A quantity-based approach to constructing climate risk hedge portfolios

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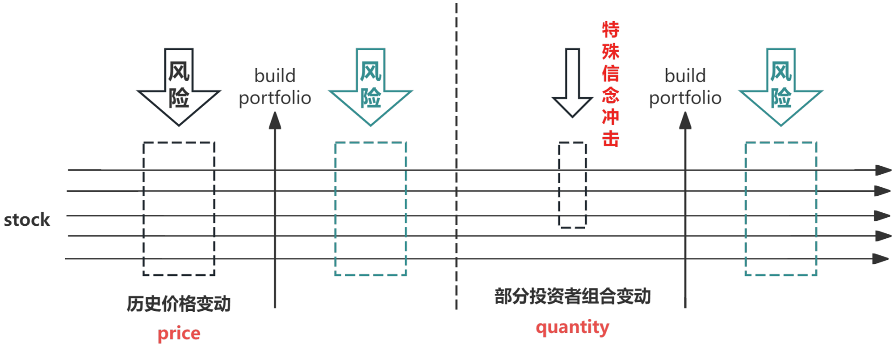
Motivation

- Climate change presents a global challenge—investors' hedging demand rising.
- Limits of current instruments：
  - small number designed to directly hedge: relatively illiquid catastrophe bonds
  - also can build hedge portfolios using other assets （exposed to climate risks）
- Limits of traditional hedging approaches：
  - Mimicking portfolio approach (Lamont, 2001)—rely on availabe long time series, frequent risk realizations, substantial time-series stability of risk exposures.
  - poorly suited in targeted risks are new or materialize infrequently—climate risk.
- propose a new quantity-based approach:
  - uses cross-sectional information on investors' trading activity
  - based on idiosyncratic climate belief shocks shift a small set of investors.

Question



- How to build climate risk hedge portfolio in the stock market?
  - new quantity-based approach v.s. mimicking portfolio、alternative approach
  - our approach have significantly better out-of-sample hedging performances

Contribution

- contributes to literature on **Climate Risk and Asset Markets**
  - prior: valuation discount of high-pollution firms (Hsu et al., 2022) and investor expectations about ESG performance;hedge climate news (Giglio et al., 2023)
  - expand: provide a framework to hedge climate risks using quantity datas
- contributes to literature on **Belief Formation and Action**
  - prior: how personal experiences shape beliefs and subsequent actions, local house price influence expectations about future national trends.(K&Z, 2019).
  - expand: trading responses of mutual fund investors to local climate,house price,unemployment shocks-construct portfolios
- contributes to literature on **Quantity-Based Asset Pricing**
  - uses quantity and holdings data for asset pricing (Berk & van Binsbergen, 2016).
  - quantity-based information is valuable for predicting price movements in response to aggregate shocks.

Design

Simple Model: investor i,stockA\B.

supply of A: $\int_{i=0}^{i=1} q_A(p_A, \epsilon_A(i), \epsilon_B(i))\, di = \bar{A}$

belief $\epsilon_A(i) = \nu_A + \omega_A(i)$. $\frac{\partial q}{\partial \omega_A(i)} = \frac{\partial q}{\partial \epsilon_A(i)}$

change in $\omega_A(i)$: Stable Equilibrium Price: $\frac{\partial p_A^*}{\partial \omega_A(i)} = 0.$

individual demand adjust: $\frac{\partial q_A^*}{\partial \omega_A(i)} \neq 0.$

change in ν_A : $\frac{\partial p_A^*}{\partial \nu_A} = -\int_{i=0}^{i=1} \frac{\partial q}{\partial \epsilon_A(i)} di / \frac{\partial q_A}{\partial p_A}$

Identify Idiosyncratic Belief Shocks

three criteria ⇒ **shock**

1. shocks shift demands by influence beliefs
2. affect a few investors
3. similar to changes in aggregate climate risk

local extreme heat events	Investor Disclosures shareholder reports

local google search $\log(G_{t,s}) = \beta_S S_{t,s} + \delta_s + \gamma_t + \varepsilon_{t,s}$

Construct Invest Portofolio

ind level

shock → **fund Holding Active Changes** ⇒ $\beta_t^{I,S}$ ⇒ five years prior to t: $\hat{\beta}_t^{I,S}$

$QP_t^S = \sum_I \hat{\beta}_{t-1}^{I,S}(R_t^I - R_t^f)$

$ActiveChanges_{f,t}^I = \beta_t^{I,S} S_{f,t} + \delta_s + \gamma_t^I + \varepsilon_{f,t}^I$

Evaluating Portfolio Performance

Quantify: QP_t^S

narrative

mimicking

⇒ target risk : CC_c, t

news index: (Engle;Ardia;Faccini).
National Google searches.
National Temperature Deviations.

- out-of-sample correlation
- other macro risk: house, employment

Design-Idiosyncratic Belief Shocks Measure

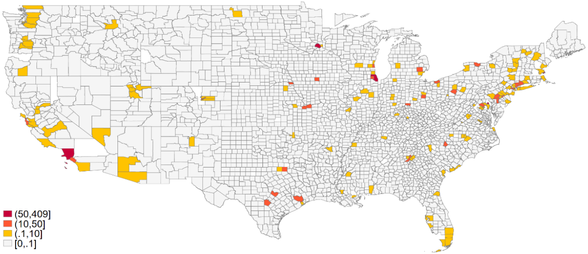
- demand shift by belief, few investor, similar to agg
- **Extreme Heat:**
  - motivated by lots literature:local extreme heat events drive climate change attention and beliefs in affected populations (Zaval et al. 2014⋯).
  - baseline： events that involve fatalities or injuries due to extreme heat.
  - a county-month as experiencing a heat shock if there were positive
  - to fund level: eg 2 mutual fund advisers in county A and 1 adviser in county B, A shock, the fund is affected by 2/3 of a local extreme heat shock
- **Investor Disclosures:** direct
  1. semi-annual shareholder reports of actively managed mutual funds
  2. extract sentences： climate change， carbon emission⋯ （Google word2vec）
  3. extracted passages: extract one sentence before and after selected sentence
  4. feed into GPT4: classify whether refers to physical， transitional climate risk

Design-Idiosyncratic Belief Shocks Measure

Table 2: Heat Shocks and Climate Attention

	Log(Google Search Volume)
Heat Shock	0.016*
	(0.008)
R^2	0.75
State & Month FE	Y
N	5,823

Figure 1: Locations of Mutual Fund Advisers



Design-Idiosyncratic Belief Shocks Measure

- sample with 2,496 unique funds, 57,961 fund-quarter observations between 2010 and 2019.

Table 1: Summary Statistics on Idiosyncratic Climate Belief Shocks

Panel A: Local Shocks: Summary

		Frequency	
Climate Shock	Event Description	Monthly	Sample
Heat Shock	Injuries or fatalities	0.10%	1.32%
Disclosure Shock	Change in fund disclosures about transition risk	-	0.15%
Pooled Shock	Pool of heat and disclosure shock	-	1.76%

Panel B: Local Shocks: Sample Jaccard Correlations across Fund-Quarters

	Heat Shock	Disclosure Shock
Heat Shock	1.00	
Disclosure Shock	0.00	1.00

Design-mutual fund holdings

- restrict our analysis to actively managed funds
- Thomson Reuters S12: portfolio holdings of U.S. mutual funds.
- **Measuring Active Portfolio Changes:**
  - fund f and month t with a holdings report,active change in industry I holdings as:

$$ActiveChanges^{I}_{f,t} = 100 * \left[\left(\frac{\sum_{j \in I} P_{j,t-3} S_{f,j,t}}{\sum_{j} P_{j,t-3} S_{f,j,t}} \right) - \left(\frac{\sum_{j \in I} P_{j,t-3} S_{f,j,t-3}}{\sum_{j} P_{j,t-3} S_{f,j,t-3}} \right) \right] \frac{1}{(Share^{I}_{t-3})}.$$

- **Estimating the Response to Idiosyncratic Climate Shocks:**

$$ActiveChanges^{I}_{f,t} = \beta^{I,S}_{t} S_{f,t} + \delta^{I}_{t} + \epsilon^{I}_{f,t},$$

result-beta

Table 3: Industry-Specific Climate Quantity Betas

GICS	Description	Pooled Shock	Disclosure Shock	Heat Shock
2030	Transportation	4.79*	24.42**	0.95
2510	Auto & Components	4.21*	24.58*	2.88
4530	Semiconductors & Equip.	2.46	3.80	4.60**
2010	Capital Goods	2.38*	13.07**	0.53
1510	Materials	1.69	6.45	1.34
4010	Banks	1.60*	1.58	2.46**
3030	Household & Pers. Prod.	1.34	6.18	-0.14
1010	Energy	1.32*	4.50	1.77*
4520	Tech. Hardw. & Equip.	0.96	-8.40	3.81***
2530	Consumer Services	0.20	-2.06	0.27
4020	Diversified Financials.	-0.12	2.15	0.44
4510	Software & Services	-0.19	2.46	0.91
3010	Food & Staples Retailing	-0.21	0.14	0.94
3020	Food, Bev. & Tobacco	-0.69	5.65	-1.91*
2520	Consum. Durables & Apparel	-0.69	1.27	3.67
5020	Media & Entertainment	-0.85	3.85	-1.48
5010	Communication Services	-0.94	1.32	-0.77
5510	Utilities	-1.08	7.60	-2.43*
3520	Pharma., Biotech., & Life Sc.	-1.19	5.05	-1.84**
3510	Health Care Equip. & Serv.	-1.78	-10.06	-1.11
4030	Insurance	-1.90	-4.13	-2.13
2020	Commercial & Prof. Serv.	-2.20	-10.89	-3.52
6010	Real Estate	-2.72**	-4.15	-3.60**
2550	Retailing	-3.52**	5.84	-6.37***

- the Auto & Components industry has a relative market cap of 1.1% , pool shock: $1.1\% \times 4.21 = 4.5$bp; for the disclosure shock is 27bp.

result-Portfolio Construction

- estimating β using data from the five years prior to t
- compute excess returns of each of the 24 industries R_t^I
- use the estimated β as the portfolio weights,excess return of quantity based hedge portfolio is:

$$QP_t^S = \sum_I \widehat{\beta}_{t-1}^{I,S}(R_t^I - R_t^f).$$

- **Climate Hedge Targets:**
  - climate news measures: AR(1) innovations in month t as $CC_{c,t}$,Engle et al. (2020),Ardia et al. (2021).Faccini et al. (2021).
  - National Google searches
  - National Temperature Deviations: AR(1) of nationwide monthly max temperature, control month fixed effects

result-Portfolio Construction

- **Narrative approach:**ex-ante view of the possible exposures
  1. long position of 50 in the company with the highest ESG score (Engle et al.,2020)
  2. industries view——using four ETFs:long PBD,ICLN and short XLE,IYE
  3. stranded asset portfolio as in Jung et al. (2021) shorts 0.3XLE + 0.7KOL-SPY
  4. long position of 50 in the company with the lowest carbon intensity
  5. sentiment analysis of climate sentence in 10-K(Baz et al. 2023).

- **Mimicking portfolio approach:**
  - $CC_{c,t} = \mathbf{w}_c \mathbf{R}_t + \varepsilon_{c,t}$,estimated each month using five-year rolling windows
  - Asset Selection:(1)S&P 500 ETF ;(2)+ FF3 (3)+ Ind ETFs: (PBD,XLE) ; (4)Ind Portfolios: 24 GICS industry (5) 207 factor zoo portfolio(C& Z,2022)
  - (4)(5) using LASSO,minimize overfitting

result-Portfolio Construction

Table 7: Climate Hedge Performance of Various Portfolios

		Faccini et al.				Engle et al.		Ardia et al.	Google	Temp.
	Avg.	IntSummit	GlobWarm	NatDis	Narrative	WSJ	CHNEG	MCCC	National	National
Pooled Shock	0.18***	0.23	0.26**	0.12	0.02	0.08	0.13	0.31*	0.38***	0.11
Heat Shock	0.17***	0.38***	0.18	0.05	0.06	0.05	0.10	0.25**	0.34*	0.14
Disclosure Shock	0.11**	0.10	0.15	0.26**	0.01	0.06	0.06	0.23	0.06	0.09
Emission Portfolio	0.08*	-0.03	0.13	0.06	-0.03	0.20	0.31**	0.18	0.05	-0.15
Long PBD ETF	0.07	0.06	0.09	0.19	0.04	-0.02	-0.03	0.23	0.02	0.05
Short Stranded Asset	0.02	-0.06	0.05	0.25***	0.12	-0.01	0.14	-0.11	0.04	-0.20
Long ICLN ETF	0.01	0.02	-0.02	0.22**	-0.06	-0.06	-0.11	0.12	-0.04	0.00
Short IYE ETF	-0.08*	-0.08	-0.16	-0.10	0.13	-0.12	0.06	-0.27**	-0.05	-0.09
Short XLE ETF	-0.08*	-0.09	-0.16	-0.12	0.14	-0.12	0.05	-0.27**	-0.05	-0.07
10-K Negative Portfolio	-0.09**	0.04	-0.01	0.02	0.08	-0.16	-0.17	-0.26**	-0.30***	-0.09
Sustainalytics Portfolio	-0.10**	0.13	-0.08	0.06	0.07	-0.25**	-0.23	-0.20	-0.27**	-0.14
Lasso: All Industry+FF	-0.02	0.15*	0.08	0.14*	0.04	0.01	-0.06	-0.36***	-0.19*	0.00
Lasso: Factor Zoo	-0.03	0.09	-0.03	-0.06	-0.12	-0.10	0.00	-0.04	0.00	0.00
Reg: ETFs+FF	-0.03	0.01	0.05	0.05	-0.04	0.11	-0.17	-0.32**	0.03	-0.02
Reg: FF 3-Factors	-0.04	-0.02	0.06	0.06	-0.11	0.20	-0.27**	-0.26	0.00	0.01
Reg: SPY ETF	-0.09**	-0.09	-0.03	-0.12	-0.08	-0.17	-0.14	-0.13	-0.00	-0.07

- A positive correlation means the portfolio effectively hedges negative climate news

result-Robustness

- Portfolio Construction
  - Fixed Effects, Winsorizing, Total Changes,No Industry Weighting, No ESG Fund,Heat Shock Measure···
- Notable Exception:Rolling Window
  - 1 Year: Reduces data by 80%, impairing industry quantity beta identification
  - 3-Year: Performs moderately worse than the 5-year baseline, but better than the 1-year window.
- Hedging Macro Factors:

	Hedge Target	
	Growth in House Prices	Δ Unemployment Rate
Mimicking Portfolio Approaches		
Reg: Fama-French Three-Factors	**0.11**	-0.03
Reg: SPY	**0.13**	-0.01
Lasso Reg: All-Industries + Fama-French	**0.01**	-0.13
Quantity-based Approaches		
Quantity: Local Shocks	**0.18**	**0.20**
Quantity: Disclosure	**0.14**	**0.10**

ideas

- 方法层面：
  - 扩展到股票层面：使用机器学习方法解决稀疏性问题，如不按照行业，使用 PCA 在股票层面分组；多纳入几种特殊信念冲击
  - 跨资产组合，如受到冲击的基金经理可能增加债券类别资产的配置
  - 也考察投资组合的经济绩效
- 应用层面：
  - 新风险、不稳定的风险：AI 应用、数据网络安全、生物多样性……

question

- 问题 1：从 mimicking 到 quantity 的逻辑？
  - mimicking 使用的是股票自身历史价格计算风险暴露，其 beta 完全取决于资产价格对 macro risk 的反应，当可用数据时间跨度够长、风险发生较频繁时，数据才有效，算出的 beta 才更有信息含量。
  - 气候风险本身近几年才被投资者重视（2016 年巴黎协定），且其发生具有随机性、偶然性，并不频繁，故数据可用性低，难以从价格市场反应中获取有效的 mimicking beta, 噪音较大
  - 如何挖掘有效市场反应呢？既然没有这么长的有效时序数据来从“以前”推断“未来”，能否寻找一些横截面上的有效数据来“以小见大”呢？
  - 因此本文使用一小部分面临特殊气候冲击的投资者（基金经理）的投资持仓反应变动计算 beta，这种小部分变动不会影响市场整体价格，称之为 quantity-based

question

- 问题 2：为什么这里选用 active change，而不是其他？

$$ActiveChanges^{I}_{f,t} = \beta^{I,S}_{t} S_{f,t} + \delta^{I}_{t} + \epsilon^{I}_{f,t},$$

  - 针对问题 1，我们需要分析市场在经受气候风险冲击后，由信念变化所引发的一系列反应，例如价格波动、持仓变化和关注度等。
  - 首先，选择市场价格并不合适，因为特质性冲击通常不会显著影响价格。
  - 其他可能的信念冲击反应，例如分析师预测、消费者购买行为、银行信贷分配以及当地居民对相关股票或公司的关注度等，也可以选择。然而，本文的目标是构建投资组合，因此选择投资反应作为研究重点更为直接。
  - 同时，由于普通投资者的持仓数据较难获取，共同基金占据了投资者群体的重要份额，其投资组合的持有量可按季度观测，同时其地理分布数据也可以与局部气候冲击相匹配，是一个自然的选择。
  - 若使用其他代理变量可以转换研究框架，不专注于风险对冲组合。例如，可以探讨银行信念变化所带来的影响等，以寻找新的研究价值。

question

- 问题 3：构建投资组合时为什么这样加权?

$$QP_t^S = \sum_I \widehat{\beta}_{t-1}^{I,S}(R_t^I - R_t^f).$$

  - 首先，所计算出的 $beta^{I,S}$ 表示受到特质冲击的基金经理对 I 行业投资份额的变动
  - 这些受到冲击的基金经理信念被改变，进行投资时会考虑到气候风险
  - 由此，按照该公式就可以相同比例地模仿这些基金经理如何做多、做空各类资产来构造投资组合，理论上在再面临气候风险时会取得良好的风险对冲表现。

Thanks!