Asymmetry Variables

	count	Mean	p50	SD
AD	16037	-.2208391	-.0070152	1.321496
RAD	16034	4.11561	2.554354	4.105668
C2	17510	-.0559223	-.0229584	1.01088
PIN	17656	1.078089	.6959364	1.142027
ILL	17652	-1.620119	-1.389836	1.231184
LR	17760	.7363737	.3583898	.9760499
GAM	15590	2.888314	2.773041	1.244558
ASY	14707	-.1702508	-.2279681	1.482204

This table reports summary statistics of the firm characteristics and the information asymmetry variables over the sample period 2004Q1-2020Q4.

2.5 Empirical Analysis

2.5.1 Empirical strategy

To examinate the impact of green taste (GSV growth rate) on asymmetric information, we run the following regression

$$InfoAsy_{i,q} = \alpha_i + \Big(\beta_0 + \beta_1 \cdot ENSCORE_{i,q-4}\Big)\,\Delta GSV_{i,q} + \gamma X_{i,q} + \epsilon_{i,q} \tag{1}$$

where $InfoAsy_{i,q}$ is our measure information asymmetry of firm i at quarter q, which is the first principal component of the seven measures. $ENSCORE_{i,q-4}$ is the ENSCORE of firm i in the previous year, $\Delta GSV_{i,q}$ is the growth rate of GSV of keywrod *Climate Change* in U.S. $X_{i,q}$ is the control variables, which include market value, stock return volatility, analyst coverage, etc. The coefficient of interest is β_1. We expect that β_1 is negative and significant, indicating that a higher climate attention reduces green firm's information. In addition to this OLS setting, we use the global temperature as an instrument variable for $\Delta GSV_{i,q}$ to identify the casual relation. Choi et al. (2020) shows that higher temperature increases climate change concern. Standard errors are clustered at firm level. And we also have the year fixed effects to avoids the impacts from macroeconomic shocks.

To test the results of category learning, we follow Huang et al. (2019) to construct firm-level category learning using the daily correlation between the firm's stock return and the market return. We do this for every firm in each quarter. In addition, we consider also the R^2 of univariate regression of the firm's stock return on the market return as an alternative measure of category learning. The latter is simply the square of the former. Then, we run the following regression to test the category learning results:

$$Cat_{i,q} = \alpha_i + (\beta_0 + \beta_1 \cdot ENSCORE_{i,q-4})\Delta GSV_q + \gamma X_{i,q} + \epsilon_{i,q} \tag{3}$$

where $Cat_{i,q}$ is the category learning measure of firm i on quarter q. $ENSCORE_{i,q-4}$ is the ENSCORE of firm i at the previous year. Again, standard errors are clustered at firm level and we have also year fixed effects.

The parameter of interest is β_1. If β_1 is negative and significant, it means that a higher climate attention decreases category learning of green firms compared to brown ones.

2.5.2 Green taste and information asymmetry

We first test the impact of green taste on green firms' information asymmetry, and the results reported on Table 2 implies that greater green GSV reduces information asymmetry.

Tables 2 reports the results of regressions using *Climate Change* as green keywords when collect the GSV data to construct green taste measure and using principal component of seven information asymmetry variables following Bharath et al. (2009) as the main information asymmetry measure. Columns (1) and (2) are OLS regression estimates, while columns (3) and (4) are the estimates with the temperature as instrumental variable for green taste. This table shows that greater green taste from investors reduces green firms' information asymmetry. According to the result of column (4), when there's one standard deviation increase of green GSV growth rate, there's 27.8& reduction in information asymmetry of green firms.

We also test the results with alternative green keywords to capture green taste. Table A1 shows the results of regressions using growth rate of GSV on *Global Warming* as green taste measure. The positive and significant effects of green taste remain.

Table 2: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE × growthcc	-0.174***	-0.164***	-0.677***	-0.697***
	(-6.27)	(-6.03)	(-8.15)	(-8.12)
ENSCORE	-0.467***	0.00355	-0.474***	0.00422
	(-5.39)	(0.04)	(-5.49)	(0.04)
growthcc	0.101***	0.133***	0.180***	0.391***
	(8.48)	(11.14)	(4.61)	(9.64)
logmkv	-1.392***	-1.180***	-1.392***	-1.188***
	(-42.33)	(-32.75)	(-42.32)	(-32.92)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adjusted R^2	0.321	0.408	0.231	0.149
Observations	48478	48478	48478	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthcc* is measured by the growth rate of Google Search Volume (GSV) of keywords *Climate Change*. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

2.5.3 Green Taste and category learning

However, Table 3 suggests that higher green taste decreases category-learning in green sector,

Table 3: Green Taste and Category Learning

	OLS		IV	
	(1)	(2)	(3)	(4)
	cat_firm	cat_firm_sq	cat_firm	cat_firm_sq
ENSCORE × growthcc	-0.0139***	-0.0223***	-0.0192	-0.0525***
	(-3.22)	(-5.60)	(-1.33)	(-3.78)
ENSCORE	0.0270***	0.0303***	0.0268***	0.0302***
	(2.71)	(3.21)	(2.70)	(3.20)
growthcc	-0.0155***	-0.0176***	-0.0421***	-0.0373***
	(-8.80)	(-12.02)	(-6.76)	(-6.63)
logmkv	0.0276***	0.0275***	0.0288***	0.0286***
	(9.47)	(10.57)	(9.81)	(10.93)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.395	0.396	0.002	0.003
Observations	52829	52829	52829	52829

This table reports estimates for the coefficients from the regression of Equation (3). The regressions use *Climate Change* as keywords when collect GSV data. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.

Further more, we test whether the coefficient of green taste, $\beta_0+\beta_1 \cdot AveENSCORE_{p,q-4}$, is significantly different from than zero. The result of F-test rejects the null hypothesis that the coefficient of ΔGSV_q is zero, which implies green taste has significant impact on category learning behaviour.

2.5.4 Asset pricing implications

In this section, we examine the asset pricing implication of information asymmetry. This investigation sheds light on how information asymmetry affect the cost of capital. Specifically, in each quarter, we construct five portfolios based on each firm's information asymmetry in the last quarter. We then obtain the monthly value-weighted return for each portfolio. We run time-series regression of all the portfolio returns on common asset pricing factors,

$$r_{p,m} = \alpha_p + \beta_p Factor_m + \epsilon_{p,m}$$

where $r_{p,m}$ is the return of portfolio p at month m, $Factor_m$ includes the CAPM (Sharpe, 1964), Fama-french three and five factors (Fama and French, 1993, 2015).

Table 4: **Asset pricing implication**

	L	2	3	4	H	H-L
$E(r_{i,t})$	0.50	0.86	1.09	1.29	1.59	1.09
s.e.	(0.42)	(0.39)	(0.37)	(0.37)	(0.38)	(0.28)
CAPM						
α	-0.39	0.02	0.19	0.44	0.66	1.06
s.e.	(0.13)	(0.14)	(0.11)	(0.16)	(0.22)	(0.30)
FF3						
α	-0.51	0.02	0.28	0.53	0.83	1.34
s.e.	(0.14)	(0.13)	(0.08)	(0.13)	(0.22)	(0.31)
FF5						
α	-0.47	0.01	0.27	0.50	0.85	1.32
s.e.	(0.13)	(0.12)	(0.09)	(0.12)	(0.23)	(0.31)
No. of firms	443	445	444	444	443	

Table 4 shows the abnormal returns α for all the five portfolios and a portfolio that long the top one and shorts the bottom one (a high-minus-low portfolio). First, we find an increasing raw return from low information asymmetry portfolio to high ones. The portfolio with the highest information asymmetry carries a significant 1.09% (s.e.=0.28%) higher monthly return than that with lowest information asymmetry. This difference remains significant and even becomes larger after controlling for common asset pricing factor (1.06%, 1.34%, and 1.32% for CAPM, Fame-French three and five factors). This result is consistent with Easley and O'hara (2004) that investors demand compensation for holding stocks that are less transparent and more uncertain. Thus lower information asymmetry benefit firms by lowering its cost of equity capital.

2.5.5 Capital Structure

In this section, we further justify the importance of asymmetric information in firms' capital structure and explore how does the existence of category learning affect the capital structure. Pecking order theory (Myers, 1984; Myers and Majluf, 1984) suggests that the cost of financing and the ratio of debt to equity should increase with the asymmetric information.

Following Bharath et al. (2009), we augment the model of Rajan and Zingales (1995) to include the asymmetric information measures and run firm-quarter panel regression.

$$\begin{aligned} Leverage_{it} = \quad & a + \mu_i + b_1 ASY_{it} + b_2 Cat_{it} + b_3 Tangibility_{it} + b_4 Qratio_{it} \\ & + b_5 Firmsize_{it} + b_6 Profitability_{it} + \varepsilon_{it} \end{aligned} \tag{C.4}$$

where $Leverage_{it}$ is firm i's market leverage at quarter t, which is total debt divided by market value of total assets, as in Ferris et al. (2018). Total debt is the sum of short-term debt $DLCq$ and the long-term debt $DLTTq$, and the market value of total assets is total debt plus market value of equity ($PRCCq \times CSHPRq$) plus preferred stock $PSTKq$

(or $PSTKRq$ if missing) minus deferred taxes and investment tax credit $TXDITCq$. Firm size is log of sales scaled by the quarterly GDP deflator with baseline year 2012 ($log(Sale)/GDPDeflator$).Tangibility is quarterly Property Plant and Equipment Net (PPENTq) divided by the book value of total assets (ATq). And Profitability is calculated by operating income before depreciation divided by the book value of total assets ($OIBDPq/ATq$).

Table 5 reports estimates for coefficients from the above equation (C.4). It shows that when there's higher asymmetric information, there's higher leverage of firms, which is in line with the findings of Bharath et al. (2009).

Besides, column (3) of the table 5 suggests that investors' category learning behaviour decreases the leverage level of firms.

As higher green attention reduces information asymmetry, according to the results of table 5, the leverage will decrease with lower information asymmetry.

For robustness check, we also test the results of alternative leverage measures. Table A4 reports the results of book leverage. The main conclusions still hold.

2.6 Conclusion

In this paper, we investigate the impact of green taste on asymmetric information and category learning. Using the GSV on *Climate Change* and asymmetric information measure developed by Bharath et al. (2009), we empirically find that greater public attention on environmental issues reduces asymmetric information, especially for the green firms which have high ENSCORE. In addition, higher green taste also leads to less category learning behavior for green firms (Peng and Xiong, 2006). This is because more attention is allocated to the specific information of green firms, making their price reflect more firm-specific information. We document that such a decrease in information asymmetry and category learning lowers the cost of equity capital and decreases leverage for green

Table 5: Leverage, Asymmetric Information and Category Learning

	(1) mktlev	(2) mktlev	(3) mktlev
ASY	0.0194***	-0.00185	0.0198***
	(0.00222)	(0.00266)	(0.00230)
tangibility	0.191**	0.163**	0.189**
	(0.0767)	(0.0764)	(0.0765)
qratio	-0.0168***	-0.0137***	-0.0166***
	(0.00304)	(0.00277)	(0.00304)
firmsize	1.365**	1.720***	1.448**
	(0.551)	(0.596)	(0.560)
profit	-0.364***	-0.364***	-0.377***
	(0.0848)	(0.0907)	(0.0906)
AD		-0.00194*	
		(0.00111)	
RAD		0.0000849	
		(0.000793)	
C2		0.000654	
		(0.000960)	
PIN		0.0217***	
		(0.00376)	
ILL		0.0237***	
		(0.00327)	
LR		0.00331*	
		(0.00185)	
GAM		0.00363**	
		(0.00143)	
cat_firm			-0.0202*
			(0.0105)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	11525	11274	11503
R^2	0.821	0.826	0.819

This table reports estimates for the coefficients from the regression of Equation (C.4). We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.

firms. We propose a model with green preference and attention allocation to explain the empirical result. The model sheds new light on how the interaction between green taste and attention allocation affects the cross-section of the stock market.

2.7 Appendices

2.7.1 Appendix A. Derivation of time-0 utility

Put the expression of portfolio allocation X to U_0,

$$\begin{aligned}
U_0 &= E_0\Bigg[W_0 + \frac{1}{\gamma}\left(E_1(f) - p + b\right)' V_1(f)^{-1}\left(E_1(f) - p + b\right) \\
&\quad -\frac{\gamma}{2}\left[\frac{1}{\gamma^2}\left(E_1(f) - p + b\right)' V_1(f)^{-1} V_1(f) V_1(f)^{-1}\left(E_1(f) - p + b\right)\right]\Bigg] \\
&= W_0 + \frac{1}{2\gamma} E_0\left[\left(E_1(f) - p + b\right)' V_1(f)^{-1}\left(E_1(f) - p + b\right)\right]
\end{aligned}$$

Note that $E_1(f) = E_1(\mu + \Gamma\tilde{f}) = \mu + \Gamma\hat{\mu}$, $E_1(f)$ is normally distributed. Thus U_0 is an expectation of a non-central χ^2-distributed random variable. According to Van Nieuwerburgh and Veldkamp (2010), this equals

$$\begin{aligned}
U_0 &= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left(V_1(f)^{-1} V_0\left(E_1(f)\right)\right) + E_0\left(E_1(f) - p + b\right)' V_1(f)^{-1} E_0\left(E_1(f) - p + b\right)\right] \\
&= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left(\left(\Gamma\hat{\Sigma}\Gamma'\right)^{-1}\Gamma(\Sigma - \hat{\Sigma})\Gamma'\right) + (\mu - p + b)'\left(\Gamma\hat{\Sigma}\Gamma'\right)^{-1}(\mu - p + b)\right] \\
&= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left(\left(\Gamma'\right)^{-1}\left(\hat{\Sigma}^{-1}\Sigma - I\right)\Gamma'\right) + \left(\Gamma^{-1}(\mu - p + b)\right)'\hat{\Sigma}^{-1}\left(\Gamma^{-1}(\mu - p + b)\right)\right] \\
&= W_0 + \frac{1}{2\gamma}\left[\text{Trace}\left(\left(\Gamma'\right)^{-1}\hat{\Sigma}^{-1}\Sigma\Gamma'\right) - 3 + \left(\Gamma^{-1}(\mu - p + b)\right)'\hat{\Sigma}^{-1}\left(\Gamma^{-1}(\mu - p + b)\right)\right]
\end{aligned}$$

where Trace$(\cdot)$ is the trace of a matrix. Given the relation that Trace(AB) = Trace(BA), $\text{Trace}\left((\Gamma')^{-1}\hat{\Sigma}^{-1}\Sigma\Gamma'\right) = \text{Trace}\left(\Gamma'(\Gamma')^{-1}\hat{\Sigma}^{-1}\Sigma\right) = \text{Trace}\left(\hat{\Sigma}^{-1}\Sigma\right)$. Note that both $\hat{\Sigma}$ and Σ are diagonal matrix, and considering that $\Gamma^{-1} = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix}$, we can rewrite the objective function as

$$U_0 = W_0 + \frac{1}{2\gamma}\left[\sum_{i=1}^{3}\hat{\Sigma}_{ii}^{-1}\left(\Sigma_{ii}+\theta_i^2\right)-3\right]$$

where the 3×1 vector θ is given by

$$\theta = \Gamma^{-1}\left(\mu - p + b\right) = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \mu_1 - p_1 + g \\ \mu_2 - p_2 \\ \mu_3 - p_3 \end{bmatrix} = \begin{bmatrix} \mu_1 - p_1 + g - \mu_3 + p_3 \\ \mu_2 - p_2 - \mu + p_3 \\ \mu_3 - p_3 \end{bmatrix}$$

which is the synthetic expected excess payoffs for three factors, taking into account the green taste. Essentially, the objective function is a linear function on the posterior precision on the three factors, with the weights depending on the prior variances and excess payoffs.

If we assume the learning function to be a square root function, the optimization problem is

$$\max_{\kappa_m,\kappa_{z,1},\kappa_{z,2}} \quad \left(\Sigma_{11}+\theta_1^2\right)\sqrt{\kappa_{z,1}} + \left(\Sigma_{22}+\theta_2^2\right)\sqrt{\kappa_{z,2}} + \left(\Sigma_{33}+\theta_3^2\right)\sqrt{\kappa_m}$$
$$s.t. \quad \kappa_m + \kappa_{z,1} + \kappa_{z,2} \leq K$$

2.7.2 Appendix B. Information asymmetry measures

This appendix explains how we construct the measures of information asymmetry.

- George et al. (1991); Roll (1984):

  Using a simple price dynamics model, George et al. (1991) find that the proportion of quoted spread due to adverse selection, π_i, can be estimated with the following regression for an individual stock i:

$$\hat{s}_{it} = \alpha_i + \beta_i s_{it} + \epsilon_{it}$$

where s_{it} is the relative quoted bid-ask spread of stock i at time t. $\hat{s}_{it}$ is Roll (1984)'s effective bid-ask spread measure calculated using the squared root of negative autocovariance between consecutive returns,

$$\hat{s}_{it} = \begin{cases} 2\sqrt{-Cov(r_{i,t}, r_{i,t-1})} & \text{if } Cov(r_{i,t}, r_{i,t-1}) < 0 \\ -2\sqrt{Cov(r_{i,t}, r_{i,t-1})} & \text{if } Cov(r_{i,t}, r_{i,t-1}) \geq 0 \end{cases}$$

where the autocovariance is estimated using 60-day rolling windows. According to George et al. (1991), $r_{i,t}$ could be: (i) the abnormal returns (i.e. the residuals of a regression of raw returns on expected returns), and (ii) the raw returns net of the bid returns. The unbiased estimation of π_i will be $1-\hat{\beta}_i^2$ for the first case and $1-\hat{\beta}_i$ for the second. In the following parts, we refer to these two measures as AD and RAD

- Llorente et al. (2002):

  Llorente et al. (2002) estimates the relative intensity of speculative vs. hedging trades, based on the idea that speculative (hedging) trades generate momentum (reversal) of stock return when the volume is high. Then the intensity of speculative trading serves as a proxy for information asymmetry. Specifically, they ran the following regression,

$$R_{i,t+1} = C0_i + C1_i R_{i,t} + C2_i V_{i,t} R_{i,t} + \epsilon_{i,t}$$

  where $R_{i,t}$ is the raw stock return. $V_{i,t}$ is the logarithm of turnover ratio, detrended by subtracting a 200-day moving average. A high and positive estimated coefficient $C2_i$ indicates a high degree of information asymmetry. We refer to this measure as C2.

- Easley et al. (1996):

  Perhaps the most popular measure of information asymmetry is the probability of informed trading (PIN) proposed by Easley et al. (1996). They use the information in the trade data to estimated the probability of informed vs. uninformed trading when new information occurs. Specifically, they use the buy/sell trade quotes to estimate the model parameters and elicit the PIN using maximum likelihood method. We refer to this measure as PIN

- Amihud et al. (1997); Amihud (2002):

  These two measures are quite straightforward, both measures the extend to which price responses to the order flow. The sensitivity of price to volume is known to capture the liquidity which is strongly related to adverse selection. Specifically, Amihud (2002) propose the following illiquidity measure

  $$ILL_{i\tau} = 1/D_{i\tau} \sum_{t=1}^{D_{i\tau}} \frac{|R_{it}|}{V_{it}}$$

  where R_{it} and V_{it} are return and dollar volume of stock i at day t within a time interval τ (quarterly or yearly). $D_{i\tau}$ is the total number of days with available R_{it} and V_{it}.

  Alternatively, the Amivest liquidity ratio (Amihud et al., 1997) captures similar notion,

  $$LR_{i\tau} = -\frac{\sum_{t=1}^{D_{i\tau}} V_{it}}{\sum_{t=1}^{D_{i\tau}} |R_{it}|}$$

  Thus, higher ILL and LR indicate lower liquidity and a higher degree of information asymmetry. We label them as ILL and LR, respectively.

- Pástor and Stambaugh (2003):

  Our last measure of liquidity/information asymmetry is from Pástor and Stambaugh (2003). They measure relies on the idea that order flows induce greater return reversal when liquidity is lower. Thus they propose the following regression

$$r^e_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i \text{sign}(r^e_{i,t}) V_{i,t} + \epsilon_{i,t}$$

where r^e is the stock return in excess to the market return. $V_{i,t}$ is the dollar trading volume. When the estimated coefficient γ_i is negative and high in magnitude, the reversal effect is strong and liquidity is low. Thus the negative of γ_i measures the liquidity and information asymmetry. We refer to this measure as GAM.

- Finally, we construct the first principal component of all these measures of information asymmetry. We do this by first normalize each measure for each firm over the whole sample period. Then we take the first principal component of the seven measures for each firm.

2.7.3 Appendix C. Additional Results

Table A1: Green Taste and Information Asymmetry

	OLS		IV	
	(1)	(2)	(3)	(4)
	ASY	ASY	ASY	ASY
ENSCORE × growthgm	-0.235***	-0.222***	-0.514***	-0.502***
	(-7.18)	(-6.96)	(-8.34)	(-7.86)
ENSCORE	-0.472***	-0.00608	-0.498***	-0.0188
	(-5.45)	(-0.06)	(-5.78)	(-0.20)
growthgm	0.145***	0.191***	0.128***	0.272***
	(10.67)	(14.11)	(4.68)	(9.69)
logmkv	-1.394***	-1.184***	-1.391***	-1.185***
	(-42.33)	(-32.82)	(-42.31)	(-32.89)
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Adjusted R^2	0.322	0.409	0.233	0.155
Observations	48478	48478	48478	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthgm* is measured by the growth rate of Google Search Volume (GSV) of keywords *Global Warming*. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A2: Green Taste and Information Asymmetry

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE × growthcc	-0.159***	0.0357	0.124***	-0.0927***	-0.119***	0.117***	-0.0741**	-0.164***
	(-4.70)	(1.33)	(3.58)	(-8.16)	(-7.72)	(5.92)	(-2.45)	(-6.03)
ENSCORE	-0.0650*	-0.0167	0.0164	-0.0122	-0.0212	0.0147	-0.0768	0.00355
	(-1.79)	(-0.47)	(0.42)	(-0.22)	(-0.34)	(0.36)	(-1.53)	(0.04)
growthcc	0.0316**	-0.0126	0.0165	0.0121***	0.0828***	0.142***	0.00760	0.133***
	(2.24)	(-1.10)	(1.19)	(2.75)	(11.40)	(18.51)	(0.66)	(11.14)
logmkv	0.111***	0.0311***	-0.0343***	-0.663***	-1.125***	-0.338***	-0.0455***	-1.180***
	(9.40)	(2.98)	(-3.15)	(-26.10)	(-38.74)	(-22.62)	(-2.90)	(-32.75)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.212	0.917	0.030	0.715	0.654	0.246	0.332	0.408
Observations	50438	50438	52593	52691	52688	52718	48634	48478

Panel B. IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AD	RAD	C2	PIN	ILL	LR	GAM	ASY
ENSCORE × growthcc	-0.230**	0.0327	-0.349***	-0.288***	-0.483***	-0.317***	-0.139	-0.697***
	(-1.96)	(0.37)	(-3.19)	(-8.37)	(-9.69)	(-5.51)	(-1.46)	(-8.12)
growthcc	-0.0245	-0.152***	-0.112**	0.0705***	0.364***	0.107***	0.379***	0.391***
	(-0.43)	(-3.61)	(-2.45)	(4.67)	(15.86)	(4.35)	(9.19)	(9.64)
ENSCORE	-0.0653*	-0.0172	0.0155	-0.0120	-0.0201	0.0145	-0.0756	0.00422
	(-1.80)	(-0.48)	(0.40)	(-0.22)	(-0.32)	(0.35)	(-1.50)	(0.04)
logmkv	0.114***	0.0374***	-0.0257**	-0.664***	-1.134***	-0.334***	-0.0617***	-1.188***
	(9.58)	(3.56)	(-2.36)	(-26.15)	(-38.84)	(-22.43)	(-3.91)	(-32.92)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.001	-0.004	-0.015	0.181	0.299	0.027	-0.030	0.149
Observations	50438	50438	52593	52691	52688	52718	48634	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthcc* is measured by the growth rate of Google Search Volume (GSV) of keywords *Climate Change*. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A3: Green Taste and Information Asymmetry

Panel A. OLS regressions

	(1) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) ASY
ENSCORE × growthgm	-0.196***	0.0236	0.0903**	-0.0872***	-0.125***	0.0699***	0.00635	-0.222***
	(-4.76)	(0.66)	(2.38)	(-6.31)	(-7.39)	(3.44)	(0.19)	(-6.96)
ENSCORE	-0.0742**	-0.0157	0.0201	-0.0156	-0.0261	0.0178	-0.0754	-0.00608
	(-2.05)	(-0.44)	(0.51)	(-0.28)	(-0.42)	(0.43)	(-1.50)	(-0.06)
growthgm	0.0264	-0.0268*	0.0219	0.0303***	0.0899***	0.124***	0.154***	0.191***
	(1.61)	(-1.92)	(1.48)	(5.82)	(12.19)	(15.05)	(11.55)	(14.11)
logmkv	0.112***	0.0320***	-0.0345***	-0.664***	-1.126***	-0.338***	-0.0539***	-1.184***
	(9.46)	(3.07)	(-3.17)	(-26.10)	(-38.73)	(-22.66)	(-3.45)	(-32.82)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.212	0.917	0.030	0.715	0.654	0.243	0.335	0.409
Observations	50438	50438	52593	52691	52688	52718	48634	48478

Panel B. IV regressions

	(1) AD	(2) RAD	(3) C2	(4) PIN	(5) ILL	(6) LR	(7) GAM	(8) ASY
ENSCORE × growthgm	-0.186**	0.00603	-0.290***	-0.221***	-0.341***	-0.240***	-0.0571	-0.502***
	(-2.13)	(0.09)	(-3.49)	(-8.52)	(-9.08)	(-5.48)	(-0.80)	(-7.86)
growthgm	-0.0147	-0.104***	-0.0747**	0.0512***	0.256***	0.0766***	0.257***	0.272***
	(-0.37)	(-3.55)	(-2.31)	(4.81)	(15.88)	(4.42)	(9.08)	(9.69)
ENSCORE	-0.0740**	-0.0170	0.00377	-0.0210	-0.0338	0.00479	-0.0775	-0.0188
	(-2.03)	(-0.48)	(0.10)	(-0.38)	(-0.54)	(0.12)	(-1.54)	(-0.20)
logmkv	0.114***	0.0362***	-0.0268**	-0.664***	-1.132***	-0.333***	-0.0588***	-1.185***
	(9.59)	(3.46)	(-2.47)	(-26.14)	(-38.85)	(-22.41)	(-3.75)	(-32.89)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.002	-0.001	-0.008	0.181	0.309	0.028	0.003	0.155
Observations	50438	50438	52593	52691	52688	52718	48634	48478

This table reports estimates for the coefficients from the regression of Equation (1). Green taste *growthgm* is measured by the growth rate of Google Search Volume (GSV) of keywords *Global Warming*. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm to account for serial correlation in outcomes.

Table A4: Book Leverage, Asymmetric Information and Category Learning

	(1)	(2)	(3)
	booklev	booklev	booklev
ASY	0.00490**	-0.00252	0.00528**
	(0.00212)	(0.00279)	(0.00226)
tangibility	0.125	0.121	0.124
	(0.0876)	(0.0882)	(0.0877)
qratio	-0.00148	-0.00103	-0.00137
	(0.00453)	(0.00471)	(0.00454)
firmsize	1.474	1.685*	1.562
	(0.994)	(1.019)	(1.009)
profit	-0.408***	-0.425***	-0.414***
	(0.111)	(0.125)	(0.117)
AD		0.000537	
		(0.000998)	
RAD		0.000396	
		(0.000973)	
C2		0.000710	
		(0.00118)	
PIN		0.00878*	
		(0.00497)	
ILL		0.00665*	
		(0.00398)	
LR		-0.00109	
		(0.00183)	
GAM		0.00563***	
		(0.00186)	
cat_firm			-0.0210
			(0.0135)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	11525	11274	11503
R^2	0.780	0.779	0.779

This table reports estimates for the coefficients from the regression of Equation (C.4) with the book leverage as the capital structure measure. We do not report the coefficient for the intercept. t statistics are reported in parentheses.* $p < .10$, ** $p < .05$, *** $p < .01$. The standard errors are clustered by firm.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets 5, 31–56.

Amihud, Y., Mendelson, H., Lauterbach, B., 1997. Market microstructure and securities values: Evidence from the tel aviv stock exchange. Journal of financial Economics 45, 365–390.

Aouadi, A., Arouri, M., Teulon, F., 2013. Investor attention and stock market activity: Evidence from france. Economic Modelling 35, 674–681.

Baker, M., Bergstresser, D., Serafeim, G., Wurgler, J., 2018. Financing the response to climate change: The pricing and ownership of us green bonds. Tech. rep., National Bureau of Economic Research.

Bank, M., Larch, M., Peter, G., 2011. Google search volume and its influence on liquidity and returns of german stocks. Financial markets and portfolio management 25, 239.

Bharath, S. T., Pasquariello, P., Wu, G., 2009. Does asymmetric information drive capital structure decisions? The review of financial studies 22, 3211–3243.

Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. The Review of Financial Studies 33, 1112–1145.

Cooper, M. J., Dimitrov, O., Rau, P. R., 2001. A rose. com by any other name. The journal of Finance 56, 2371–2388.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance 66, 1461–1499.

Ding, R., Hou, W., 2015. Retail investor attention and stock liquidity. Journal of International Financial Markets, Institutions and Money 37, 12–26.

Djerf-Pierre, M., 2012. When attention drives attention: Issue dynamics in environmental news reporting over five decades. European Journal of Communication 27, 291–304.

Durnev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797–836.

Easley, D., Kiefer, N. M., O'hara, M., Paperman, J. B., 1996. Liquidity, information, and infrequently traded stocks. The Journal of Finance 51, 1405–1436.

Easley, D., O'hara, M., 2004. Information and the cost of capital. The journal of finance 59, 1553–1583.

Edmans, A., 2011. Does the stock market fully value intangibles? employee satisfaction and equity prices. Journal of Financial economics 101, 621–640.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Ferris, S. P., Hanousek, J., Shamshur, A., Tresl, J., 2018. Asymmetries in the firm's use of debt to changing market values. Journal of Corporate Finance 48, 542–555.

Gao, Y., Wang, Y., Wang, C., Liu, C., 2018. Internet attention and information asymmetry: Evidence from qihoo 360 search data on the chinese stock market. Physica A: Statistical Mechanics and its Applications 510, 802–811.

George, T. J., Kaul, G., Nimalendran, M., 1991. Estimation of the bid–ask spread and its components: A new approach. The Review of Financial Studies 4, 623–656.

Goldstein, I., Kopytov, A., Shen, L., Xiang, H., 2021. On esg investing: Heterogeneous preferences, information, and asset prices. Information, and Asset Prices (April 9, 2021) .

Goldstein, I., Yang, L., 2015. Information diversity and complementarities in trading and information acquisition. The Journal of Finance 70, 1723–1765.

Grossman, S. J., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. The American economic review 70, 393–408.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. Journal of financial economics 93, 15–36.

Huang, S., Huang, Y., Lin, T.-C., 2019. Attention allocation and return co-movement: Evidence from repeated natural experiments. Journal of Financial Economics 132, 369–383.

Kacperczyk, M., Van Nieuwerburgh, S., Veldkamp, L., 2016. A rational theory of mutual funds' attention allocation. Econometrica 84, 571–626.

Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. The Review of financial studies 15, 1005–1047.

Myers, S. C., 1984. The capital structure puzzle. The Journal of Finance 39, 574–592.

Myers, S. C., Majluf, N. S., 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of financial economics 13, 187–221.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political economy 111, 642–685.

Pástor, L., Stambaugh, R. F., Taylor, L. A., 2020. Sustainable investing in equilibrium. Journal of Financial Economics .

Pedersen, L. H., Fitzgibbons, S., Pomorski, L., 2020. Responsible investing: The esg-efficient frontier. Journal of Financial Economics .

Peng, L., 2005. Learning with information capacity constraints. Journal of Financial and Quantitative Analysis 40, 307–329.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563–602.

Peress, J., 2010. The tradeoff between risk sharing and information production in financial markets. Journal of Economic Theory 145, 124–155.

Rajan, R. G., Zingales, L., 1995. What do we know about capital structure? some evidence from international data. The journal of Finance 50, 1421–1460.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. The Journal of finance 39, 1127–1139.

Sankaraguruswamy, S., Shen, J., Yamada, T., 2013. The relationship between the frequency of news release and the information asymmetry: The role of uninformed trading. Journal of Banking & Finance 37, 4134–4143.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance 19, 425–442.

Sims, C. A., 2003. Implications of rational inattention. Journal of monetary Economics 50, 665–690.

Van Nieuwerburgh, S., Veldkamp, L., 2010. Information acquisition and under-diversification. The Review of Economic Studies 77, 779–805.

Wurgler, J., 2000. Financial markets and the allocation of capital. Journal of financial economics 58, 187–214.

Chapter 3

Applying Lehmann‘s Informativeness Order in Precautionary Principal

3.1 Introduction

The comparison between information structures dated back to Blackwell et al. (1951) and Blackwell (1953). His definition on the relative informativeness of information structures (or, experiments) is that, an experiment A is more informative than B if and only if a decision maker with any utility function prefers to observe experiment A over B. This happens whenever experiment A is a “garbling" of B, i.e., B can obtained from A by adding noise that is not related to the underlying state. While this definition of ordering is general, it is also very incomplete (Cabrales et al., 2013). For example, Lehmann (1988) shows that, surprisingly, Blackwell’s informativeness ranking fails to compare two location experiments with uniform noises.[1]

To address this limitation of Blackwell’s informativeness ranking. Lehmann (1988) introduce a new method to rank experiments focusing on the monotone decision problem

[1]Specifically, let two experiments be $X \sim U[\omega - \frac{1}{2}, \omega - \frac{1}{2}]$ and $Y \sim U[\omega - \frac{\rho}{2}, \omega - \frac{\rho}{2}]$ where $0 < \rho < 1$. It is intuitive that Y is more informative than X. However, these two experiments cannot be compared using Blackwell informativeness unless $\rho = \frac{1}{k}$ for some positive integer k (see Theorem 3.1 in Lehmann (1988)).

(Karlin and Rubin, 1956). A Lehmann higher ranked experiment induces higher expected utility for all monotone decision problems. This approach is less strict than the Blackwell's ranking and thus compares more cases. Lehmann's ranking is later proved to be applicable to utilities with single-crossing properties (Persico, 2000) and more general interval dominance order (IDO) properties (Quah and Strulovici, 2009). This concept is then applied in the literature to study various economic problems.[2] However, it has not been applied in environmental economics to study the effect of better future information structure on current actions. Given the increasing concern on climate change during recent decades, we believe this application could help policymaker better decide the timing of climate mitigation when facing decreased future uncertainty.

Gollier et al. (2000) investigate how learning about climate damage in the future affects emission decisions today. They find that when absolute prudence is bigger than twice the absolute risk aversion, a better information structure in the future reduces emission today. This so called *Precautionary Principal* depends on interplay among the wealth effect, precautionary effect, and irreversibility effect. However, their analysis ranks experiments according to the Blackwell's order. As such, it would be interesting to see how does the condition on utility change when we apply the informativeness order by Lehmann. As Lehmann's order is less strict compared to Blackwell's, we expected the condition on utility that supports the precautionary principal to be less strict in our case than in the case of Gollier et al. (2000).

3.2 Lehmann's informativeness order

Consider the underlying state $\omega \in \Omega$, which is unobservable to a decision maker. Instead, the decision maker observe a signal X, of which the distribution is contingent on

[2] For example, information acquisition in auctions (Persico, 2000); information contents of prices in the financial market (Bond, 2019); informativeness of sample selections (Tillio et al., 2021); insurance and monopoly pricing problem.

the underlying state. In addition, the conditional distribution depends on an additional parameter θ which can be interpreted as "regimes" using the language from Bond (2019). Specifically, the distribution of the signal is

$$P(X < x|\omega, \theta) = F(x|\omega, \theta)$$

Lehmann provides a precise definition when two experiments with different regimes θ_1 and θ_2 can be compared.

Definition 1. *An experiment with regime θ_1 is more Lehmann informative than that with regime θ_2 if and only if the function $F^{-1}(F(x|\omega, \theta_2)|\omega, \theta_1)$ is nondecreasing in ω for all x.*

Example 1 Consider the case of location experiments with uniform noises. Let $\omega \in \mathbb{R}$ to be the state variable and the signal follows the distribution $X \sim U[\omega - \frac{1}{2\theta}, \omega + \frac{1}{2\theta}]$ with $\theta > 0$. Thus a higher θ indicates a more precise signal and thus should be more informative.

The CDF of the signal is

$$F(x|\omega, \theta) = \theta(x - \omega) + \frac{1}{2}$$

Thus

$$F^{-1}(F(x|\omega, \theta_2)|\omega, \theta_1) = \frac{\theta_2}{\theta_1}(x - \omega) + \omega = \frac{\theta_2}{\theta_1}x + (1 - \frac{\theta_2}{\theta_1})\omega$$

Clearly, this is nondecreasing in ω if and only if $\theta_2 \leq \theta_1$, which says the experiment with θ_1 is Lehmann more informative than θ_2, consistent with the intuition.

3.3 Model

The model considered here follows Gollier et al. (2000). Consider a two-period model where agent chooses consumption c_1 and c_2 of the two periods. Consumption in both periods induce pollution that accumulates through time with an uncertain damage at time-2 consumption. The damage intensity is given by a random variable x of which the decision maker learns the true value by observing an experiment y. Thus agent solves

$$\max_{c_1} u(c_1) + E_y \left(\max_{c_2} E_{x|y} v(c_2 - x(\delta c_1 + c_2)) \right)$$

where u and v are increasing and concave.

Let $C = \delta c_1 + c_2$ and $z = 1 - x$, then the problem becomes

$$\max_{c_1} u(c_1) + E_y \left(\max_{C} E_{z|y} v(-\delta c_1 + zC) \right)$$

We assume the signal y conditional on the state z is distributed as $F(y|z, \theta)$, which satisfies the MLR. This can be written explicitly as

$$\max_{c_1} u(c_1) + \int_y \left(\max_C \int_z v(-\delta c_1 + zC) dG(z|y, \theta) \right) dF(y, \theta)$$

where $G(z|y, \theta)$ is the posterior distribution of state variable z conditional on observing signal y with regime θ. $F(y, \theta)$ is the unconditional distribution of y with regime θ. Let $C(y, \theta)$ be the solution of the problem inside the parenthesis, namely,

$$C(y, \theta) = \arg\max_C \int_z v(-\delta c_1 + zC) dG(z|y, \theta)$$

Then the F.O.C. indicates

$$\int_z z v'(-\delta c_1 + zC) dG(z|y, \theta) = 0$$

The F.O.C. with respect to c_1 is

$$u'(c_1) = \delta \underbrace{\int_y \int_z v'(-\delta c_1 + zC(y,\theta)) dG(z|y,\theta) dF(y,\theta)}_{J(c_1,\theta)}$$

Suppose that θ characterises Lehmann informativeness, we want to see how $J(c_1,\theta)$ changes with respect to θ. This determines how c_1 changes with respect to θ: given that $u'(c_1)$ $(J(c_1,\theta))$ is decreasing (increasing) in c_1, if $\frac{dJ(c_1,\theta)}{d\theta} \geq 0$, an increase in θ decreasing first-period consumption.

Inspired by Persico (2000), we introduce the function $T(y|z,\theta,\eta) = F^{-1}(F(y|z,\eta)|z,\theta)$ where $\eta < \theta$. From the functional form, it is immediate that

$$y|z \sim F(y|z,\eta) \quad \Leftrightarrow \quad T(y|z,\theta,\eta)|z \sim F(y|z,\theta)$$

Given this relation, we can transform the variable y in $J(c_1,\theta)$. Specifically

$$\begin{aligned} J(c_1,\theta) &= \int_y \int_z v'(-\delta c_1 + zC(y,\theta)) dG(z|y,\theta) dF(y,\theta) \\ &= \int_z \int_y v'(-\delta c_1 + zC(y,\theta)) dF(y|z,\theta) dF(z) \\ &= \int_z \int_y v'(-\delta c_1 + zC(T(y|z,\theta,\eta),\theta)) dF(y|z,\eta) dF(z) \\ &= \int_y \int_z v'(-\delta c_1 + zC(T(y|z,\theta,\eta),\theta)) dG(z|y,\eta) dF(y,\eta) \end{aligned}$$

Thus,

$$\begin{aligned}
\left.\frac{dJ(c_1,\theta)}{d\theta}\right|_{\theta=\eta} &= \left.\int_y\int_z \frac{d}{d\theta}v'(-\delta c_1 + zC(T(y|z,\theta,\eta),\theta))dG(z|y,\eta)dF(y,\eta)\right|_{\theta=\eta} \\
&= \int_y\int_z zv''(-\delta c_1 + zC(y,\eta))\left.\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\right|_{\theta=\eta} dG(z|y,\eta)dF(y,\eta) \\
&= -\int_y\int_z zv'(-\delta c_1 + zC(y,\eta))\left[\gamma_A(-\delta c_1 + zC(y,\eta))\left.\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\right|_{\theta=\eta}\right] dG(z|y,\eta)dF(y,\eta)
\end{aligned}$$

where $\gamma_A = -\frac{v''}{v'}$ is the absolute risk aversion. Note that the following F.O.C. for C holds

$$\int_z zv'(-\delta c_1 + zC(y,\eta))dG(z|y,\eta) = 0$$

In addition, $zv'(-\delta c_1 + zC(y,\eta))$ is quasi-monotone on z (it crosses the horizontal axis only once). Thus we have the following proposition

Proposition 6. *If the function* $\gamma_A(-\delta c_1 + zC(y,\eta))\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\Big|_{\theta=\eta}$ *is nondecreasing (nonincreasing) in* z*, then* $J(c_1,\theta)$ *is nonincreasing (nondecreasing) in* θ*.*

Proof The proof follows Lemma 1 of Persico (2000).

Lemma 3.3.1. *(Persico, 2000) Let* (c,d) *be an interval of the real line,* $J(\cdot)$ *a nondecreasing function,* $H(\cdot)$ *a quasi-monotone function. Assume that for some measure* μ *on* $\mathcal{R}$ *that*

$$\int_c^d H(v)d\mu(v) = 0$$

Then

$$\int_c^d H(v)J(v)d\mu(v) \geq 0$$

Note that

$$\left.\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\right|_{\theta=\eta} = \left.\frac{\partial}{\partial\theta}C(y,\theta)\right|_{\theta=\eta} + \left.\frac{\partial}{\partial y}C(y,\theta)\frac{\partial}{\partial\theta}T(y|z,\theta,\eta)\right|_{\theta=\eta}$$

The above equations use the fact $T(y|z,\eta,\eta) = y$. In the above equation, only the term $\frac{\partial}{\partial\theta}T(y|z,\theta,\eta)\Big|_{\theta=\eta}$ is dependent on the state variable z. Moreover, it is increasing in z, To see this

$$\frac{\partial}{\partial\theta}T(y|z,\theta,\eta)\Bigg|_{\theta=\eta} = \lim_{\theta\to\eta}\frac{T(y|z,\theta,\eta)-y}{\theta-\eta}$$

Note that by definition, $\eta < \theta$, so the experiment with regime θ is more Lehmann informative than that with regime η. By definition, $T(y|z,\theta,\eta)$ is increasing in z. Thus $\frac{\partial}{\partial\theta}T(y|z,\theta,\eta)\Big|_{\theta=\eta}$ is also increasing in z. Since $v(-\delta c_1 + zC)$ satisfies a monotone decision problem and $F(y|z,\theta)$ satisfies the MLR, the optimal action is increasing in the signal realizations: $\frac{\partial}{\partial y}C(y,\theta) \geq 0$. As a result, $\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\Big|_{\theta=\eta}$ as a whole is increasing in z.

Question: We need to examine the monotonicity of the function

$$\gamma_A(-\delta c_1 + zC(y,\eta))\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)\Bigg|_{\theta=\eta}$$

1. When γ_A is constant (CARA): $J(c_1,\theta)$ is nonincreasing in θ, better Lehmann information structure leads to higher time-1 consumption

2. When γ_A is decreasing (DARA) and $\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)$ is positive: the effect is not clear because monotonicity of the multiplication between an positive increasing function and a positive decreasing one is not clear.

3. When γ_A is decreasing (DARA) and $\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)$ is negative: the multiplication is increasing. Better Lehmann information structure leads to higher time-1 consumption

4. When γ_A is increasing (IARA) and $\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)$ is positive: the multiplication is increasing. Better Lehmann information structure leads to higher time-1 consumption.

5. When γ_A is increasing (IARA) and $\frac{d}{d\theta}C(T(y|z,\theta,\eta),\theta)$ is negative: the effect is not clear because monotonicity of the multiplication between an positive increasing function and a negative increasing one is not clear.

3.4 Examples

Example 1. CARA utility and Normal signals Assume that the prior and conditional likelihood of the signal are normal, that utility is CARA. Specifically, $z \sim N(\mu, \sigma^2)$, $y|z \sim N\left(z, \frac{1}{\theta}\sigma_y^2\right)$ where $\theta > 0$ is the regime parameter, and $v(c) = -\exp(-\gamma c)$. An increase in θ makes the signal Lehmann more informative. To see this, first note that this family of signals satisfy monotone likelihod ratio (MLR) property, due to the logconcavity of normal distribution.[3] In addition, a signal $Y_1$with regime θ_1 is Blackwell more informative than a signal Y_2 with regime θ_2 if $\theta_1 \geq \theta_2$, since Y_2 can be garbled from Y_1 by adding a noise $\varepsilon \sim N\left(0, \left(\frac{1}{\theta_2} - \frac{1}{\theta_1}\right)\sigma_y^2\right)$. Under the condition that both experiments satisfy MLR property. Y_1 is Blackwell more informative than Y_2 implies that Y_1 is Lehmann more informative than Y_2.[4]

Note that the posterior is given by $z|y \sim N\left(\frac{\sigma^2 y + \frac{1}{\theta}\sigma_y^2\mu}{\sigma^2 + \frac{1}{\theta}\sigma_y^2}, \frac{\frac{1}{\theta}\sigma^2\sigma_y^2}{\sigma^2 + \frac{1}{\theta}\sigma_y^2}\right)$. The second period optimization problem is

$$\begin{aligned} & \max\nolimits_C \quad \int_z -\exp\left(-\gamma\left(-\delta c_1 + zC\right)\right) dG(z|y) \\ \Leftrightarrow\ & \max\nolimits_C \quad -\exp\left(\gamma\delta c_1 - \gamma C\mathrm{E}(z|y) + \frac{1}{2}\gamma^2 C^2 \mathrm{Var}(z|y)\right) \end{aligned}$$

The solution is

[3] For location experiements, the conditional distribution of signal is $F(y|z) = F(y-z)$. Thus MLR means $f(y+\epsilon-z)/f(y-z)$ is increasing in z, or the first-order derivative of $\log f$ is decreasing. This means the logconcavity of f.

[4] Y_1 is Blackwell more informative than Y_2 is equivalent to that Y_1 delivers greater expected utility than Y_2 for all decision problem. Y_1 is Lehmann more informative than Y_2 is equivalent to that Y_1 delivers greater expected utility than Y_2 for all monotone decision problem (under the assumption that $Y_1$and Y_2 are both MLR). Thus, the former implies the latter.

$$C^*(y) = \frac{\mathrm{E}(z|y)}{\gamma \mathrm{Var}(z|y)} = \frac{\theta\sigma^2 y + \sigma_y^2 \mu}{\gamma \sigma^2 \sigma_y^2}$$

Put it back to the expected utility, and note that the unconditional distribution of y is $N\left(0, \sigma^2 + \frac{1}{\theta}\sigma_y^2\right)$, the second period expected utility is

$$\begin{aligned}
& E_y\left(\max_C E_{z|y} v(-\delta c_1 + zC)\right) \\
= & \int_y -\exp\left(\gamma\delta c_1 - \frac{\left(\theta\sigma^2 y + \sigma_y^2\mu\right)^2}{2\sigma^2\sigma_y^2\left(\theta\sigma^2 + \sigma_y^2\right)}\right) \frac{1}{\sqrt{2\pi\left(\sigma^2 + \frac{1}{\theta}\sigma_y^2\right)}} \exp\left(-\frac{(y-\mu)^2}{2\left(\sigma^2 + \frac{1}{\theta}\sigma_y^2\right)}\right) dy \\
= & -\frac{\exp\left(\gamma\delta c_1\right)}{\sqrt{2\pi\left(\sigma^2 + \frac{1}{\theta}\sigma_y^2\right)}} \int_y \exp\left(-\frac{y^2}{2\sigma_y^2/\theta} - \frac{\mu^2}{2\sigma^2}\right) dy \\
= & -\exp\left(\gamma\delta c_1 - \frac{\mu^2}{2\sigma^2}\right)\sqrt{\frac{\sigma_y^2}{\theta\sigma^2 + \sigma_y^2}}
\end{aligned}$$

Thus the F.O.C. of time-1 consumption is

$$u'(c_1) = \gamma\delta \exp\left(\gamma\delta c_1 - \frac{\mu^2}{2\sigma^2}\right)\sqrt{\frac{\sigma_y^2}{\theta\sigma^2 + \sigma_y^2}}$$

Assuming concavity of first-period utility u (so u' is decreasing), and note that the right hand side is increasing in c_1. Thus there exists an unique solution of c_1. The right hand side is decreasing in θ, thus a increase in θ shifts down the upward-sloping curve and increase the optimal c_1. This is the first case discussed in point 1.

Example 2. HARA utility and binary signals with three states In this example, we aim to consider a case where two experiments are Lehmann ranked but not Blackwell ranked. The goal is to see how the conditions derived in Gollier et al. (2000) can be relaxed to fit the Lehmann informativeness order. We are considering simple examples with binary signals. As noted by Jewitt (2007) and Kim (2018), if the number of states is two, then Blackwell's notion is equivalent to that of Lehmann. Therefore we need at least three states to construct the example.

Now, suppose that the random variable z takes three values: $z_1 = -1$, $z_2 = 0$, $z_3 = 1$ with equiprobable prior $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$.[5] Suppose there are two experiments, P and Q, with binary signals and the following structure:

P :

	z_1	z_2	z_3
s_1	0.9	0.5	0.1
s_2	0.1	0.5	0.9

,

Q :

	z_1	z_2	z_3
s_1	0.8	0.5	0.3
s_2	0.2	0.5	0.7

Note that even though Q seems less "precise" than P, they are not Blackwell ordered. To see this, suppose there is a garbling matrix G that garbles P to Q, then $Q = G \cdot P$. Let $G = \begin{bmatrix} a & b \\ 1-a & 1-b \end{bmatrix}$, then we get the equations $0.9a + 0.1b = 0.8$, $0.5a + 0.5b = 0.5$, and $0.1a + 0.9b = 0.3$. Clearly there is no solution for a and b.[6]

However, it can be easily shown that P is Lehmann more informative than Q. According to the Proposition 1 of Jewitt (2007), Lehmann's information order is equivalent to Blackwell's order on dichotomies. That is, suppose both P and Q satisfy MLR, then P is Lehmann more informative than Q if and only if P is Blackwell more informative than Q for any two states $\{\omega_1, \omega_2\} \in \Omega$. Consider the previous three equations that pins down the garbling matrix. Each combination of two equations can be solved with $a, b \in (0, 1)$.

[5]Note that we need the support of z includes both positive and negative values so that the optimal value of C does not go to infinity.

[6]Given that P and Q are not Blackwell ordered, there exists a (non-monotone) decision problem that Q is preferred to P. For example, let the state-contingent payoffs of two action a_1, a_2 to be

	z_1	z_2	z_3
a_1	0	0	0
a_2	10	−19	10

Suppose the prior is $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$. Then, with experiment P, the DM will choose a_2 regardless of the signal realizations. Thus his ex ante expected utility is the expected utility under prior, $\frac{1}{3}$. With experiment Q, the DM will choose a_2 with signal s_1 and a_1 with signal s_2. The ex ante expected utility will be $\frac{1}{2} > \frac{1}{3}$. Thus he gets higher utility with a seemingly less precise experiment. This is because the signals in weaker experiment differentiate the probability of state 2, which separates agent's optimal actions.

Thus P is Blackwell more informative than Q on dichotomies, and therefore P is Lehmann more informative than Q.

Now, we want to check the conditions on preference that leads to precautionary principal under Lehmann's notion of informativeness. We consider the case where agent has Hyperbolic Absolute Risk Aversion (HARA) utility functions in the second period

$$v(C) = \frac{\gamma}{1-\gamma}\left[\eta + \frac{-\delta c_1 + zC}{\gamma}\right]^{1-\gamma}$$

where it is required that $\eta + \frac{-\delta c_1 + zC}{\gamma} > 0$. Note that the posteriors of the two experiments are

P :

	s_1	s_2
z_1	$\frac{9}{15}$	$\frac{1}{15}$
z_2	$\frac{5}{15}$	$\frac{5}{15}$
z_3	$\frac{1}{15}$	$\frac{9}{15}$

,

Q :

	s_1	s_2
z_1	$\frac{8}{16}$	$\frac{2}{14}$
z_2	$\frac{5}{16}$	$\frac{5}{14}$
z_3	$\frac{3}{16}$	$\frac{7}{14}$

First consider experiment P, the ex-post expected utility after observing signal $s_1$is

$$v(C|s_1) = \frac{1}{15}\frac{\gamma}{1-\gamma}\left\{9\left[\eta + \frac{-\delta c_1 - C}{\gamma}\right]^{1-\gamma} + 5\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{1-\gamma} + \left[\eta + \frac{-\delta c_1 + C}{\gamma}\right]^{1-\gamma}\right\}$$

The F.O.C. indicates that the optimal C is given by

$$C^*(s_1) = \frac{1 - 9^{\frac{1}{\gamma}}}{1 + 9^{\frac{1}{\gamma}}}(\eta\gamma - \delta c_1)$$

Thus the value function conditional on signal s_1 is

$$v(C^*|s_1) = \frac{1}{15}\frac{\gamma}{1-\gamma}\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{1-\gamma}\left\{9\left[\frac{2 \cdot 9^{\frac{1}{\gamma}}}{1 + 9^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 5 + \left[\frac{2}{1 + 9^{\frac{1}{\gamma}}}\right]^{1-\gamma}\right\}$$

Similarly, the value function conditional on signal s_2 is

$$v(C^*|s_1) = \frac{1}{15}\frac{\gamma}{1-\gamma}\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{1-\gamma}\left\{\left[\frac{2}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 5 + 9\left[\frac{2\cdot 9^{\frac{1}{\gamma}}}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma}\right\}$$

Since both signal have equal posterior probabilities. The ex-ante expected utility of experiment P is

$$v(C^*|P) = \frac{1}{30}\frac{\gamma}{1-\gamma}\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{1-\gamma}\left\{2\left[\frac{2}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 10 + 18\left[\frac{2\cdot 9^{\frac{1}{\gamma}}}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma}\right\}$$

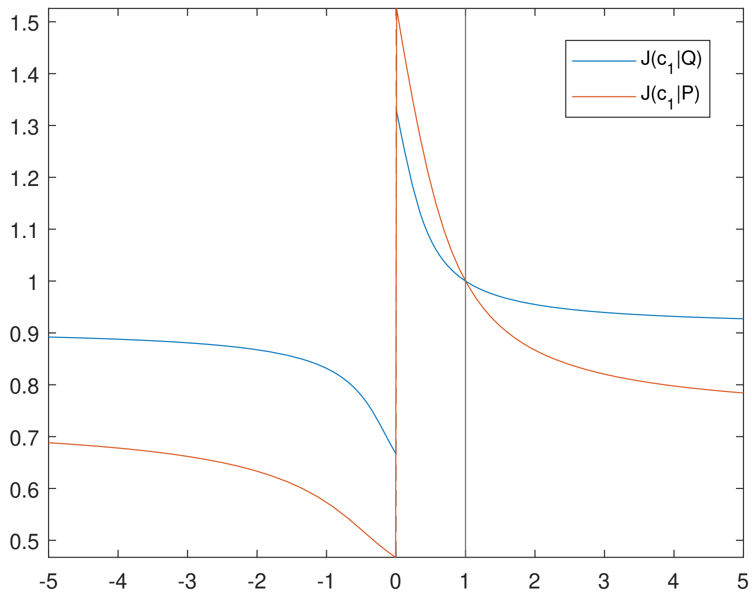
The function J is characterized by

$$J(c_1|P) = -\frac{\partial v(C^*|P)}{\partial c_1} = \frac{\delta}{30}\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{-\gamma}\left\{2\left[\frac{2}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 10 + 18\left[\frac{2\cdot 9^{\frac{1}{\gamma}}}{1+9^{\frac{1}{\gamma}}}\right]^{1-\gamma}\right\}$$

Following the same procedure, we can get the function J under experiment Q:

$$J(c_1|Q) = \frac{\delta}{30}\left[\eta + \frac{-\delta c_1}{\gamma}\right]^{-\gamma}\left\{8\left[\frac{2\left(\frac{8}{3}\right)^{\frac{1}{\gamma}}}{1+\left(\frac{8}{3}\right)^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 3\left[\frac{2}{1+\left(\frac{8}{3}\right)^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 2\left[\frac{2\left(\frac{2}{7}\right)^{\frac{1}{\gamma}}}{1+\left(\frac{2}{7}\right)^{\frac{1}{\gamma}}}\right]^{1-\gamma} + 7\left[\frac{2}{1+\left(\frac{2}{7}\right)^{\frac{1}{\gamma}}}\right]\right.$$

It remains to compare these two functions and see when $J(c_1|P) > J(c_1|Q)$, which leads to a lower optimal c_1 under the Lehmann more informative experiment P, i.e., the precautionary principal. To do this, we can focus on the terms in the curly bracket. The following figure plots the two functions when γ changes from -5 to 5.



Clearly, $J(c_1|P) > J(c_1|Q)$ if and only if $0 < \gamma < 1$. This is consistent with the result in Gollier et al. (2000). That is, a (Blackwell) better information structure in the future reduces efficient level of period-1 consumption if and only if $0 < \gamma < 1$ under HARA utility. Here we find that this also holds using Lehmann's informativeness order for this specific example.

3.5 Conclusion

The study on how optimal carbon mitigation action should respond to a better information about climate change in the future have received much attention in the literature. However, the traditional information criterion proposed by Blackwell et al. (1951) is usually restricted, making many information structures incomparable with each other. As such, this proposal aim to extend the previous work on the precautionary principal (Gollier et al., 2000) by using a more generalized information criterion from Lehmann (1988). Further study to get a more clear condition on the precautionary principal using Lehmann's information criterion is promising, since it could help policymaker better decide the timing of climate mitigation when facing decreased future uncertainty.

References

Blackwell, David, 1953, Equivalent comparisons of experiments, *The annals of mathematical statistics* 265–272.

Blackwell, David, et al., 1951, Comparison of experiments, in *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability*, The Regents of the University of California.

Bond, Philip, 2019, Ordering information content using the quantile function, Working paper.

Cabrales, Antonio, Olivier Gossner, and Roberto Serrano, 2013, Entropy and the value of information for investors, *American Economic Review* 103, 360–77.

Gollier, Christian, Bruno Jullien, and Nicolas Treich, 2000, Scientific progress and irreversibility: an economic interpretation of the 'precautionary principle', *Journal of Public Economics* 75, 229–253.

Jewitt, Ian, 2007, Information order in decision and agency problems, *Nuffield College* .

Karlin, Samuel, and Herman Rubin, 1956, The theory of decision procedures for distributions with monotone likelihood ratio, *The Annals of Mathematical Statistics* 272–299.

Kim, Yonggyun, 2018, Extending blackwell and lehmann: The monotone quasi-garbling order, *Economic Research Initiatives at Duke (ERID) Working Paper* .

Lehmann, E.L., 1988, Comparing location experiments, *Annals of statistics* 16, 521–533.

Persico, Nicola, 2000, Information acquisition in auctions, *Econometrica* 68, 135–148.

Quah, John K-H, and Bruno Strulovici, 2009, Comparative statics, informativeness, and the interval dominance order, *Econometrica* 77, 1949–1992.

Tillio, Alfredo Di, Marco Ottaviani, and Peter Norman Sørensen, 2021, Strategic sample selection, *Econometrica* 89, 911–953.