Explaining Greenium in a Macro-Finance Integrated Assessment Model

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Climate Change is Accelerating

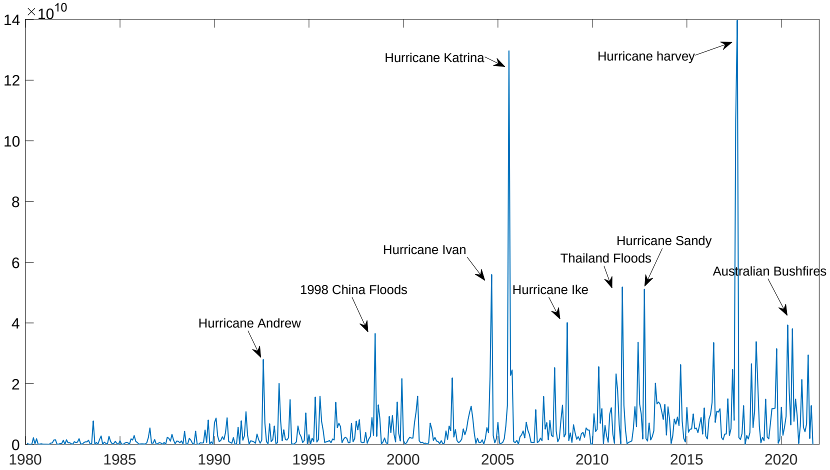

Figure 1: Global economic losses (in USD) due to climate disasters (Source: The International Disaster Database)

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- **Theoretically:** improves traditional climate economics models to explain asset prices

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3. A disaster shock increases (decreases) capital investment of green (brown) firms
   - green firms enjoy investment compensation due to climate disasters

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   - Climate feedback + investment friction: heterogeneous disaster exposures of green and brown stocks $\Rightarrow$ **greenium**
   - Model quantitatively matches IRFs of prices & investments to a disaster $\Leftarrow$ **New in this paper**

Literature

Climate risk in financial markets

- Chava (2014), Görgen et al. (2019), In et al. (2017), Bolton and Kacperczyk (2020, 2021), Hsu et al. (2020), Bansal et al. (2016a,b), Engel et al. (2020), Choi et al. (2020), Pastor et al. (2019), Barnett et al. (2020), Barnett (2017), Giglio et al. (2020), etc.

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IAM and Production-based AP

- **IAM:** Nordhaus (1992, 2013, 2014), Bosetti et al. (2006), Popp (2006), Golosov et al. (2014), Acemoglu et al. (2012), Daniel et al. (2016), Lemoine and Rudik (2017), etc.
- **Production-based AP:** Cochrane (1991), Jermann (1998), Croce (2014), Kaltenbrunner and Lochstoer (2010), Papanikolaou (2011), Kung and Schmid (2015), etc

This paper: bridges and improves the two approaches $\Rightarrow$ AP in IAM and climate risk in macrofinance

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- Disaster Index: a first handy climate disaster risk measure
  - Monthly aggregated economic loss (in USD) due to climate-related disasters
    - 5892 Disasters: Hurricane (1922), Wildfire (197), Flood (3114), Extreme temperature (371), Drought (286), Glacial lake outburst (2)
  - **Source**: The International Disaster Dataset

QUANTIFYING GREENIUM: FACTOR REGRESSION

CUMULATIVE RETURNS

I regress monthly value-weighted return of Brown-minus-Green (BMG) portfolio on **global** AP factors

$$R^{ex}_{BMG,t} = \alpha + \beta \cdot F_t + \epsilon_t$$

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Table 1: Abnormal return of Brown-minus-Green portfolio

Factors	Constant	CAPM	FF3	FF5	FF5&MOM
BMG α (%)	3.83***	2.43**	2.17**	3.91***	3.98***
s.e. (%)	(1.39)	(1.18)	(0.98)	(1.22)	(1.25)

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- green portfolio delivers 3.83% lower average return

Quantifying Greenium: Factor Regression

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- greenium remains significant after controlling for other risk factors

QUANTIFYING GREENIUM: ALTERNATIVE TESTS

- Double sorting See
- Fama-Macbeth regression See
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- Subcategories of ENSCORE See
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Quantifying Greenium: Alternative Tests

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Takeaway: greenium is significantly negative across different specifications

HEDGING DISASTERS: STOCK RETURNS

- Frequency: Monthly
- **Specification 1**

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

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- $AR_{i,t}$ is risk-adjusted stock return (in percentage)
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- **Specification 2**

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

  where $Quintile_{i,t}$ is a set of dummies indicating which quintile of ENSCORE that firm i is in (5=Green, 1=Brown)

Hedging Disasters: Stock returns

Table 2: Abnormal stock return and disaster shock

	(1)	(2)
$logdamage$	-0.282***	-0.285***
	(0.012)	(0.012)
$ENSCORE \times logdamage$	0.0380***	
	(0.006)	
Quintile 2		0.0239***
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Firm FE	Yes	Yes
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Obs.	384,224	381,554
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- Robustness tests:
  1. Event study on Hurricane Katrina, U.S. Drought & Wildfires
  2. Controlling for geographic characteristics
  3. Excluding financial crisis
  4. Placebo tests using earthquake

Hedging Disasters: Investments

- Frequency: Quarterly
- **Specification 1**

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  ↪ investment flows from brown to green firms
- Robustness tests:
  1. Event study
  2. Alternative measures of investment

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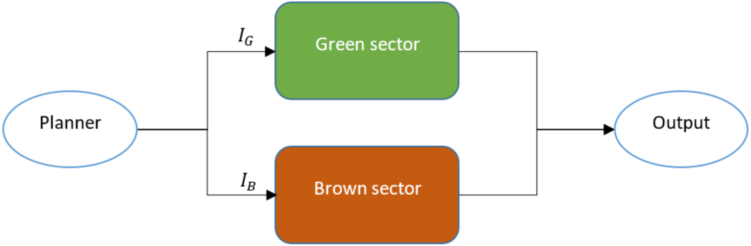

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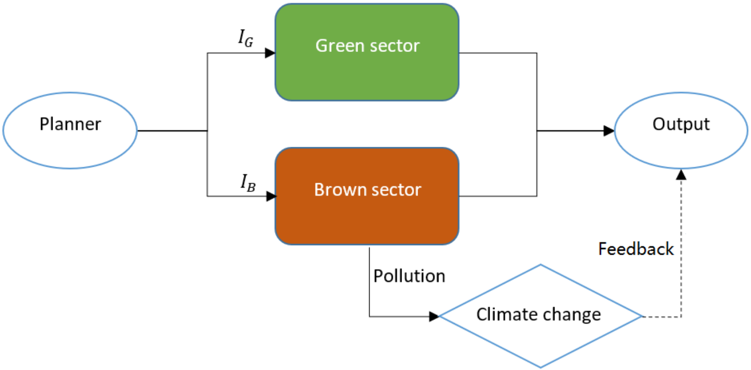
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I_B
Green sector
Brown sector
Output
Pollution
Climate change
Feedback

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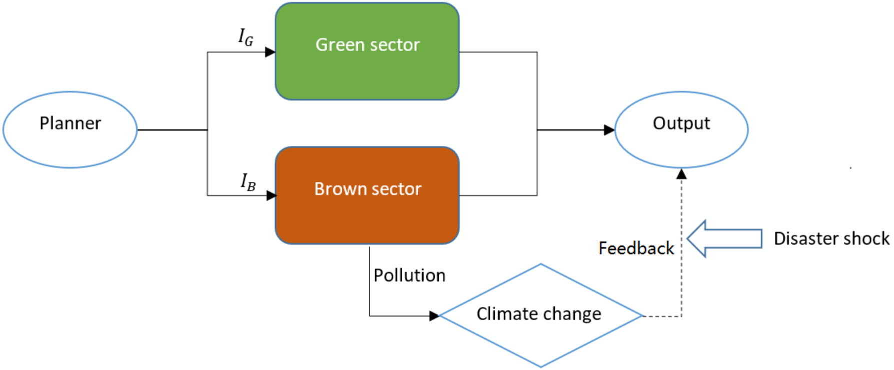
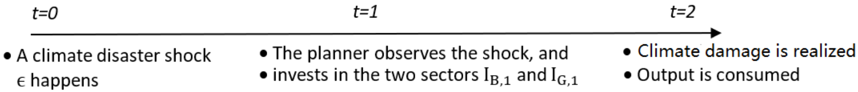


An exogenous disaster shock increases belief on climate feedback ⇒ lower brown investment and higher green investment

MODEL SETUP

- Timeline



Model Setup

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t=0	t=1	t=2
• A climate disaster shock ϵ happens	• The planner observes the shock, and • invests in the two sectors $I_{B,1}$ and $I_{G,1}$	• Climate damage is realized • Output is consumed

- Production function & climate damage

$$Y_2 = \left(1 - \underbrace{D(I_{B,1}, \epsilon)}_{\text{climate damage}}\right) \cdot \underbrace{f\left(I_{G,1}, I_{B,1}\right)}_{\text{Pre-damage output}}$$

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- Preferences

$$U_1 = W(C_1, E_1[U_2])$$

DISASTER SHOCK INCREASES GREEN INVESTMENT AND THE SDF

Proposition 1

Optimal investment in the green (brown) sector increases (decreases) with the disaster shock ϵ, i.e., $\frac{\partial I_{G,1}}{\partial \epsilon} > 0 \left(\frac{\partial I_{B,1}}{\partial \epsilon} < 0\right)$.

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Takeaway: A positive disaster shock leads to bad economic state: an **adverse** shock with **negative** price of risk.

Green Stock Hedges Disaster

Details

Proposition 3

With a convex investment friction (standard q-theory), green (brown) stock appreciates (depreciates) after a positive disaster shock, i.e.,

$$r_{i,1} = E_0[r_{i,1}] + \beta_i \epsilon, \quad \forall i \in \{B, G\}$$

where $\beta_G > 0$ *and* $\beta_B < 0$.

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Empirical Analysis

A Two-Period Model

Macro-Finance IAM

Conclusion

Preference

- Recursive preference (Epstein and Zin, 1989)

$$W(C,U') = \left\{ (1-\beta)C^{1-\frac{1}{\psi}} + \beta \left(E\left[U'(\mathcal{S}')^{1-\gamma} \middle| \mathcal{S} \right] \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}}$$

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- Standard setting: $\gamma > \frac{1}{\psi}$ i.e., agent prefers early resolution of uncertainty $\Rightarrow$ high price of risk on news shock

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- CES aggregation between green & brown outputs (Acemoglu et al., 2012)

$$Y = \left(\omega Y_B^{\frac{\varepsilon-1}{\varepsilon}} + (1-\omega) Y_G^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

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- Capital accumulation with **convex investment friction** (Jermann, 1998)

$$K_i' = (1-\delta_K) K_i + I_i - K_i G\left(I_i / K_i\right) \quad i \in \{B, G\}$$

Climate Feedback

- Climate feedback on the level of output (Golosov et al., 2014)

$$\tilde{Y} = \left[1 - e^{-\lambda(M - \bar{M})}\right] \cdot Y$$

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  - λ is the damage intensity $\Leftarrow$ key risk factor for greenium
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- Shocks in the model $\epsilon_a, \epsilon_x, \epsilon_\lambda \sim N(0, \Sigma)$

Model Solving and Calibration

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- Calibration (i) follows literature, (ii) uses regressions and GMM

  Calibration | Sensitivity analysis | In-sample simulation
- Quantitative performance?

Matching Moments in the data

Table 4: Data and model simulation

	Data		Model	
	Estimate	SE	Macrofin IAM	Traditional IAM
Panel A. Economic quantities				
$\sigma(\Delta y)$ (%)	2.43	(0.31)	2.42	
$\sigma(\Delta c)$ (%)	2.05	(0.25)	2.77	
$\sigma(\Delta i_B)$ (%)	3.32	(0.51)	2.98	
$\sigma(\Delta i_G)$ (%)	6.52	(0.80)	6.40	
Panel B. Climate quantities				
$\sigma(\Delta T)$ ($^{\circ}C$)	0.12	(0.01)	0.13	
$\sigma(\Delta M)$ (ppm)	0.65	(0.06)	0.53	
$\sigma(\Delta E)$ (ppm)	0.06	(0.01)	0.07	
Panel C. Asset prices				
$E(R_B - R_G)$ (%)	3.83	(1.54)	3.22	
$E(R^{ex}_{MKT})$ (%)	6.68	(1.90)	6.43	
$E(r_f)$ (%)	0.85	(0.51)	0.79	

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$E(R^{ex}_{MKT})$ (%)	6.68	(1.90)	6.43	-0.72
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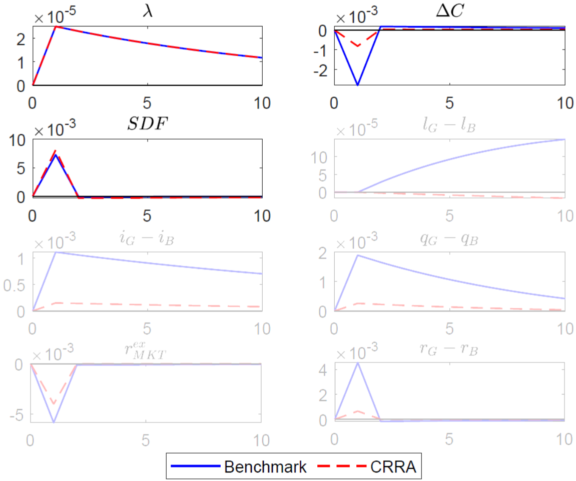
Takeaway: Macro-finance IAM is important – captures both **quantities** and **asset prices**

Impulse Response Functions to a Disaster Shock



After a disaster shock:

- SDF increase $\Rightarrow$ an adverse shock

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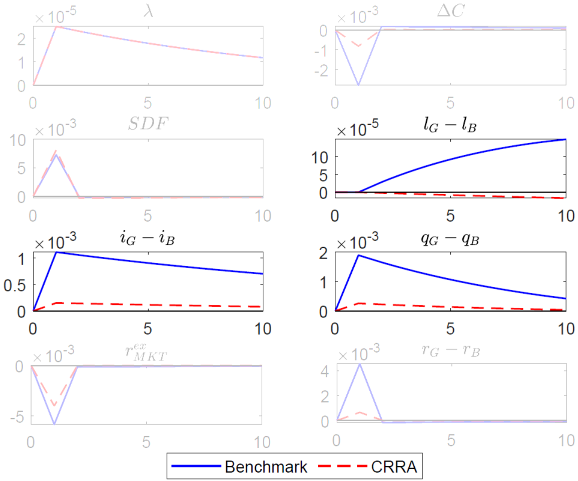

After a disaster shock:

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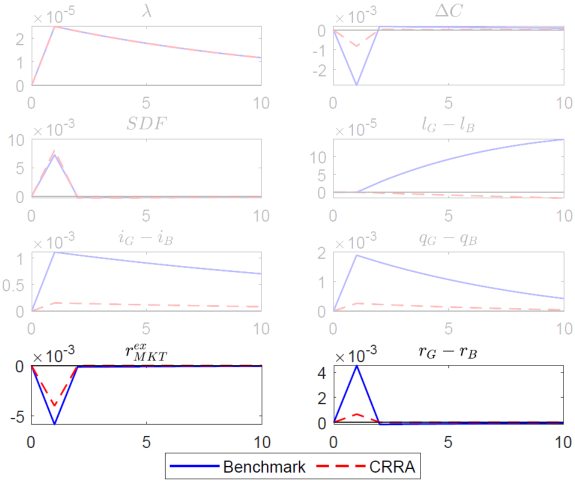

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  $\Rightarrow$ negative greenium

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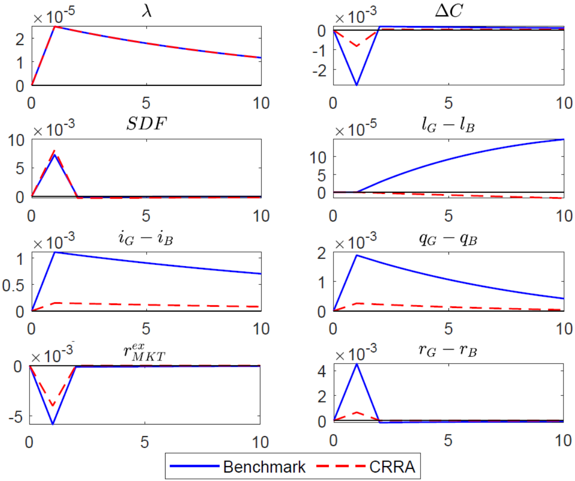

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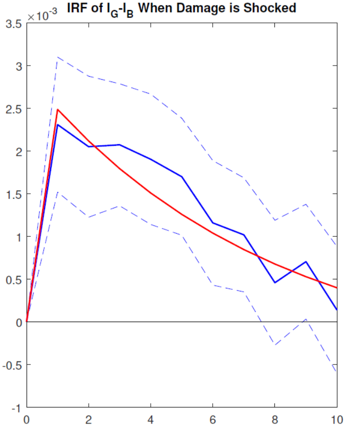
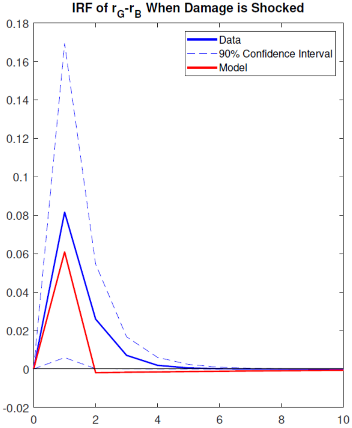
Impulse Response Functions: Model vs. Data





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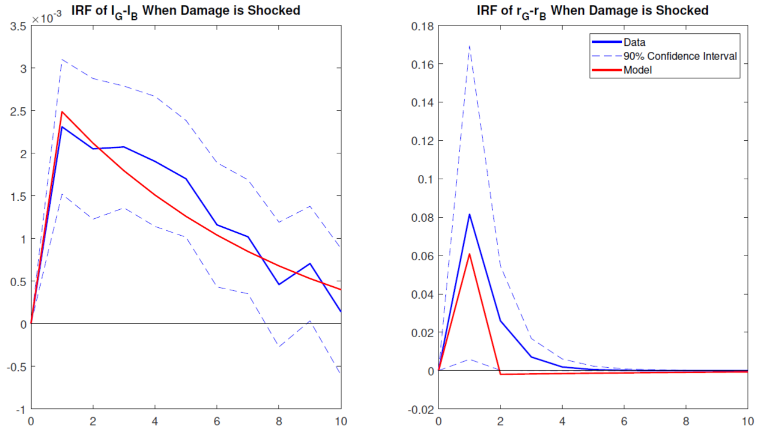

Model matches IRFs in the data: **Novel in the literature**

Policy Implication: Social Cost of Carbon

- SCC corresponds to the *shadow price of carbon*, Q_M, which follows the AP rule

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- High risk premium ($r_{Q_M} - r_f$) drives down the present value (55.6 $\rightarrow$ 40.4)

	SCC	r_{Q_M}	r_f
Benchmark	40.38	4.71%	0.83%
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Takeaway: SCC is **40.4 USD per tonne of Carbon**: a new lower bound in literature

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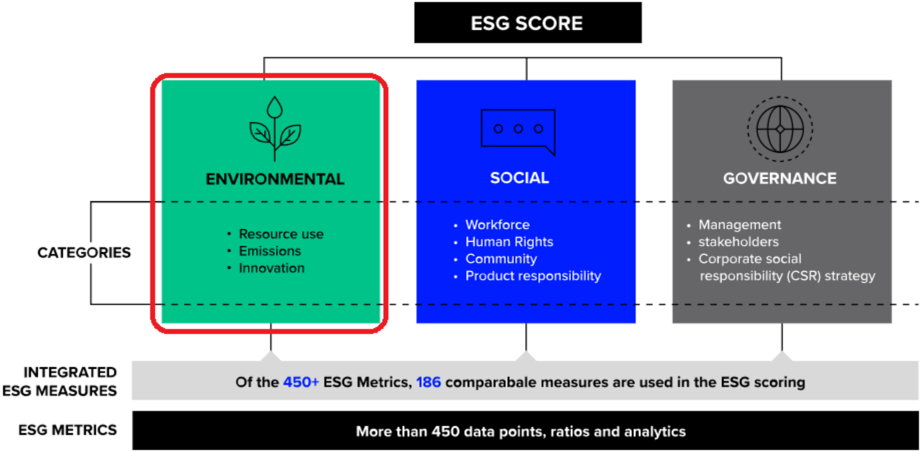
What we learn:

- Marginal climate damage commands high discount rate, and carbon price is low

Asset4 ESG Score

BACK



Summary Statistics

BACK

Table 5: Portfolio summary statistics (annual average)

Portfolios	Brown	Green	BMG
ENSCORE ($0 \sim 100$)	0.13	68.99	-68.86*
Observations	475	482	-7
Panel A. Financial characteristics			
Market Value (billion $)	6.23	26.53	-20.3*
Book/Market (%)	53.77	60.41	-6.64
Investment/Asset (%)	4.44	1.90	2.54*
Revenue/Asset (%)	84.36	87.60	-3.24
R&D/Asset (%)	6.07	3.12	2.95*
Tangibility (%)	27.09	31.45	-4.36*
Leverage (%)	38.35	40.68	-2.33*
Panel B. Geographic characteristics			
Latitude	34.25	39.98	-5.73*
Dist2Sea (km)	152.98	120.87	32.11*
PDSI[1]	-0.89	-1.57	0.68*

[1]: Palmer Drought Severity Index (Palmer, 1965)

*: significant at 5%

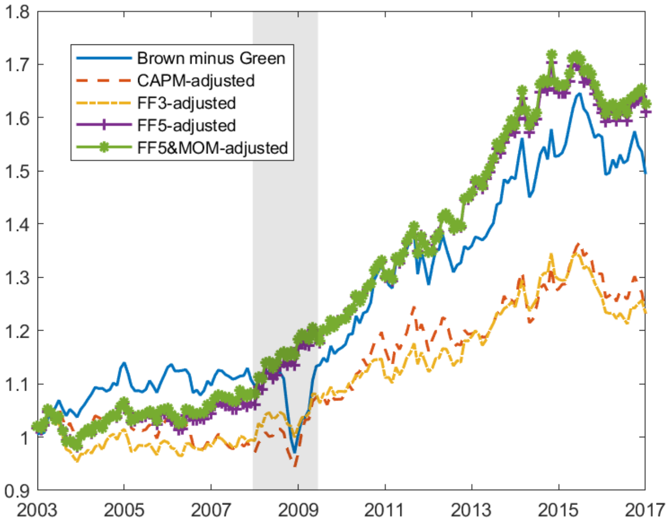
Industries with highest weights in the H and L portfolios

BACK

High ENSCORE portfolio		Low ENSCORE portfolio	
Industries	**FF49 code**	**Industries**	**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

Evidence of Greenium: risk-adjusted abnormal return

BACK



EVIDENCE OF GREENIUM: DOUBLE SORTING (1/2)

BACK

1. In each year, I first divide firms into two groups according to one characteristics of previous year relative to industry peers
2. Then within each group, I further divide firms into five portfolios according to their ENSCORE

	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)

Evidence of Greenium: Double sorting (2/2)

BACK

	L	2	3	4	H	L - H	L	2	3	4	H	L - H
	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)

Evidence of Greenium: Fama-Macbeth regression

BACK

$$R_{i,t} = \beta_0 + \beta_1 ENSCORE_{i,t-12} + \beta_2 X_{i,t-12} + \epsilon_{i,t}$$

	(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

Evidence of Greenium: Price of risk (1/2)

BACK

1. I construct a $Brown\,Minus\,Green$ factor using the excess return of a low-minus-high portfolio on ENSCORE
2. I identify price of risk using a two-pass regression

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

where

- R_t^p is the return of a testing portfolio from Kenneth French's data library
- F_t is the FF5 factors

A positive λ_{BMG} means that the greenium exists in a wide cross-section of testing portfolios

Evidence of Greenium: Price of risk (2/2)

BACK

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)

EVIDENCE OF GREENIUM: SUBCATEGORY OF ENSCORE (1/3)

BACK

	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)

Evidence of Greenium: Subcategory of ENSCORE (2/3)

BACK

	L	2	3	4	H	L - H
			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)

EVIDENCE OF GREENIUM: SUBCATEGORY OF ENSCORE (3/3)

BACK

	L	2	3	4	H	L - H
			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)

EVIDENCE OF GREENIUM: U.S. SAMPLE

BACK

	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)

EVIDENCE OF GREENIUM: SUBSAMPLE

BACK

	$E[R^{ex}]$	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)

EVIDENCE OF GREENIUM: SUBSAMPLE (FIXING FIRMS)

BACK

	$E[R^{ex}]$	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)

EVIDENCE OF GREENIUM: CARBON EMISSION INTENSITY

BACK

	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)

Evidence of Greenium: MSCI ENSCORE

BACK

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

EVIDENCE OF GREENIUM: ANNUAL CHANGE OF ENSCORE

BACK

	L	2	3	4	H	L - H
Δ ENSCORE	-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)

Event study on returns

	$R_{i,t\to t+M} = \alpha + \beta \cdot Brown_i + \gamma X_{i,t} + \epsilon_{i,t}$				
M	1m	2m	3m	6m	12m
	Panel A. Hurricane Katrina (obs.=721)				
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
	Panel B. 2012 US drought (obs.=844)				
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
	Panel C. 2018 California wildfires (obs.=1475)				
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

Event study on investment

BACK

$$\Delta I/A_{i,t} = \alpha + \beta \cdot Brown_i + \gamma X_{i,t} + \epsilon_i$$

	$I \equiv \Delta$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

Derivation of the stock returns

BACK

Capital accumulation under investment friction

$$K_{i,2} = G(I_{i,1}, K_{i,1}) = I_{i,1}^{\xi} K_{i,1}^{1-\xi}, \quad \forall i \in \{B, G\}$$

where $0 < \xi < 1$

Returns are related to investments (Cochrane 1991)

$$R_{i,1} = \frac{\overbrace{Q_{i,1} G'_{K_{i,1}}}^{\text{capital gain}} + \overbrace{MPK_1}^{\text{dividend}}}{Q_{i,0}} = \frac{1}{Q_{i,0}} \left(\frac{\xi}{1-\xi} \frac{I_{i,1}}{K_{i,1}} + \alpha \frac{Y_1}{K_{i,0}} \right), \quad \forall i \in \{B, G\}$$

where $G'_{K_{i,1}} = \frac{\partial G}{\partial K_{i,1}}$, and $Q_{i,1} = \frac{1}{G'_{I_{i,1}}}$ is Tobin's Q of sector i.

Sensitivity analysis

BACK

Table 6: 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				
r_{SCC}	4.71%	6.56%	15.91%				
Risk-free rate	0.83%	4.67%	17.37%				
Climate damage	0.51%	0.41%	0.18%				
Temperature	0.95	0.80	0.36				
I_G/I_{total}	62.80%	59.84%	55.49%				
l_G	61.38%	59.11%	55.32%				
$R\&D/Y$	0.89%	0.53%	0.20%				

Takeaway

- Subjective discount rate & IES are essential to quantify the SCC

Sensitivity analysis

BACK

Table 6: 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			40.65	39.44	40.34	40.43
r_{SCC}	4.71%			4.69%	4.80%	4.72%	4.71%
Risk-free rate	0.83%			0.78%	0.94%	0.75%	0.95%
Climate damage	0.51%			0.70%	0.03%	0.55%	0.45%
Temperature	0.95			1.24	0.07	1.01	0.86
I_G/I_{total}	62.80%			45.17%	98.36%	48.64%	76.81%
l_G	61.38%			44.47%	98.09%	47.58%	75.29%
$R\&D/Y$	0.89%			0.65%	1.36%	0.47%	1.46%

Takeaway

- Subjective discount rate & IES are essential to quantify the SCC
- Substitution & R&D efficiency matter for equilibrium allocation btw. green/brown investments

CALIBRATION

BACK

Table 7: Calibration

Literature		Regression		GMM	
μ	1.8%	ρ_M	0.98	ρ_λ	0.92
σ	3.35%	ρ_T	0.17	σ_λ	2.5×10^{-5}
ρ_x	0.96	σ_M	0.45	ξ	1.71
φ_x	0.2	σ_T	0.092	ν	0.074
ω	0.59	χ	3.088	η	0.67
ε	3			b	7.99
δ_K	0.06			ζ	1.64
α	0.34				
β	0.974				
γ	10				
ψ	2				
$\bar{\lambda}$	5.05×10^{-5}				
k	4				
δ_H	0.1				

Calibration

BACK