FINM 35000: Topics in Economics

Week 3: Climate Risk

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Logistics

- I will post homework 2 tomorrow
- Remember that you can let us know if you would like to switch groups (email Lisheng)
- Reminder that TA session is on Sunday at 5pm (email at least 24 hours in advance)
- Reminder that if you have feedback about the course, you can submit it here at any time: https://forms.gle/vcASo5yRXuadFRTH7
- I will post instructions for the final project before next lecture

Regulation (continued)

Avramov et al. (2022): Overview

- Last week we talked about disclosure and labeling regulations. Why are such regulations important?
  - One answer: how can investors choose to consider ESG when there is no standard definition of what it means to be "green"
- This paper: analyzes the implications of ESG rating uncertainty for equity markets
- Measures ESG rating uncertainty as the standard deviation of ESG ratings from six major providers

Avramov et al. (2022): Model

- Portfolio weights with and without ESG uncertainty:

$$X_i = \frac{1}{a_i}\left(\Sigma_r + \frac{d_i^2}{a_i^2}\Sigma_g + 2\frac{d_i}{a_i}\Sigma_{rg}\right)^{-1}\left(\mu_r + \frac{d_i\mu_g}{a_i}\right)$$

- Expected returns without ESG uncertainty:

$$\underbrace{\mu_r = \beta_m\mu_m}_{\text{CAPM}} - \underbrace{\frac{\overline{d}}{a}g}_{\text{ESG Adjustment}}$$

- With ESG uncertainty, the primary difference is that β_m is replaced by a weighted average of:
  1. β_m (CAPM beta)
  2. ESG beta: covariance between the greenness of an asset and the greenness of the market portfolio
  3. ESG-return cross-covariance beta: contribution of an asset to the aggregate covariance between returns and greenness

Avramov et al. (2022): Hypotheses

1. Investor demand for risky assets increases with the ESG score and decreases with ESG rating uncertainty
2. Negative relation between the ESG rating and CAPM alpha when there is no uncertainty in ESG ratings
3. Positive relation between ESG uncertainty and CAPM alpha

Avramov et al. (2022): Results I

Table 1

Institutional ownership of portfolios sorted by ESG rating and uncertainty.

At the end of year t, stocks are independently sorted into quintiles according to their ESG ratings and ESG rating uncertainty to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and ESG-rating-uncertainty portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and ESG rating uncertainty, respectively. For each of the 25 portfolios, we compute the average institutional ownership in each quarter in year $t+1$ and rebalance the portfolios at the end of year $t+1$. Panel A reports the time-series averages of quarterly institutional ownership of norm-constrained institutions for each of the 25 portfolios and the average difference in institutional ownership between high- and low-ESG-rating portfolios ("HML-R"), as well as between high- and low-ESG-rating-uncertainty portfolios ("HML-U"). Panels B and C report similar statistics for average ownership of hedge funds and other institutions, respectively. The Online Appendix provides a detailed definition for each variable. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Norm-constrained institutions

ESG rating	ESG uncertainty							
	Low	2	3	4	High	HML-U	t-stat	All
Low	0.170	0.183	0.187	0.178	0.179	0.009	(0.80)	0.177
2	0.185	0.192	0.207	0.209	0.184	−0.001	(−0.23)	0.195
3	0.189	0.215	0.210	0.212	0.191	0.002	(0.40)	0.200
4	0.211	0.211	0.211	0.215	0.211	0.000	(0.04)	0.211
High	0.228	0.236	0.238	0.225	0.181	−0.047***	(−2.73)	0.230
HML-R	0.058***	0.053***	0.050***	0.047***	0.002			0.053***
	(10.21)	(12.00)	(8.33)	(8.51)	(0.08)			(11.39)

Panel B: Hedge funds

ESG rating	ESG uncertainty							
	Low	2	3	4	High	HML-U	t-stat	All
Low	0.157	0.157	0.160	0.156	0.130	−0.027***	(−3.70)	0.157
2	0.143	0.147	0.155	0.153	0.149	0.006	(1.31)	0.149
3	0.153	0.144	0.144	0.149	0.153	−0.000	(−0.08)	0.150
4	0.148	0.144	0.140	0.142	0.141	−0.006*	(−1.96)	0.142
High	0.127	0.124	0.128	0.128	0.119	−0.008	(−1.33)	0.127
HML-R	−0.031***	−0.033***	−0.032***	−0.029***	−0.011			−0.030***
	(−6.14)	(−8.15)	(−6.30)	(−5.57)	(−1.25)			(−8.06)

Panel C: Other institutions

ESG rating	ESG uncertainty							
	Low	2	3	4	High	HML-U	t-stat	All
Low	0.347	0.367	0.357	0.363	0.317	−0.030**	(−2.57)	0.356
2	0.343	0.374	0.387	0.390	0.354	0.010	(1.43)	0.370
3	0.370	0.373	0.371	0.384	0.360	−0.011	(−1.66)	0.368
4	0.382	0.375	0.378	0.369	0.360	−0.022***	(−3.25)	0.370
High	0.363	0.368	0.363	0.357	0.328	−0.035	(−1.63)	0.363
HML-R	0.016	0.001	0.006	−0.005	0.011			0.007
	(1.28)	(0.13)	(0.59)	(−0.37)	(0.35)			(0.71)

Avramov et al. (2022): Results II

Table 2

Performance of portfolios sorted by ESG rating and uncertainty.

At the end of year t, stocks are first sorted into quintiles according to their ESG rating uncertainty. Within each ESG rating uncertainty group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and ESG-rating-uncertainty portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and ESG rating uncertainty, respectively. For each of the 25 portfolios, we compute the value-weighted return in each month in year $t+1$ and rebalance the portfolios at the end of year $t+1$. Panel A reports the time-series averages of monthly returns for each of the 25 portfolios, as well as for the investment strategy of going long (short) the low- (high)-ESG-rating stocks ("LMH-R"). The column "All" reports similar statistics for portfolios sorted by ESG ratings only. The row "All" reports returns for portfolios sorted by ESG uncertainty only, as well as the investment strategy of going long (short) the high (low) ESG-uncertainty stocks ("HML-U"). In Panel B, portfolio returns are further adjusted by the CAPM. The Online Appendix provides a detailed definition for each variable. Newey-West adjusted t-statistics are shown in parentheses. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

	Panel A: Return						Panel B: CAPM-adjusted return					
ESG rating	ESG uncertainty						ESG uncertainty					
	Low	2	3	4	High	All	Low	2	3	4	High	All
Low	1.235***	1.113***	0.767**	0.875**	0.760**	0.923**	0.168	0.064	−0.311*	−0.141	−0.101	−0.101
	(2.95)	(2.99)	(1.98)	(2.30)	(2.32)	(2.58)	(0.93)	(0.40)	(−1.82)	(−0.89)	(−0.58)	(−0.84)
2	1.245***	1.026***	1.093***	1.043***	1.095***	0.963***	0.187	0.076	0.115	0.042	0.151	−0.008
	(3.36)	(2.84)	(3.30)	(2.74)	(2.91)	(2.85)	(1.16)	(0.38)	(0.77)	(0.29)	(0.77)	(−0.07)
3	1.096***	0.965***	1.050***	1.104***	0.949***	1.021***	0.040	−0.031	0.002	0.064	0.079	0.053
	(2.69)	(2.83)	(2.86)	(2.89)	(3.15)	(3.11)	(0.23)	(−0.20)	(0.02)	(0.46)	(0.42)	(0.64)
4	0.730**	0.695*	1.105***	1.019***	0.990***	1.017***	−0.192	−0.389***	0.108	0.040	0.006	0.095
	(2.09)	(1.81)	(2.90)	(2.96)	(2.68)	(3.42)	(−1.24)	(−3.28)	(0.55)	(0.34)	(0.03)	(1.32)
High	0.642*	0.842**	0.855***	1.184***	0.854***	0.805**	−0.230*	−0.063	−0.012	0.245*	−0.001	−0.095
	(1.97)	(2.53)	(3.06)	(3.62)	(2.81)	(2.57)	(−1.95)	(−0.55)	(−0.10)	(1.83)	(−0.01)	(−1.49)
LMH-R	0.594***	0.271	−0.088	−0.309	−0.094	0.118	0.398*	0.128	−0.299	−0.387*	−0.100	−0.006
	(2.72)	(1.30)	(−0.39)	(−1.43)	(−0.42)	(0.78)	(1.86)	(0.58)	(−1.25)	(−1.75)	(−0.42)	(−0.04)
ESG rating	ESG uncertainty						ESG uncertainty					
	Low	2	3	4	High	HML-U	Low	2	3	4	High	HML-U
All	0.753**	0.875***	0.935***	1.083***	0.940***	0.187	−0.155**	−0.090	−0.003	0.120*	0.071	0.226*
	(2.31)	(2.61)	(3.07)	(3.28)	(3.29)	(1.40)	(−1.98)	(−1.20)	(−0.04)	(1.72)	(0.84)	(1.67)

Avramov et al. (2022): Results III

Table 3
ESG rating, uncertainty, and stock returns.
This table presents the results of the following monthly Fama-MacBeth regressions, as well as their corresponding Newey-West adjusted t-statistics:

$$Perf_{i,m} = \alpha_0 + \beta_1 ESG_{i,m-1} + \beta_2 ESG_{i,m-1} \times Low\ ESG\ Uncertainty_{i,m-1} + \beta_3 Low\ ESG\ Uncertainty_{i,m-1} + \boldsymbol{\beta}_4' \boldsymbol{M}_{i,m-1} + e_{i,m},$$

where $Perf_{i,m}$ refers to the excess return (models 1 to 4) or CAPM-adjusted return (models 5 to 8) of stock i in month m, $ESG_{i,m-1}$ refers to the ESG rating. $Low\ ESG\ Uncertainty_{i,m-1}$ refers to a dummy variable that takes a value of one if the ESG rating uncertainty is in the bottom quintile across all stocks in that month and zero otherwise. The vector $\boldsymbol{M}$ stacks all other control variables, including the Log(Size), Log(BM), 6M Momentum, Log(Illiquidity), Gross Profitability, Corporate Investment, Leverage, Log(Analyst Coverage) and Analyst Dispersion. The Online Appendix provides a detailed definition for each variable. Numbers with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

Stock returns regressed on lagged ESG rating and uncertainty

	Excess return				CAPM-adjusted return			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ESG	0.002	0.098	0.062	0.199	0.042	0.139	0.162	0.301
	(0.01)	(0.65)	(0.33)	(1.03)	(0.23)	(0.91)	(0.77)	(1.65)
ESG × Low ESG Uncertainty			−0.163*	−0.223*			−0.254**	−0.312**
			(−1.91)	(−1.75)			(−2.26)	(−2.36)
Low ESG Uncertainty			0.114*	0.109			0.125**	0.114
			(1.86)	(1.38)			(2.20)	(1.61)
Log(Size)	−0.100	−0.036	−0.101	−0.038	−0.044	0.111	−0.044	0.111
	(−1.28)	(−0.27)	(−1.30)	(−0.29)	(−0.59)	(0.77)	(−0.60)	(0.77)
Log(BM)	0.001	0.009	−0.001	0.008	−0.021	0.019	−0.024	0.017
	(0.01)	(0.14)	(−0.01)	(0.12)	(−0.19)	(0.18)	(−0.21)	(0.17)
6M Momentum	0.336	0.188	0.335	0.194	0.275	0.105	0.276	0.111
	(0.70)	(0.40)	(0.69)	(0.42)	(0.50)	(0.20)	(0.50)	(0.21)
Log(Illiquidity)		0.056		0.056		0.103**		0.103**
		(1.00)		(1.03)		(2.17)		(2.15)
Gross Profitability		0.178		0.180		0.355*		0.359*
		(0.99)		(1.00)		(1.83)		(1.85)
Corporate Investment		0.037		0.037		−0.005		−0.007
		(0.49)		(0.50)		(−0.08)		(−0.09)
Leverage		−0.037		−0.037		−0.034		−0.034
		(−0.78)		(−0.79)		(−0.73)		(−0.73)
Log(Analyst Coverage)		−0.019		−0.019		−0.174		−0.175
		(−0.15)		(−0.14)		(−1.40)		(−1.41)
Analyst Dispersion		−0.536***		−0.539***		−0.828***		−0.831***
		(−2.67)		(−2.71)		(−4.37)		(−4.37)
Constant	2.309*	1.800	2.281*	1.775	0.591	−0.555	0.533	−0.614
	(1.71)	(1.09)	(1.70)	(1.09)	(0.46)	(−0.31)	(0.42)	(−0.34)
Obs	283,671	254,873	283,671	254,873	272,728	245,451	272,728	245,451
R-squared	0.045	0.080	0.048	0.082	0.043	0.076	0.045	0.078

Social Cost of Carbon

- Reminder: what is SCC designed to measure?
  - Monetary value of all future net damages associated with a 1 ton increase in $CO2$ emissions
  - In other words, how much should society be willing to pay for a 1 ton reduction in $CO2$ emissions
- Greenstone et al. (2023) use \$51 (Obama administration), \$190 (EPA in 2022) and \$250 (includes effects on migration and conflict)
- \$250 comes from Carleton and Greenstone (2022), how do they calculate this number?

Carleton and Greenstone (2022): SCC Calculations

- Seven “ingredients”:
  1. A climate module that measures the effect of emissions on the climate
  2. A damages module that translates climate changes into economic damages
  3. A discounting module that calculates the present value of future damages
  4. Whether to include global or only domestic climate damages
  5. Socioeconomic and emissions trajectories that predict how the global economy and CO2 emissions will grow in the future
  6. How to value uncertainty
  7. How to treat equity

Carleton and Greenstone (2022): Ingredients 1-4

- Ingredient 1: How do we convert carbon emissions into climate change? Requires modeling the path from emissions $\Longrightarrow$ atmospheric C02 $\Longrightarrow$ warming, sea level rise, etc.
- Ingredient 2: How do physical damages translate into economic damages? Should reflect geographic differences in the effect of temperature (e.g. effect of a temperature increase is different in Arizona and Minnesota) and adaptation
- Ingredient 3: Need discounting to determine how to value a $1 of damage in 10 years vs. in 50 years
- Ingredient 4: Most common to estimate global damages (although Trump administration focused on only domestic, leading to SCC of $3-$5 per ton)

Carleton and Greenstone (2022): Ingredients 5-7

- Ingredient 5: Relation between emissions and climate damages is nonlinear, which means that higher emissions results in a higher SCC. Wealthier economies generate higher emissions, which means that marginal tons do more damage and thus increase the SCC. Wealthier countries are also better able to invest in adaptations that reduce the SCC.
- Ingredient 6: Calculating the SCC involves uncertainty about future economic growth, temperature sensitivity to additional emissions, and the economic damages from a given level of climate change. How should the SCC account for this uncertainty?
- Ingredient 7: An additional dollar is worth more (in terms of utility) to a poor person than a wealthy person meaning that who is impacted by climate damages matters

E.U. Emissions Trading System: Overview

- Largest carbon market in the world
- Established in 2005, covers more than 11,000 heavy energy-using installations and airlines ($\sim$40% EU greenhouse gas emissions)
- Operates using cap and trade:
  - Cap is set on the total amount of certain greenhouse gases that can be emitted by installations in the system (and decreases over time)
  - Emission allowances are auctioned off or allocated for free among the companies in the system, and can subsequently be traded
- Aim is for the E.U. to be climate-neutral by 2050
- There are futures on the price of European emission allowances (EUA)

E.U. Emissions Trading System: History

- Phase 1 (2005-2007):
  - Almost all allowances were freely allocated at the national level
  - Caps were set on the basis of estimates (b/c no reliable emissions data)
- Phase 1 (2008-2012):
  - Countries had concrete emissions targets from Kyoto Protocol
  - Caps now based on actual emissions
  - Countries started to hold auctions (less free allocation of credits)
- Phase 3 (2013-2020):
  - Single, EU-wide cap on emissions in place of the previous national caps
  - Auctioning became default for allocation
- Phase 4 (2021-2030):
  - Pace of annual reductions in total allowances is increased to 2.2 percent from the previous 1.74

Känzig (2023): Overview

- Big picture question: what are the economic impacts of carbon pricing?
- Finds that a tighter carbon pricing regime leads to:
    1. Higher energy prices
    2. Lower emissions
    3. More green innovation
    4. Less economic activity
    5. Higher inequality

Känzig (2023): Carbon Policy Surprises

- Carbon policy surprises are defined as the change in the EUA futures price on the day of a regulatory event compared to the last trading day before the event

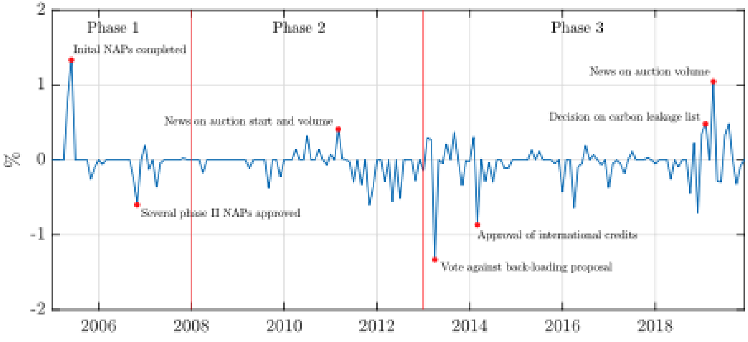
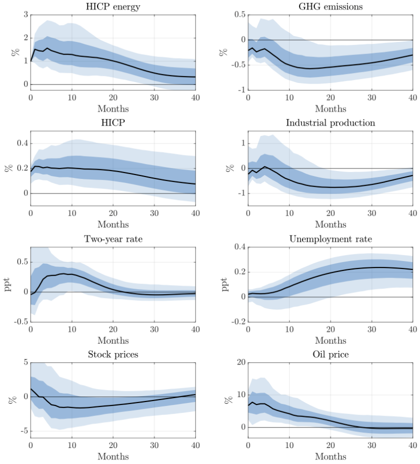


Figure 2: The Carbon Policy Surprise Series

Känzig (2023): Empirical Design

- Uses carbon policy surprises as an instrument in a vector autoregression (VAR)
- Variables in the VAR are:
  1. Energy component of inflation
  2. Total greenhouse gas emissions
  3. Headline inflation
  4. Industrial production
  5. Unemployment rate
  6. Two year interest rate
  7. Stock market index
  8. Brent crude oil price (inflation adjusted)

Känzig (2023): Results I



First stage regression: F-statistic: 17.43, R^2: 2.85%

Figure 3: Impulse Responses to a Carbon Policy Shock

Notes: Impulse responses to a carbon policy shock, normalized to increase the HICP energy by 1 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

Känzig (2023): Results II

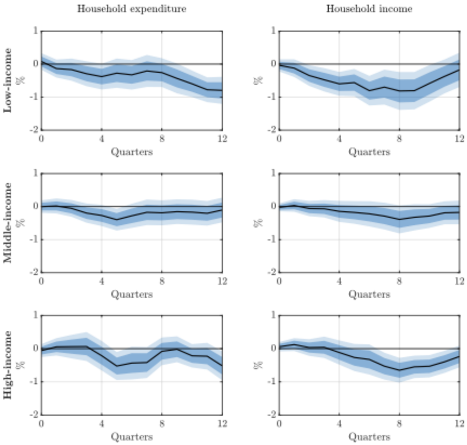


Figure 6: Household Expenditure and Income Responses by Income Group

Notes: Impulse responses of total expenditure (excluding housing) and current total disposable household income for low-income (bottom 25 percent), middle-income (middle 50 percent) and high-income households (top 25 percent). The households are grouped by total normal disposable income and the responses are computed based on the median of the respective group.

Bolton et al. (2023): Overview

- Research question: how does carbon pricing affect financial performance?
- Findings:
  - For firms with a significant shortfall in emissions allowances, an increase in daily carbon prices is associated with a decrease in contemporaneous stock prices
  - For firms with a greater permit coverage, an increase in daily carbon prices is associated with higher contemporaneous stock prices

Bolton et al. (2023): Empirical Design

$$\Delta P\%_{i\tau} = \beta_1 SHORTFALL_{it-1}^{COVERAGE<50\%} \times \Delta EUA\%_\tau + \beta_2 \Delta EUA\%_\tau$$
$$+ \beta_3 SHORTFALL_{it-1}^{COVERAGE<50\%} + \gamma^T x_{it-1} + \alpha_\tau + \varepsilon_{it}$$

- $\Delta P\%_{i\tau}$ is the percentage change of firm i's stock price on day τ
- $\Delta EUA\%_\tau$ is the percentage change in carbon prices from day $\tau - 1$ to day τ
- $SHORTFALL_{it-1}^{COVERAGE<50\%}$ is an indicator for whether firm i's free permits are less than 50% of its regulated emissions in year $t-1$

Bolton et al. (2023): Results

Table 4: Carbon Prices, Permit Shortfall and Stock Returns

	(1) $RET_{i\tau}$	(2) $RET_{i\tau}$	(3) $RET_{i\tau}$
$SHORTFALL_{it-1}^{COVERAGE<50\%} \times \Delta EUA\%_{\tau}$	-0.0123**	-0.0123**	-0.0124**
	(0.0061)	(0.0061)	(0.0061)
$SHORTFALL_{it-1}^{COVERAGE<50\%}$	0.0006	0.0006	0.0030
	(0.0083)	(0.0083)	(0.0081)
$LOG(ASSETS_{it-1})$		-0.0235*	-0.0279**
		(0.0134)	(0.0134)
$TANGIBILITY_{it-1}$		0.0132	0.0119
		(0.0254)	(0.0233)
$LEVERAGE_{it-1}$		0.0190	0.0278
		(0.0897)	(0.0848)
$LOG(MV_{i\tau-1})$		0.0183	0.0196*
		(0.0118)	(0.0117)
$LOG(M/B_{i\tau-1})$		-0.0466***	-0.0495***
		(0.0094)	(0.0096)
$NET\ INCOME_{it-1}/EQUITY_{it-2}$		0.0145	0.0142
		(0.0294)	(0.0280)
$CASH_{it-1}/ASSETS_{it-1}$		0.0125	0.0021
		(0.0508)	(0.0511)
$LOG(TURNOVER_{it-1})$		0.0085	0.0088
		(0.0082)	(0.0080)
$\beta_{i\tau}^{SMB}$			-0.0119
			(0.0144)
$\beta_{i\tau}^{HML}$			-0.0079
			(0.0113)
$\beta_{i\tau}^{RMW}$			0.0168*
			(0.0091)
$\beta_{i\tau}^{CMA}$			0.0023
			(0.0081)
$\beta_{i\tau}^{MKT}$			-0.0154
			(0.0259)
$\beta_{i\tau}^{WML}$			0.0013
			(0.0135)
$VOLATILITY_{i\tau}$			1.0461
			(1.2613)
Constant	0.0296***	-0.2952***	-0.3015***
	(0.0020)	(0.0682)	(0.0844)
Observations	427,701	427,701	427,701
Industry FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Cluster	Firm & Date	Firm & Date	Firm & Date
Firms	284	284	284
Adj. R-Sq.	0.251	0.251	0.251

NOTES: This table reports results from OLS panel regressions. The dependent variable is $RET_{i\tau}$, the return for firm i from day $\tau - 1$ to day τ. Variable definitions are provided in Table A1. Variables are winsorized at the 1% and 99% levels. The sample consists of listed firms in ETS-participating countries with a positive amount of ETS verified emissions in year $t - 1$. The sample period begins in 2013 and ends in 2020. Industry is defined by 2-digit NACE codes. Standard errors are two-way clustered at the firm and date level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Climate Risk

Defining Climate Risk

- Two types of climate risk:
  1. **Physical:** the firm's operations will be affected by changing weather patterns and increasingly frequent natural disasters
  2. **Transition:** the firm's ability to operate profitably will be affected by regulations intended to mitigate the effects of climate change (e.g. carbon taxes or emission standards) or by decreased demand for its products as a result of concerns about climate change
- Important to note that these are very distinct concepts and have different policy implications
  - There is a tradeoff between policies that help physical risky firms (strict environmental regulation to mitigate climate change) and policies that help transition risky firms (less environmental regulation)
  - Many firms are exposed to both, but generally transition risk is more near term

Why Do Investors Care About Climate Risk?

- Recall:

$$
\begin{aligned}
p_t &= \mathbb{E}_t[m_{t+1} x_{t+1}] \\
&= \mathrm{Cov}_t(m_{t+1}, x_{t+1}) + \mathbb{E}_t[m_{t+1}]\mathbb{E}_t[x_{t+1}] \\
&= \mathrm{Cov}_t(m_{t+1}, x_{t+1}) + \frac{\mathbb{E}_t[x_{t+1}]}{R_f},
\end{aligned}
$$

  where $m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)}$
- Climate risk can affect both the covariance of an asset's payoff with consumption and its expected cash flows
- Example: how does climate risk affect an asset's covariance?
  - Consider a an asset exposed to physical risk that pays off only when there are no wildfires (i.e. in a good state where consumption is high)
  - This asset's cash flows positively covary with consumption (i.e. negatively covary with the m_{t+1})
  - This asset will have a lower price than a similar asset with the same expected cash flows that pays off in the state where wildfires occur (the second asset can be considered a wildfire hedge)

Measuring Climate Risk

- Three classes of methods to measure firm-level climate risk exposure:
  1. Fundamental information or ESG scores (e.g. carbon emissions, industry, product offerings)
  2. Past responses to climate shocks such as physical shocks, climate policy shocks
  3. Text-based measures

Measuring Climate Risk: Method 1 (Fundamental Information) Overview

- This method uses the researcher's prior beliefs about which firms are exposed to climate risk
- For transition risk, these could be firms with high carbon emissions or those who make products that are only useful to carbon-intense industries (for example parts for oil rigs)
- For physical risk, these could be firms with physical assets located in certain geographic areas

Measuring Climate Risk: Method 1 (Fundamental Information) Example

- Cheema-Fox et al. (2022) develops a method to identify firms that produce products and services that help reduce carbon emissions
- They find that their climate solutions portfolio exhibits higher revenue growth, higher investment in R&D and talent, and lower profitability
- They also find that this portfolio exhibits superior stock market performance since 2018 and is only weakly correlated with a portfolio that underweights firms with high carbon emissions
- How do they identify climate solutions firms?
  - Create a list of 164 climate solutions keywords (e.g. plant-based, green building, solar power, carbon sequestration, electric vehicle)
  - Find firms whose business descriptions include at least one of these keywords
  - Refine sample (see section 2 of the paper for details)

Measuring Climate Risk: Method 2 (Past Response to Shocks) Overview

- This method relies on the assumption that climate risky assets are those that have performed poorly when climate shocks have occurred in the past
- For example, if the stock price of an oil firm fell when strict environmental regulations were passed, this procedure would label it as transition risky

Measuring Climate Risk: Method 2 (Past Response to Shocks) Example

- Engle et al. (2020) construct a climate news series, which measures the intensity of negative climate news in a given month
- They use this series to identify climate hedging stocks, which are those that perform well when this index spikes (climate hedging is the opposite of climate risky)
- When does the climate news series spike? Usually around events related to global climate policy

Engle et al. (2020) Climate News Series

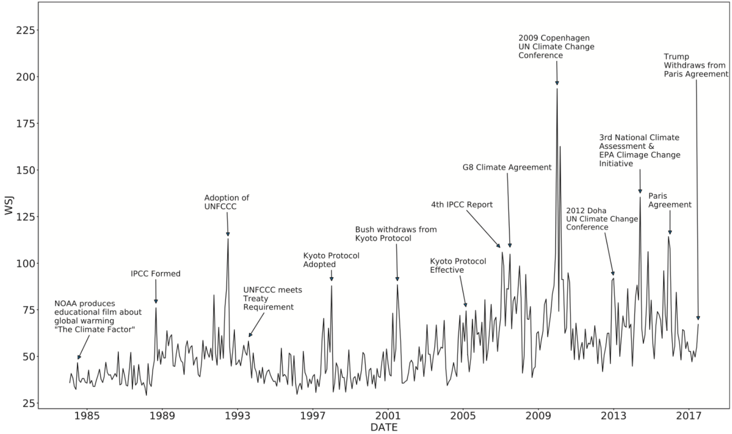


Figure 2
WSJ Climate Change News Index
This figure shows the WSJ Climate Change News Index from 1984 to 2017, annotated with climate-relevant news announcements.

Measuring Climate Risk: Combining Methods 1 and 2: Example

- Huij et al. (2021) estimate asset-level climate risk exposure by regressing stock returns on a pollutive minus clean portfolio (a portfolio that is long polluting stocks and short clean stocks)
- This procedure essentially defines climate riskiness as the correlation between a stock's returns and the returns of the pollutive minus clean portfolio
- They call this measure of climate risk carbon beta
- Finding 1: returns to stocks with high carbon betas are lower during months in which climate change is more frequently discussed in the news, during months in which temperatures are abnormally high, and during exceptionally dry months
- Finding 2: variation in carbon betas correlates with green patent issuance and forward-looking measures of climate risk.

Measuring Climate Risk: Method 3 (Text-Based) Overview

- What types of text data might be useful for measuring exposure to climate risk?
  - Corporate filings (10-K, 8-K, etc.)
  - Earnings calls
  - Business descriptions
  - Probably lots more!
- How is climate change exposure measured using text data? Several different approaches, spanning from very simple (dictionary-based methods) to much more complicated (methods based on deep learning models such as BERT). Examples:
  - Create a list of climate-related keywords and count their occurrence (e.g. Li et al. 2020)
  - Create a list of climate "seed phrases" and use machine learning to augment it with related phrases (e.g. Sautner et al. 2020)
  - Topic modeling (e.g. Li and Yu 2022)
  - Deep-learning methods (e.g. Kölbel et al. 2020)

Measuring Climate Risk: Method 3 (Text-Based) Example

- Sautner et al. (2020) use a keyword discovery algorithm to measure exposure to opportunity, physical and regulatory shocks associated with climate change
- They find that the measures are useful in predicting job creation in disruptive green technologies and green patenting and that it is reflected in options and equity markets
- A companion paper, Sautner et al. (2021) looks in more detail at the effect of these measures on equity prices

Short Aside: An Interesting Paper Related to Textual Analysis for Identifying Climate Risk

- Leippold (2022) is a paper that consists mostly of a transcript of an "interview" with a large language model about climate change (available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4237242`)
- For example:

Do you believe that we are on the right track to mitigating climate change?

GPT-3: *No, I do not believe that we are on the right track to mitigating climate change. Despite the clear evidence of the threat posed by climate change, and the urgent need for action, greenhouse gas emissions continue to rise globally. This is largely due to our continued reliance on fossil fuels for energy. To avoid catastrophic temperature rises, we must rapidly transition away from fossil fuels and towards renewable energy sources such as solar and wind power.*[11]

Measuring Climate Risk: Pros and Cons of the Three Methods

- Fundamental Information:
  - Pros: usually quantitative (straightforward to estimate accurately), focuses on a specific dimension of climate risk
  - Cons: generally backward-looking (e.g. if a firm is investing in technology to drastically improve their emissions, looking at past emissions ignores this), focuses on a specific dimension (this can be a pro or a con)
- Past Response to Shocks:
  - Pros: quantitative, available for all firms
  - Cons: backward-looking, most severe shocks have not materialized
- Text-based measures:
  - Pros: forward-looking, flexible (can measure many aspects of climate risk in a consistent way)
  - Cons: many subjective choices required, relies on documents written by humans (are these documents accurate? what are the incentives of the authors?)

Empirical Papers Related to Climate Risk

Alekseev et al. (2021): Motivation

- Limited availability of assets used to hedge climate risk
- Problem: there is limited time series data from which we can learn the correlation of assets with climate risk
- Solution: use cross-sectional information on the response of investors to geographically localized heat shocks to identify how fund managers adjust their portfolio during times of increased (local) attention to climate change

Alekseev et al. (2021): Defining Local Shocks

- The authors present four criteria that shocks must satisfy:
  1. Shift asset demand of affected investors through influencing their attention to or beliefs about climate risks
  2. Only affect a small group of investors so that they affect individual investors' asset demand, but not prices
  3. Need to be able to observe trading behavior of affected investors
  4. Shifts in asset demand in response to local shocks need to correspond to shifts in response to global climate shocks
- Local heat shocks satisfy all four conditions

Response to Local Shocks

$$ActiveChanges^I_{f,t} = \beta^I S_{loc(f),t} + \delta^I_t + \epsilon_{f,t},$$

where $ActiveChanges^I_{f,t}$ is the change in fund f's investment in industry I driven by active trading at time t, $S_{loc(f),t}$ is the local climate shock experienced by the managers of fund f at time t, δ^I_t is a time fixed effect.

- Panel regression, estimated separately for each industry
- β^I measures the differential change in fund holdings of that industry for funds affected by a "local" climate shock, relative to the change in holdings for funds that were not affected by a local climate shock
- Authors highlight that materials and real estate have the some of the lowest values for β_S and autos and energy are toward the top

Table 4: Industry Climate-β Coefficients

GICS	Description	Avg.	Fatalities/Injuries	Indemnities	Record Temp.
2510	Auto & Components	0.11	0.07	0.15	0.15
4520	Tech. Hardw. & Equip.	0.09	0.05	0.21	0.06
2030	Transportation	0.06	0.02	0.13	0.08
4530	Semiconductors & Equip.	0.05	0.05	−0.01	0.12
3010	Food & Staples Retailing	0.04	0.03	0.08	0.03
5010	Communication Services	0.03	0.04	0.02	0.00
1010	Energy	0.02	0.03	0.04	−0.01
3020	Food, Bev. & Tobacco	0.02	0.01	0.07	−0.01
4020	Diversified Financials.	0.02	0.01	0.01	0.04
5510	Utilities	0.02	0.01	0.03	0.02
4010	Banks	0.02	0.04	0.01	−0.03
2010	Capital Goods	0.02	0.01	0.06	0.00
4510	Software & Services	0.00	0.01	−0.04	0.03
4030	Insurance	−0.00	−0.03	0.06	0.00
3520	Pharma., Biotech., & Life Sc.	−0.01	0.01	−0.02	−0.02
6010	Real Estate	−0.01	−0.03	0.00	−0.00
5020	Media & Entertainment	−0.02	−0.03	0.05	−0.06
3030	Household & Pers. Prod.	−0.02	0.01	−0.07	−0.03
2530	Consumer Services	−0.02	−0.06	−0.02	0.05
1510	Materials	−0.03	−0.03	−0.01	−0.03
3510	Health Care Equip. & Serv.	−0.03	−0.02	−0.07	−0.01
2550	Retailing	−0.05	−0.07	0.01	−0.05
2520	Consum. Durables & Apparel	−0.06	0.02	−0.19	−0.08
2020	Commercial & Prof. Serv.	−0.12	−0.13	−0.28	0.09

Alekseev et al. (2021): Forming Quantity-Based Hedge Portfolios

- The excess returns of the quantity-based hedge portfolio are given by:

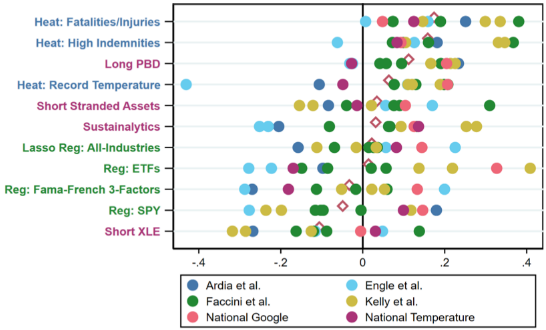
$$QP_{S,t} = \sum_{I} \widehat{\beta_{S,t-1}}(R_t^I - R_t^f)$$

- As their hedge target, they use climate news series from Engle et al. (2020), Crimson Hexagon, Ardia et al. (2020), Faccini et al. (2021) and Kelly (2021), as well as national Google searches and national temperature deviations from Barnett (2017)

Alekseev et al. (2021): Evaluating Hedge Performance

- Criterion to compare is out of sample correlation between the hedging portfolio returns and the AR(1) innovations to the various climate news series
- The quantity-based portfolios seem to do relatively well:

Figure 2: Climate Hedge Performance of Various Portfolios



Bolton and Kacperczyk (2021a): Overview

- Research question: do carbon emissions affect the cross section of U.S. stock returns?[1]
- Main finding: the stocks of firms with higher carbon emissions earn higher returns, indicating that investors demand compensation for their exposure to carbon risk

[1] In another paper, Bolton and Kacperczyk (2021b), the same authors address a similar question for global stocks

Bolton and Kacperczyk (2021a): Empirical Strategy

- They estimate the relationship between emissions and returns:

  $$RET_{i,t} = \alpha_0 + \alpha_1 \log(EMISSIONS)_{i,t} + \alpha_2 Controls_{i,t} + \mu_t + \varepsilon_{i,t},$$

  where $RET_{i,t}$ is the return of stock i in month t and μ_t are time fixed effects.
- Emissions could be either Scope 1, Scope 2 or Scope 3[2]
  - Scope 1 is direct emissions from production
  - Scope 2 is indirect emissions from the consumption of purchased electricity, heat or steam
  - Scope 3 is indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc.
- They also add industry fixed effects in an alternative specification (we will discuss in detail what this means later in the lecture)

[2] https://www.carbontrust.com/resources/briefing-what-are-scope-3-emissions for details

Bolton and Kacperczyk (2021a): Results

Table 8
Carbon emissions and stock returns.

The sample period is 2005–2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level (in parentheses). All regressions include year-month fixed effects. In the regressions for columns 4 through 6, we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of total firm-level emissions; Panel B reports the results for the percentage change in carbon total emissions; Panel C reports the results for carbon emission intensity. ***1% significance; **5% significance; *10% significance.

Panel A: Total emissions						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
LOG (SCOPE 1 TOT)	0.043**			0.164***		
	(0.023)			(0.036)		
LOG (SCOPE 2 TOT)		0.098**			0.167***	
		(0.042)			(0.048)	
LOG (SCOPE 3 TOT)			0.135**			0.312***
			(0.046)			(0.071)
LOGSIZE	−0.140	−0.184	−0.193	−0.302*	−0.327*	−0.410**
	(0.163)	(0.167)	(0.165)	(0.148)	(0.154)	(0.163)
B/M	0.460	0.469	0.444	0.656**	0.642**	0.562**
	(0.260)	(0.266)	(0.258)	(0.234)	(0.229)	(0.224)
LEVERAGE	−0.559*	−0.579*	−0.498*	−0.699***	−0.712***	−0.790***
	(0.272)	(0.280)	(0.274)	(0.177)	(0.171)	(0.167)
MOM	0.321	0.348	0.338	0.284	0.294	0.301
	(0.276)	(0.272)	(0.274)	(0.291)	(0.290)	(0.290)
INVEST/A	−2.218	−1.914	−1.587	0.277	0.267	0.699
	(1.740)	(1.794)	(1.838)	(2.111)	(2.126)	(2.082)
ROE	0.010*	0.009	0.008	0.009*	0.009*	0.007*
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
HHI	0.032	−0.026	0.137	0.130*	0.052	0.111
	(0.110)	(0.112)	(0.101)	(0.072)	(0.073)	(0.071)
LOGPPE	−0.015	−0.027	−0.045	0.020	0.019	−0.017
	(0.100)	(0.088)	(0.090)	(0.058)	(0.058)	(0.057)
BETA	0.059	0.023	0.047	0.045	0.040	0.063
	(0.131)	(0.131)	(0.130)	(0.148)	(0.147)	(0.146)
VOLAT	0.978	0.674	0.749	0.622	0.501	0.549
	(3.571)	(3.415)	(3.506)	(3.290)	(3.285)	(3.269)
SALESGR	0.692	0.688	0.672	0.679	0.686	0.648
	(0.429)	(0.430)	(0.420)	(0.412)	(0.412)	(0.407)
EPSGR	0.592**	0.589**	0.575**	0.637**	0.636**	0.615**
	(0.234)	(0.231)	(0.232)	(0.231)	(0.233)	(0.227)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	184,288	184,216	184,384	184,288	184,216	184,384
R-squared	0.203	0.204	0.204	0.206	0.206	0.206

Pankratz and Schiller (2021): Overview

- Research question: how does physical climate risk affect firms' financial performance and operational risk management in global supply chains?
- Finding 1: weather shocks at supplier locations reduce the operating performance of suppliers and their customers
- Finding 2: customers respond to perceived changes in their suppliers' climate risk exposure by becoming more likely to terminate supplier relationships (replacing them with suppliers that have lower expected climate risk exposure)

Pankratz and Schiller (2021): Measuring Physical Risk Exposure and Its Effects

- Three types of data:
  1. Supplier-customer relationships (from FactSet Revere)
  2. Firm locations (from FactSet Fundamentals and Orbis). Importantly, this includes plants and establishments, not just headquarters.
  3. Exposure to extreme temperatures, floods and other natural disasters
- Main empirical specification:

$$y_{it} = \sum_{t=-3}^{0} \beta_t \times W_{it} + \mu_{iq(t)} + \gamma_{n(i)t} + \theta_{d(i)t} + \delta_{BS2016,t} + \varepsilon_{it},$$

  where y_{it} is either *Revenue*/*Assets* or *Operating Income*/*Assets* of firm i in quarter t, W_{it} is the number of days on which firm i was exposed to hear and floods in quarter t and $\mu_{iq(t)}$, $\gamma_{n(i)t}$, $\theta_{d(i)t}$ and $\delta_{BS2016,t}$ are various fixed effects and controls

Pankratz and Schiller (2021): Main Results I

Table 3: Physical Climate Risk and Supplier Firm Performance

Notes. This table presents OLS regression estimates on the impact of heat and flooding at the location of the sample supplier firms on their revenues (Rev) and operating income (OpI), both scaled by assets lagged by one year. *Heat Days* (t) and *Flood Days* (t) indicate the number of days on which heat and floods occur during the financial quarter t and the three preceding quarters ($t-3$ to $t-1$). The number of observations refers to supplier firm year-quarters, and the sample period is 2003 to 2017. We exclude firms in the financial industry as well as firms with less than 10% of firm locations within 30 kilometers of the company headquarter. All regressions include firm-by-fiscal quarter fixed effects to control for time invariant firm characteristics and firm-specific seasonal effects, industry-by-year-by-quarter fixed effects, as well as controls for country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Heat

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Heat Days (t)	-0.016***	-0.015***	-0.003**	-0.003**
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-1)	-0.003	-0.002	-0.002*	-0.003*
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-2)	-0.015***	-0.014***	-0.003**	-0.003**
	(0.005)	(0.005)	(0.001)	(0.001)
Heat Days (t-3)	-0.011**	-0.011**	-0.001	-0.001
	(0.005)	(0.005)	(0.001)	(0.001)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7668	0.6258	0.6311
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

(b) Floods

	Sup Rev/L.A (t)		Sup OpI/L.A (t)	
	(1)	(2)	(3)	(4)
Flood Days (t)	-0.023***	-0.020***	-0.006***	-0.006***
	(0.007)	(0.007)	(0.002)	(0.002)
Flood Days (t-1)	-0.025***	-0.023***	-0.006***	-0.006***
	(0.006)	(0.006)	(0.002)	(0.002)
Flood Days (t-2)	-0.024***	-0.023***	-0.004**	-0.004**
	(0.006)	(0.006)	(0.002)	(0.002)
Flood Days (t-3)	-0.009	-0.008	-0.003	-0.003
	(0.007)	(0.008)	(0.002)	(0.002)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
R^2	0.7626	0.7668	0.6258	0.6311
Observations	202,438	202,438	202,438	202,438
Suppliers	5,628	5,628	5,628	5,628

Pankratz and Schiller (2021): Main Results II

Table 4: Downstream Propagation of Weather Shocks

Notes. This table presents OLS regression estimates on the impact of heat and flooding at the location of the supplier firms on their *customers'* revenues (Rev) and operating income (OpI), both scaled by assets lagged by one year. *Heat Days* (t) and *Flood Days* (t) indicate the number of days on which heat (in excess of 30 degrees Celsius) and floods occurred during the financial quarter t and the three preceding quarters across all supplier firms of a given customer. The number of observations refers to customer firm-quarters, and the sample period is 2003 to 2017. We exclude customer and supplier firms in the financial industry, supplier firms with less than 10% of firm locations within 30 kilometers of the headquarters, and customer-supplier pairs with headquarters located within 500 kilometers of each other. All regressions include firm-by-fiscal quarter fixed effects, industry-by-year-by-quarter fixed effects, and country-specific linear trends. Columns (2) and (4) additionally include interaction terms of terciles of firm size, age, and ROA with year-by-quarter fixed effects to control for firm characteristics (BS2016 FE), following Barrot and Sauvagnat (2016). Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

(a) Heat

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Heat Days (t-0)	-0.0012***	-0.0012***	-0.0002***	-0.0001*
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-1)	-0.0017***	-0.0019***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-2)	-0.0009**	-0.0011***	-0.0001*	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
Sup Heat Days (t-3)	-0.0010***	-0.0013***	-0.0002***	-0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

(b) Floods

	Cus Rev (t)		Cus OpI (t)	
	(1)	(2)	(3)	(4)
Sup Flood Days (t-0)	-0.0069***	-0.0066***	-0.0014***	-0.0012***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-1)	-0.0056***	-0.0055***	-0.0011***	-0.0010***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-2)	-0.0059***	-0.0061***	-0.0013***	-0.0012***
	(0.001)	(0.001)	(0.000)	(0.000)
Sup Flood Days (t-3)	-0.0040***	-0.0047***	-0.0007**	-0.0006*
	(0.001)	(0.001)	(0.000)	(0.000)
Firm × Fiscal-Qtr FE	Yes	Yes	Yes	Yes
Ind × Year-Qtr FE	Yes	Yes	Yes	Yes
Ctry-Linear-Trends	Yes	Yes	Yes	Yes
BS2016 FE	No	Yes	No	Yes
Observations	123700	123700	123700	123700
R^2	.884	.886	.707	.711

Aghion et al. (2023): Overview

- Research question: do consumer environmental concerns affect firms' decisions to invest in clean or dirty innovation?
- Use data from the automobile sector
- Findings:
  - Firms that operate in countries with more pro-environment attitudes are more likely to invest in clean technology
  - This effect is larger when there is more product market competition
  - Magnitude of the effect on green innovation is comparable to the effect of the increase in fuel prices

Aghion et al. (2023): Empirical Design

$$
\begin{aligned}
Innovation_{j,t} = {} & \alpha Values_{j,t} + \beta Competition_{j,t} \\
& + \gamma Values_{j,t} \times Competition_{j,t} + \delta X_{j,t} + J_j + T_t + \varepsilon_{j,t}
\end{aligned}
$$

- $Innovation_{j,t}$ is the number of clean patents filed by firm j in year t relative to the number of dirty ones
- $Values_{j,t}$ is a firm-specific weighted average of environmental values (from country-level surveys)
- $Competition_{j,t}$ is a firm-specific weighted average of competition across the countries where the firm operates

Aghion et al. (2023): Results

Table 1: The effect of Values and Competition on the direction of innovation

VARIABLES	(1) log (1+ #clean) - log (1+ #dirty)	(2) log (1+ #clean)	(3) log (1+ #dirty)	(4) log (1+ #grey)	(5) log (1+ #other)
		Panel A: Values and Competition main effects			
Values	0.107***	0.00473	-0.103***	-0.0191	-0.136***
	(0.0211)	(0.0191)	(0.0179)	(0.0157)	(0.0239)
Competition	0.269	0.514***	0.246*	0.381***	0.555***
	(0.166)	(0.144)	(0.128)	(0.108)	(0.162)
Log fuel price	0.965***	0.784***	-0.181	-0.0386	0.603***
	(0.156)	(0.138)	(0.127)	(0.114)	(0.161)
Observations	17,124	17,124	17,124	17,124	17,124
R-squared	0.122	0.179	0.026	0.052	0.050
Number of firms	8,562	8,562	8,562	8,562	8,562
		Panel B: Adding interaction term between Values and Competition			
Values	0.141***	0.0350	-0.106***	-0.0276	-0.0859***
	(0.0270)	(0.0230)	(0.0225)	(0.0200)	(0.0289)
Competition	0.167	0.422***	0.255**	0.406***	0.403**
	(0.165)	(0.140)	(0.126)	(0.107)	(0.161)
ValuesXComp	0.0296**	0.0268**	-0.00278	-0.00750	0.0441***
	(0.0136)	(0.0116)	(0.0110)	(0.00994)	(0.0139)
Log fuel price	0.596***	0.450***	-0.146	0.0549	0.0527
	(0.171)	(0.149)	(0.154)	(0.140)	(0.215)
Observations	17,124	17,124	17,124	17,124	17,124
R-squared	0.123	0.180	0.026	0.052	0.053
Number of firms	8,562	8,562	8,562	8,562	8,562

Note: Besides the coefficients shown, all specifications control for log of population and log of GDP and include firm fixed effects and a period fixed effect. Values, Competition and log of fuel prices are standardized as z-scores.

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