# How Trump and Paris Agreement shock Climate Change Exposure in stock market?

Sep 12th, 2024

## Main References:

SAUTNER, Z., VAN LENT, L., VILKOV, G. and ZHANG, R. (2023), Firm-Level Climate Change Exposure. J Finance, 78: 1449-1498. https://doi.org/10.1111/jofi.13219

Note: https://samuelssj123.github.io/shengjie.github.io//file/Reading Climate2023.pdf

Child, Travers & Massoud, Nadia & Schabus, Mario & Zhou, Yifan. (2020). **Surprise Election for Trump Connections.** Journal of Financial Economics. 140. 10.1016/j.jfineco.2020.12.004.

Note: https://samuelssj123.github.io/shengjie.github.io//file/Reading Trump2020.pdf

#### Setting:

We conduct two event studies to consider how climate change policy shocks affect the performance of public companies. When the U.S. first joined the Paris Agreement in 2015<sup>1</sup>, we expect high-polluting firms to underperform, i.e., high-Climate Exposure firms have a negative CAR. The Democratic Party is not pro-ESG, and when Trump comes to power and becomes President of the U.S.<sup>2</sup>, we expect high-polluting firms to generate positive performance, i.e., high-Climate Exposure firms have a positive CAR.

我们进行两个事件研究,考虑气候变化政策的冲击如何影响上市公司的表现。当美国在 2015 年第一次加入巴黎协定时,我们预计高污染企业的表现变差,即高 Climate Exposure 企业有负的 CAR。民主党并不支持 ESG,当特朗普上台成为美国总统后,我们预计高污染企业会产生正向的表现,即高 Climate Exposure 企业有正的 CAR。

#### Data:

#### 1) Data Source:

We use the Center for Research in Security Prices (CRSP) files to obtain stock returns, Standard and Poor's Compustat database to obtain financial information.

From text mining we get the ratio of climate change occur in the transcripts of earnings

<sup>&</sup>lt;sup>1</sup> The Paris Agreement was adopted on <u>12 December 2015(Saturday, so we choose</u> <u>14Dec2015</u> as event day) at the 21st United Nations Climate Change Conference, signed on <u>22 April 2016</u> at the United Nations building in New York, United States of America, and formally implemented from <u>4 November 2016</u> onwards.

<sup>&</sup>lt;sup>2</sup> On **9 November 2016**, at 1:40 a.m. EST, Republican presidential candidate Donald Trump won the presidential election.

conference calls. From Trucost we get data on carbon emmssion.

#### 2) Data

- Period: The sample spans the period Q1 2014 to Q2 2019.
- Data Sets:
  - Main data sets:
    - ♦ Company fundamentals: annual frequency.
    - ♦ Stock performance: daily frequency.
    - ♦ The index obtained from text mining Climate\_Regulation\_Risk, a third-party database of carbon emissions data, was merged with other data sets through cik.
  - Other data sets are required:
    - ♦ CRSP-Annual Update-Stock / Events-Names(NO period) & Delist(from Q1 2024 to Q2 2019).
    - ♦ CRSP-Annual Update-CRSP/Compustat Merged-Compustat CRSP Link.

#### Method: Event Research

**CAR(Cumulative Abnormal Returns)** mostly used to look at the sum of abnormal returns of a company's stock price over multiple days during the window before and after a certain time occurrence (Often using daily data.<sup>3</sup>). In our research, event occurrence includes **Paris Agreement Announced** and **Trump Wins Election.** 

- Abnormal return AR for a single day = daily return on the company's stock on that day benchmark's market return
- Cumulative abnormal returns CAR = sum of AR for multiple days

#### Tasks:

1. Using Jupyter to merge CRSP stock return and CompStat Fundamental Information data set by debugging the open source code.

2. Then, merging the former data to CRE and carbon data by column cik.

Note:【寻找最邻近日期<sup>4</sup>】一组是股票数据,有日期、代码、收益率等,这个日期和交易日相吻合;一组是自己制作提取的数据 CRE,有日期、代码、CRE 值,但是这个日期是和公司股东大会日期吻合的。使用 STATA 软件,将两组数据匹配,要求将 CRE 数据合并到股票数据中,先在股票数据中寻找 cik,然后看股票数据中的日期和 CRE 数据中日期最接近的 CRE 数据中的那一行,匹配给股票数据.

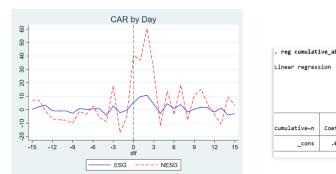
3. Event Study and cross-section regression.

<sup>&</sup>lt;sup>3</sup> Please DO NOT FORGET to convert date or month to date format in Stata and install the packages needed to run the code.

<sup>&</sup>lt;sup>4</sup> The nearest date should first satisfy that the stock trading time is **LATER** than the CRE value generation time..

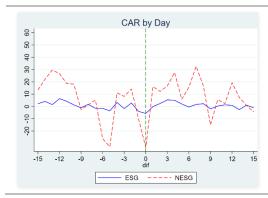
# Experiment 1 (Sep $14^{th} - 16^{th}$ ):

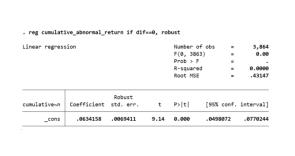
1. Trump: event windows=±15 estimation window=[-25,-15]



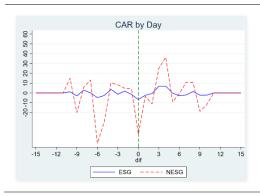
. reg cumulat:	ive_abnormal_r	eturn if di	t==⊎, rol	Dust			
Linear regres	near regression				Number of obs		3,776
			F(0, 3775)		=	0.00	
				Prob > F		=	
				R-squared		=	0.0000
				Root MSE		=	.30769
		Robust					
cumulative~n	Coefficient	std. err.	t	P> t	[95%	conf.	interval
cons	.0505114	.0050072	10.09	0.000	.0406	5943	.0603284

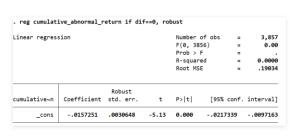
2. Paris Agreement: event windows=±15 estimation window=[-25,-15]



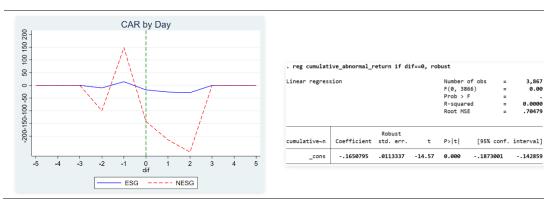


3. Paris Agreement: event windows=±10 estimation window=[-50,-10]

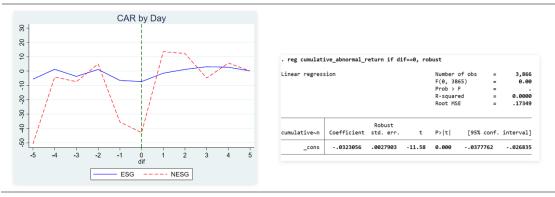




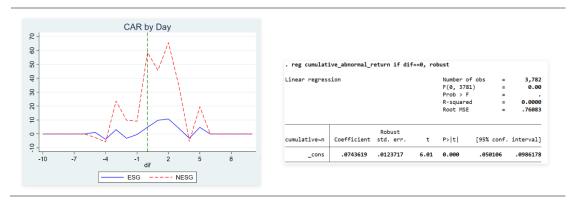
4. Paris Agreement: event windows=±2 estimation window=[-5,-2]



5. Paris Agreement: event windows=±5 estimation window=[-10,-5]



6. Trump: event windows=±5 estimation window=[-10,-15]



### All samples

	(1)	(2)	(4)	(3)	(5)
	Trump-	Paris-CAR	Paris-CAR	Paris-CAR	Paris-
	CAR $\pm 15$	$\pm 15$	$\pm 10$	$\pm 2$	CAR $\pm 5$
climaterisk	-2.1480***	1.6150***	-1.5137***	-33.3784***	-1.7476***
	(-15.8412)	(11.5430)	(-25.2203)	(-1.7e+02)	(-25.5624)
me	0.0000	-0.0000***	0.0000	-0.0000***	$0.0000^{***}$
	(0.2079)	(-6.8318)	(1.4152)	(-5.9939)	(4.0463)
cumretx	-0.0173***	$0.0007^{***}$	0.0004***	-0.0032***	$0.0002^{**}$
	(-15.2795)	(4.4539)	(6.2679)	(-14.7841)	(2.4204)
be	-0.0000***	-0.0000***	-0.0000***	$0.0000^{***}$	-0.0000***
	(-7.5926)	(-7.6786)	(-3.3437)	(17.1766)	(-4.3301)
vol	$0.0000^{***}$	$0.0000^{***}$	0.0000***	0.0000	$0.0000^{***}$

	(19.9569)	(30.7309)	(22.0421)	(1.5043)	(12.9496)	
_cons	$0.0514^{***}$	$0.0784^{***}$	-0.0119***	-0.0594***	$0.0202^{***}$	
	(30.0438)	(47.8280)	(-16.9453)	(-25.5688)	(25.1853)	
$\overline{N}$	72983	137687	137687	137687	137687	
adj. $R^2$	0.011	0.009	0.008	0.172	0.006	

#### **Only Dirty Firms Sample**

	(1)	(2)	(4)	(3)	(5)
	Trump-	Paris-CAR	Paris-CAR	Paris-CAR	Paris-CAR
	$CAR \pm 15$	±15	±10	±2	±5
climaterisk	-4.6305	1.2507	-0.5118	-2.5140	-1.7476***
	(-0.8877)	(0.4672)	(-0.3830)	(-0.2281)	(-25.5624)
me	-0.0000	-0.0000	0.0000	0.0000	$0.0000^{***}$
	(-0.6833)	(-0.1205)	(0.0303)	(0.2199)	(4.0463)
cumretx	-0.0044	-0.0005	-0.0000	-0.0027	$0.0002^{**}$
	(-0.1008)	(-0.1589)	(-0.0006)	(-0.2272)	(2.4204)
be	-0.0000	0.0000	-0.0000	0.0000	-0.0000***
	(-0.8779)	(0.5033)	(-0.5845)	(0.1016)	(-4.3301)
vol	$0.0000^{***}$	-0.0000**	$0.0000^{***}$	-0.0000	$0.0000^{***}$
	(5.9343)	(-2.1795)	(2.7257)	(-0.8553)	(12.9496)
_cons	2.6646***	2.1833***	-0.2019***	-5.5285***	$0.0202^{***}$
	(38.1171)	(64.3275)	(-11.9150)	(-39.5649)	(25.1853)
N	61876	116214	116214	116214	137687
adj. $R^2$	0.000	-0.000	0.000	-0.000	0.006

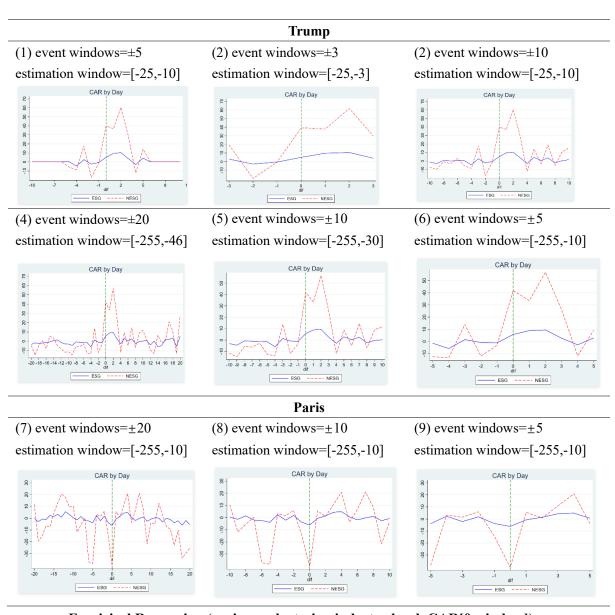
#### **Other Experiment**

	(6)	(6)
	Trump-CAR $\pm 5$	Trump-CAR $\pm 5$
	All Sample	Dirty Sample
climaterisk	10.4347***	-6.3708
	(23.7504)	(-1.1221)
me	-0.0000***	-0.0000
	(-5.8560)	(-0.9099)
cumretx	-0.0363***	-0.0029
	(-9.9050)	(-0.0624)
be	0.0000	-0.0000
	(1.4016)	(-1.1012)
vol	0.0000	$0.0000^{***}$
	(0.5216)	(7.5037)
_cons	$0.1172^{***}$	3.9426***
	(21.1274)	(51.8109)
N	73024	61917
adj. $R^2$	0.010	0.001

#### **Problem:**

It is evident that the regression *t-statistic is* disproportionately large in the results. This phenomenon may be attributed to the absence of clustering in the variance estimation process. Additionally, the issue of inference efficiency remains unaddressed, and the variance clustering necessitates adjustment. Cross-sectional regression can be adjusted to the industry level to attempt to identify the optimal window from 0 and different training windows. It is anticipated that Trump will have a positive impact, while Paris is expected to have a negative impact. It is possible that the two events may result in the same significant window.

## Experiment 2 (Sep 17th - 18th):



Empirical Regression (variance clustering industry level, CAR[0,window])

		(1)	(2)		
	car_window	nesg_car_window	car_window	nesg_car_window	
climaterisk	-0.6320	-4.5926***	-0.7219	-5.3018***	
	(-1.5016)	(-3.3192)	(-1.4816)	(-3.4553)	
me	-0.0000***	-0.0000	-0.0000***	$-0.0000^*$	
	(-3.5954)	(-1.6266)	(-3.6558)	(-1.6527)	
cumretx	-0.0104**	-0.0014	-0.0108**	-0.0022	
	(-2.1066)	(-0.2347)	(-2.1374)	(-0.3440)	
be	-0.0000	-0.0000	0.0000	-0.0000	
	(-0.0947)	(-1.5734)	(0.5643)	(-1.6220)	
vol	0.0000	$0.0000^{***}$	0.0000	$0.0000^{***}$	
	(1.2071)	(2.9180)	(1.1837)	(3.2236)	

_cons	0.0651***	2.3738***	$0.0679^{***}$	2.6004***
	(7.1933)	(88.8939)	(5.9576)	(89.6282)
$\overline{N}$	72983	61876	72983	61876
adj. $R^2$	0.019	0.001	0.026	0.001

		(3)		(4)
	car_window	nesg_car_window	car_window	nesg_car_window
climaterisk	0.2887	-4.2062***	1.7325***	-3.0698***
	(0.5021)	(-3.4326)	(3.0141)	(-3.0137)
me	-0.0000***	-0.0000	-0.0000***	-0.0000
	(-3.8906)	(-1.5247)	(-3.5185)	(-1.5243)
cumretx	-0.0095**	-0.0012	-0.0126*	-0.0020
	(-2.1370)	(-0.2004)	(-1.7980)	(-0.4067)
be	-0.0000	-0.0000	0.0000	-0.0000
	(-0.5504)	(-1.5492)	(0.5595)	(-1.5207)
vol	$0.0000^*$	$0.0000^{***}$	0.0000	$0.0000^{***}$
	(1.7317)	(2.6092)	(0.6000)	(2.7844)
_cons	$0.0702^{***}$	2.6554***	0.0677***	1.0822***
	(8.1829)	(98.8920)	(6.3404)	(54.9920)
N	72983	61876	96548	81911
adj. $R^2$	0.011	0.000	0.020	0.000

		(5)	(6)	
	car_window	nesg_car_window	nesg_car_window	car_window
climaterisk	0.2666	-2.4006***	-2.7507***	-0.7655**
	(0.7255)	(-2.9007)	(-3.1667)	(-2.2960)
me	-0.0000***	-0.0000	-0.0000	-0.0000***
	(-4.3715)	(-1.2861)	(-1.4031)	(-4.0712)
cumretx	-0.0100**	-0.0050	-0.0053	-0.0105**
	(-2.1477)	(-1.0275)	(-0.9193)	(-2.0334)
be	0.0000	-0.0000	-0.0000	0.0000
	(0.3039)	(-1.4134)	(-1.4563)	(0.3563)
vol	-0.0000	$0.0000^{**}$	$0.0000^{**}$	-0.0000
	(-0.5641)	(2.1656)	(2.5265)	(-0.5742)
_cons	$0.0649^{***}$	1.2797***	1.5057***	$0.0630^{***}$
	(8.0174)	(73.0671)	(81.0730)	(7.1270)
N	96547	81910	81910	96547
adj. $R^2$	0.018	0.000	0.000	0.026

		(7)		(8)
	car_window	nesg_car_window	car_window	nesg_car_window
climaterisk	-1.6274**	0.3239	-0.8076	-1.2434***
	(-2.4458)	(0.9196)	(-1.5976)	(-3.9896)

me	0.0000	0.0000	-0.0000	0.0000
	(0.3574)	(1.3629)	(-1.3898)	(1.4648)
cumretx	-0.0006***	-0.0005***	0.0000	$0.0001^{**}$
	(-3.9667)	(-8.7708)	(0.9123)	(2.4787)
be	0.0000	-0.0000	0.0000	-0.0000**
	(1.6434)	(-0.1190)	(0.4775)	(-2.4762)
vol	-0.0000	-0.0000	0.0000	$0.0000^{**}$
	(-0.2841)	(-1.2687)	(1.0092)	(2.4353)
_cons	-0.0378***	-2.0945***	$0.0078^{**}$	-0.9504***
	(-3.5972)	(-3.8e+02)	(2.0155)	(-2.1e+02)
N	113590	95750	113589	95749
adj. $R^2$	0.011	-0.000	0.007	-0.000

	(9)		
	car_window	nesg_car_window	
climaterisk	-2.7222***	-0.7759***	
	(-7.2262)	(-3.6854)	
me	-0.0000	0.0000	
	(-1.2890)	(1.2787)	
cumretx	$0.0003^{***}$	$0.0001^{**}$	
	(9.0995)	(2.0757)	
be	-0.0000	-0.0000***	
	(-0.1545)	(-2.7432)	
vol	0.0000	$0.0000^{**}$	
	(1.3135)	(2.5305)	
_cons	0.0113**	-0.5633***	
	(2.5850)	(-1.9e+02)	
$\overline{N}$	113590	95750	
adj. $R^2$	0.088	-0.000	

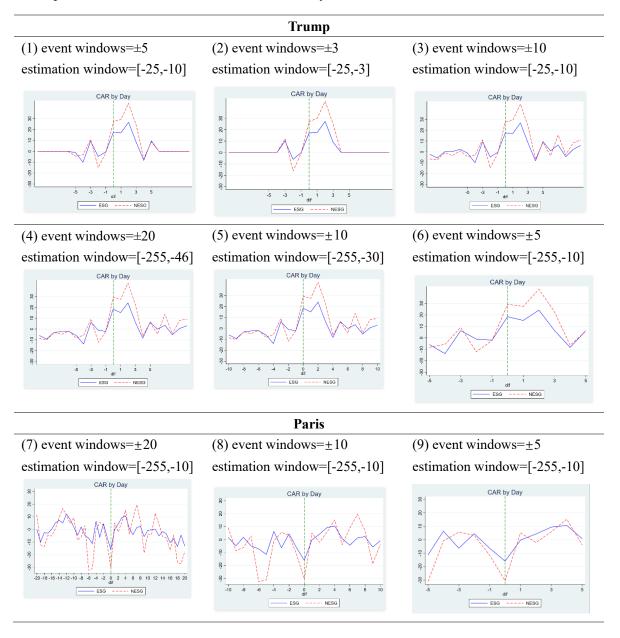
#### Problem:

A cross-sectional regression corresponds to only one event in Trump. the number of observations should just be the number of stocks in that time period. Each regression here is at 50k at least, and the 10k full sample is only 10w. there should be a mistake somewhere, the 10k full sample MEASURE is 10w, and the time period is 8/9 years, how can there not be 10w observation in one year. The reason is that the full sample was used before, and what is actually needed is to change the panel data regression to cross-section data regression.

## Experiment 3 (Sep 19th):

Change the independent variable climate\_risk to climate\_regulation\_risk.

Keep the observations NON-EMPTY in event-day.



	(2	1)	(2)		
	cumulative_abnor cumulative_abnor		cumulative_abnor cumulative_a		
	mal_return	mal_return	mal_return	mal_return	
climate_ _risk	-0.5527	-0.6112	-0.5821	-0.6045	
	(-1.3835)	(-1.5927)	(-1.2655)	(-1.4715)	
me	-0.0000***	-0.0000**	-0.0000	-0.0000	

	(-2.5999)	(-2.3763)	(-1.1138)	(-0.5572)
wt	-0.0000	0.0000	0.0000	0.0000
	(-0.6012)	(0.5116)	(0.0558)	(1.1714)
cumretx	-0.0092**	-0.0099*	-0.0095**	-0.0101*
	(-2.0113)	(-1.8158)	(-2.0640)	(-1.8685)
mebase	0.0000	$0.0000^{**}$	0.0000	$0.0000^{**}$
	(1.1437)	(2.1321)	(1.5855)	(2.2054)
lme	0.0000	0.0000	0.0000	-0.0000
	(1.2357)	(1.0411)	(0.2068)	(-0.3620)
dec_me	0.0000	-0.0000	0.0000	0.0000
	(0.4295)	(-0.3628)	(1.0812)	(0.3565)
be	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.3384)	(-0.4836)	(-0.1256)	(-0.4866)
_cons	0.0642***	0.0672***	0.0665***	0.0687***
	(7.2436)	(7.1019)	(5.9145)	(6.4765)
N	1137	746	1138	746
adj. $R^2$	0.013	0.022	0.021	0.031

	(3	3)	(4	4)
	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor
	mal_return	mal_return	mal_return	mal_return
climate_	0.4229	0.1712	1.7867***	1.2228**
_risk				
	(0.7391)	(0.2772)	(3.0327)	(1.9844)
me	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(-2.6911)	(-2.9799)	(-3.4670)	(-3.1407)
wt	0.0000	0.0000	0.0000	0.0000
	(0.1071)	(1.1807)	(0.1212)	(0.2608)
cumretx	-0.0083**	-0.0112*	-0.0112*	-0.0109*
	(-1.9929)	(-1.8309)	(-1.6526)	(-1.6683)
mebase	0.0000	$0.0000^*$	0.0000	0.0000
	(1.3462)	(1.6840)	(0.4591)	(0.4180)
lme	0.0000	0.0000	$0.0000^*$	0.0000
	(1.0579)	(1.1495)	(1.9406)	(1.6394)
dec_me	0.0000	-0.0000	0.0000	0.0000
	(0.2992)	(-0.5180)	(0.6513)	(1.0776)
be	-0.0000	-0.0000	0.0000	-0.0000
	(-0.5515)	(-0.5627)	(0.2144)	(-1.2777)
_cons	0.0694***	0.0793***	0.0682***	0.0877***
	(7.9313)	(6.8535)	(6.2941)	(6.5986)
N	1138	746	1134	742
adj. R <sup>2</sup>	0.005	0.013	0.014	0.016

	(:	5)	(6	(6)			
	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor			
	mal_return	mal_return	mal_return	mal_return			
climate_	0.3283	0.1655	-0.7151**	-0.7090**			
_risk							
	(0.8649)	(0.4036)	(-2.1362)	(-2.2380)			
me	-0.0000*	-0.0000*	-0.0000**	-0.0000			
	(-1.9244)	(-1.6914)	(-2.0225)	(-1.5976)			
wt	0.0000	0.0000	-0.0000	0.0000			
	(0.4095)	(1.2562)	(-0.0520)	(0.7861)			
cumretx	-0.0090**	-0.0093*	-0.0096*	-0.0088*			
	(-2.0582)	(-1.9655)	(-1.9393)	(-1.8596)			
mebase	0.0000	0.0000	0.0000	0.0000			
	(0.9906)	(1.0245)	(1.1105)	(1.5568)			
lme	0.0000	0.0000	0.0000	0.0000			
	(0.6693)	(0.2787)	(0.9020)	(0.3474)			
dec_me	0.0000	0.0000	0.0000	0.0000			
	(0.8026)	(0.5080)	(0.7718)	(0.4064)			
be	-0.0000	-0.0000	-0.0000	-0.0000			
	(-0.3041)	(-1.2106)	(-0.2251)	(-0.9663)			
_cons	0.0645***	0.0717***	0.0625***	0.0635***			
	(8.1041)	(7.2214)	(7.2285)	(7.5228)			
N	1134	742	1134	742			
adj. $R^2$	0.013	0.020	0.022	0.030			

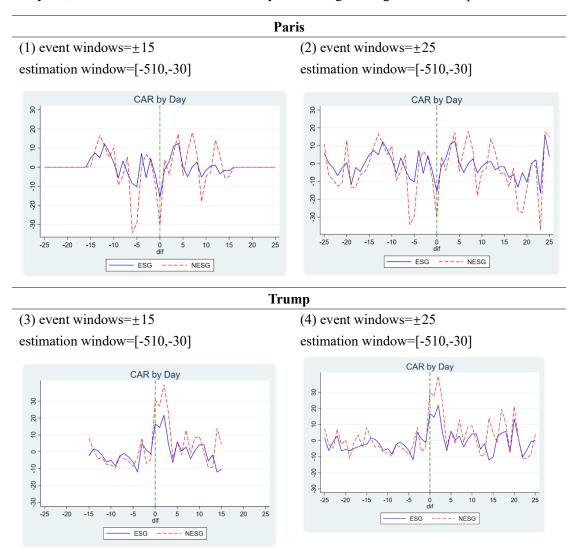
	(*)	7)	3)	3)
	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor
	mal_return	mal_return	mal_return	mal_return
climate_	-1.2622*	-1.5326**	-0.5164	-0.5548
_risk				
	(-1.9117)	(-2.4381)	(-1.1087)	(-1.1800)
me	-0.0000**	-0.0000*	-0.0000*	-0.0000
	(-2.3206)	(-1.8549)	(-1.6672)	(-1.5053)
wt	0.0000	-0.0000	-0.0000	-0.0000
	(0.8427)	(-0.0088)	(-1.0859)	(-1.2244)
cumretx	-0.0019	-0.0077	0.0007	-0.0012
	(-1.3610)	(-1.0510)	(1.0837)	(-0.2740)
mebase	$-0.0000^*$	-0.0000**	-0.0000***	-0.0000***
	(-1.9478)	(-2.3383)	(-2.7998)	(-2.7007)
lme	-0.0000***	-0.0000**	-0.0000	-0.0000
	(-3.4944)	(-2.3726)	(-1.3775)	(-1.0461)
dec_me	$0.0000^{***}$	$0.0000^{***}$	$0.0000^{***}$	$0.0000^{**}$
	(3.4989)	(3.4983)	(2.7101)	(2.4534)

be	0.0000	0.0000	0.0000	0.0000
	(0.9070)	(0.5031)	(0.5921)	(0.5441)
_cons	-0.0392***	-0.0279**	0.0052	0.0074
	(-4.0941)	(-2.0906)	(1.2867)	(0.8970)
N	1283	838	1283	838
adj. $R^2$	0.013	0.018	0.004	0.011

	(9	9)
	cumulative_abnorma	cumulative_abnorma
	l_return	l_return
climaterisk	-2.4333***	-2.4862***
	(-7.1624)	(-7.6604)
me	-0.0000	-0.0000
	(-0.8833)	(-0.9908)
wt	-0.0000	-0.0000
	(-1.2126)	(-1.1797)
cumretx	$0.0009^{*}$	0.0011
	(1.6916)	(0.3151)
mebase	-0.0000**	-0.0000**
	(-2.5203)	(-2.3718)
lme	0.0000	-0.0000
	(0.2996)	(-0.0059)
dec_me	0.0000	$0.0000^*$
	(1.4550)	(1.6889)
be	0.0000	0.0000
	(0.3596)	(0.1986)
_cons	$0.0090^{**}$	0.0104
	(2.2357)	(1.4498)
N	1283	838
adj. $R^2$	0.077	0.111

## Experiment 4(Sep 20th-23th):

The training sample and the time gap in between are tuned, and the training sample is used for two years, which can be collated for five days according to the grid of the loop.



	(1	1)	(2)		
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	
	ormal_return	ormal_return	ormal_return	ormal_return	
climate _risk	0.5496	0.3330	-0.8006**	-1.0231**	
	(0.6869)	(0.4023)	(-2.2471)	(-2.4332)	
me	-0.0000	-0.0000	-0.0000	-0.0000	
	(-1.3867)	(-1.1836)	(-1.6322)	(-1.1597)	
wt	$0.0000^*$ (1.8251)	0.0000 (0.7272)	0.0000 (1.1291)	-0.0000 (-0.3553)	

cumret	-0.0014**	-0.0093**	-0.0012	-0.0086
X				
	(-2.3127)	(-2.2598)	(-1.1510)	(-1.2244)
mebase	-0.0000	-0.0000	-0.0000	-0.0000***
	(-1.3946)	(-1.5836)	(-1.4469)	(-2.8503)
lme	-0.0000***	-0.0000**	-0.0000**	-0.0000
	(-3.2176)	(-2.0473)	(-2.1573)	(-0.7337)
dec_me	$0.0000^{**}$	$0.0000^*$	$0.0000^{**}$	$0.0000^{**}$
	(2.0330)	(1.9512)	(2.0490)	(2.1346)
be	0.0000	-0.0000	0.0000	0.0000
	(0.1347)	(-0.0001)	(0.0631)	(0.2646)
_cons	0.0046	0.0154	-0.0302***	-0.0199
	(0.9769)	(1.5701)	(-4.0237)	(-1.4029)
N	1286	840	1286	840
adj. $R^2$	0.000	0.003	0.000	0.001

	(3)	3)	mal_return         mal_return           3.4214***         2.9500***           (6.6285)         (5.7277)           -0.0000***         -0.0000*           (-3.1710)         (-1.9191)           0.0000         0.0000           (0.6065)         (0.9258)           -0.0085*         -0.0108*           (-1.7463)         (-1.7948)           0.0000         0.0000           (1.1193)         (0.8205)           0.0000         0.0000	
	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor
	mal_return	mal_return	mal_return	mal_return
climate_	3.5959***	3.2318***	3.4214***	2.9500***
_risk				
	(6.2968)	(5.0746)	(6.6285)	(5.7277)
me	-0.0000***	-0.0000**	-0.0000***	$-0.0000^*$
	(-2.8061)	(-2.3074)	(-3.1710)	(-1.9191)
wt	0.0000	0.0000	0.0000	0.0000
	(0.4986)	(0.9274)	(0.6065)	(0.9258)
cumretx	-0.0114**	-0.0137**	-0.0085*	-0.0108*
	(-2.2114)	(-2.0247)	(-1.7463)	(-1.7948)
mebase	0.0000	0.0000	0.0000	0.0000
	(1.3573)	(1.0439)	(1.1193)	(0.8205)
lme	$0.0000^*$	0.0000	0.0000	0.0000
	(1.7485)	(1.1040)	(1.5113)	(0.1774)
dec_me	-0.0000	-0.0000	-0.0000	0.0000
	(-0.6380)	(-0.0383)	(-0.1497)	(1.2973)
be	0.0000	-0.0000	0.0000	-0.0000
	(0.8485)	(-0.3149)	(0.7466)	(-1.1134)
_cons	0.0543***	$0.0704^{***}$	0.0612***	0.0834***
	(6.3002)	(5.8318)	(5.5938)	(6.1045)
N	1050	692	1050	692
adj. R <sup>2</sup>	0.054	0.068	0.036	0.054

## Experiment4: Introduction of Carbon Emissions Data (Sep 24th-30th)

#### Main References:

Patrick Bolton, Marcin Kacperczyk, **Do investors care about carbon risk?**, Journal of Financial Economics, Volume 142, Issue 2, 2021, Pages 517-549, ISSN 0304-405X, <a href="https://doi.org/10.1016/j.jfineco.2021.05.008">https://doi.org/10.1016/j.jfineco.2021.05.008</a>.

Note: https://samuelssj123.github.io/shengjie.github.io/file/Reading Carbon2021.pdf

#### Variables Selection:

di_319438	Impact Ratio: GHG Direct Cost
di_319440	Impact Ratio: GHG Indirect Cost
di_319413	Absolute: GHG Scope 1
di_319414	Absolute: GHG Scope 2 Location-based
di_319415	Absolute: GHG Scope 3 Upstream Total
di_319407	Intensity: GHG Scope 1
di_319408	Intensity: GHG Scope 2 Location-based
di_319409	Intensity: GHG Scope 3 Upstream

#### Description of variables:

CRRabsco1=climate regulation risk\*log(di 319413: Absolute: GHG Scope 1)

CRRabsco2=climate\_regulation\_risk\*log(di\_319414: Absolute: GHG Scope 2 Location-based)

CRRabsco3=climate regulation risk\*log(di 319415: GHG Scope 3 Upstream Total)

CRRgrsco1=climate regulation risk\*growth rate scope1

CRRgrsco2=climate regulation risk\*growth rate scope2

CRRgrsco3=climate regulation risk\*growth rate scope3

CRRinsco1=climate regulation risk\*di 319407: Intensity: GHG Scope 1

CRRinsco2=climate regulation risk\*di 319408: Intensity: GHG Scope 2 Location-based

CRRinsco3=climate regulation risk\*di 319409: Intensity: GHG Scope 3 Upstream

问题:在 Paris 检验中遇到了样本量过少的问题(如 16-25 页)。合并步骤是:①基本面和股票合并(通过 gvkey 和 year,其中股票月份小于 6,则合并报表滞后 1 年),保留在2015-12-14 存在的观测,大概有 1000 多个。②再和 carbon 数据合并,约剩下 236 个观测。已排查:①仅 carbon 和股票合并,保留 2015-12-14 的观测,只剩下 1000 多个。②单独 2015-12-14 的股票,有 3k 多个;单独 carbon 在 2015-12-31 的观测,有 4k 多个;单独基本面在 2015 的观测,有 1k 多个。代码在文末展示。多次检查未找到数据合并上的原因,推测是数据问题。

改进方法是:保留在 event-window 期内的全部观测。(如 16 页及之后)

我们期待的结果是在巴黎协定签署事件冲击中,公司的环境相关指标给 CAR 带来负的收益,而在特朗普上台的事件冲击中,则会带来正的收益。符合该预想的结果已用红色标记并使用黄色底色。

请注意,在每个参数调整的窗口期中,我都分别进行了18个回归检验,已控制基本面变量,只展示与环境指标相关的变量系数。

(1) event: Paris event windows=[0,3] estimation window=[-510,-30]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn ormal return	cumulative_abn ormal return	cumulative_abno rmal return	cumulative_abn ormal return	cumulative_abn ormal return	cumulative_abn ormal return	cumulative_abn ormal return	cumulative_ab normal return	cumulative_ab normal return
climate_regu	-18.4206**	-3.1285	-31.5985***	-3.8834***	-3.7712***	-3.4519***	-4.8286***	-3.6953***	-6.2187***
lation_risk									
	(-2.5379)	(-0.4858)	(-3.3096)	(-4.2956)	(-4.3177)	(-3.2991)	(-5.9437)	(-4.9891)	(-7.4226)
CRRabsco1	1.0477**								
	(2.0290)								
CRRabsco2		-0.1212							
		(-0.2175)							
CRRabsco3			2.1996***						
			(2.8556)						
CRRgrsco1				0.1715***					
				(6.9092)					
CRRgrsco2					0.0480				
					(0.3476)				
CRRgrsco3						-1.8284			
						(-0.5945)			
CRRinsco1							0.0004		
							(1.4171)		
CRRinsco2								-0.0126	
CDD' A								(-0.9279)	0.0117***
CRRinsco3									0.0117***
	0.0056	0.0120	0.0007	0.0220	0.0220	0.0242	0.0116	0.0117	(3.0401)
_cons	-0.0056	-0.0120	-0.0087	-0.0220	-0.0230	-0.0243	-0.0116	-0.0117	-0.0140
C + 1	(-0.3502)	(-0.6949)	(-0.5027)	(-0.8213)	(-0.8544)	(-0.8732)	(-0.6684)	(-0.6847)	(-0.7505)
Control		Yes Yes	Yes		Yes Yes		Yes	226	226
N . 1: P2	235	236	236	214	216	216	236	236	236
adj. $R^2$	0.200	0.175	0.220	0.166	0.162	0.163	0.182	0.183	0.190

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abno	cumulative_abno	cumulative_abn	cumulative_abn	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_a
	rmal_return	rmal_return	ormal_return	ormal_return	normal_return	normal_return	normal_return	normal_return	normal_retur
CRRabsco1	0.3320			0.4456			0.4795		
	(0.7279)			(1.2033)			(0.8641)		
CRRabsco2	-1.2443***			-1.3425***			-0.5784**		
	(-3.1652)			(-2.7818)			(-2.2718)		
CRRabsco3	0.4232			0.3932			1.9546**		
	(0.7802)			(0.7090)			(2.5865)		
CRRgrsco1		1.9181***			1.8634***			214	236
		(9.2392)			(9.4632)			0.192	0.191
CRRgrsco2		-1.7843***			-1.7797***			214	236
		(-8.4410)			(-9.6400)			0.192	0.191
CRRgrsco3		-5.9185*			-7.5321***			214	236
		(-1.9803)			(-3.5412)			0.192	0.191
CRRinsco1			0.0005			0.0008		214	236
			(1.0837)			(0.4683)		0.192	0.191
CRRinsco2			-0.0273**			-0.0294***		214	236
			(-2.2779)			(-2.6768)		0.192	0.191
CRRinsco3			-0.0084*			-0.0114**		214	236
			(-1.7694)			(-2.2062)		0.192	0.191
li_319438				-0.0004	0.0012	-0.0007		214	236
				(-0.2682)	(1.6192)	(-0.1666)		0.192	0.191
li_319440				0.0019	-0.0006	0.0132		214	236
				(0.3049)	(-0.0832)	(1.6564)		0.192	0.191
climate_regu							-28.5317**	214	236
ation_risk									
							(-2.5100)	0.192	0.191
cons	-0.0155	-0.0508*	-0.0265	-0.0162	-0.0519	-0.0317	-0.0081	214	236
	(-0.8320)	(-1.8312)	(-1.2028)	(-0.8146)	(-1.6548)	(-1.3485)	(-0.4777)	0.192	0.191
Control '	Yes Yes	Yes Yes	Yes Yes	Yes					
V	235	214	236	235	214	236	235	214	236
adj. $R^2$	0.184	0.161	0.142	0.177	0.160	0.141	0.221	0.192	0.191

(2) event: Paris event windows=[0,5] estimation window=[-510,-30]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab						
	normal_return	normal_return	normal_return						
climate_reg	-23.3552***	0.7307	-37.4770***	-4.8499***	-4.7450***	-5.0135***	-6.3231***	-4.4790***	-7.3496***
ulation_risk									
	(-3.8605)	(0.0669)	(-3.4833)	(-5.2976)	(-5.1642)	(-4.7504)	(-10.5567)	(-4.4014)	(-8.6728)
CRRabsco1	1.3453***								
	(3.0636)								
CRRabsco2		-0.5532							
		(-0.5823)							
CRRabsco3			2.6019***						
			(2.9017)						
CRRgrsco1				0.2022***					
				(8.2195)					
CRRgrsco2					0.0799				
					(0.5708)				
CRRgrsco3						2.6141			
						(0.5259)			
CRRinsco1							$0.0011^{***}$		
							(6.4266)		
CRRinsco2								-0.0152	
								(-0.9609)	
CRRinsco3									$0.0131^{*}$
									(1.8293)
_cons	0.0055	-0.0042	0.0006	-0.0113	-0.0121	-0.0108	-0.0023	-0.0025	-0.0056
	(0.3154)	(-0.2231)	(0.0296)	(-0.3848)	(-0.4084)	(-0.3497)	(-0.1194)	(-0.1326)	(-0.2622)
Control	Yes	Yes	Yes						
N	235	236	236	214	216	216	236	236	236
adj. $R^2$	0.251	0.220	0.267	0.211	0.204	0.206	0.254	0.226	0.232

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abnor	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_ab
	ormal_return	ormal_return	mal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
CRRabsco1	0.6639			0.0836			0.7940		
	(1.2671)			(0.1837)			(1.6083)		
CRRabsco2	-1.8379***			-1.2787**			-1.1243***		
	(-4.7067)			(-2.0104)			(-2.7181)		
CRRabsco3	0.5259			0.6180			$2.2187^*$		
	(0.6083)			(0.7751)			(1.9365)		
CRRgrsco1		1.9519***			1.7741***			1.6713***	
		(6.9675)			(6.4929)			(18.3069)	
CRRgrsco2		-1.8089***			-1.7393***			-1.4192***	
		(-6.4546)			(-6.5385)			(-16.6047)	
CRRgrsco3		-3.3974			-7.3326***			2.0751	
		(-0.6787)			(-2.8961)			(0.3680)	
CRRinsco1			0.0014***			0.0015			0.0011***
			(4.0244)			(0.9202)			(3.8874)
CRRinsco2			-0.0343***			-0.0365***			-0.0179*
			(-3.2541)			(-3.7904)			(-1.8248)
CRRinsco3			-0.0159***			-0.0196***			0.0010
			(-4.1982)			(-5.1021)			(0.1445)
li_319438				0.0019	0.0029***	-0.0003			
				(1.3350)	(4.7559)	(-0.0710)			
di_319440				-0.0030	-0.0068	0.0159**			
				(-0.4639)	(-0.8372)	(2.1094)			
climate_regula							-30.8320**	-4.9251***	-5.5086***
ion_risk									
							(-2.2315)	(-4.5135)	(-5.1149)
cons	-0.0065	-0.0535	-0.0165	-0.0067	-0.0517	-0.0232	0.0011	-0.0043	-0.0009
_	(-0.3003)	(-1.5774)	(-0.6760)	(-0.2966)	(-1.4068)	(-0.8879)	(0.0581)	(-0.1521)	(-0.0497)
Control		es Yes	Yes	Yes	Yes	Yes	` ` ` ` ` ` ` ` ` ` ` ` ` ` ` ` ` ` ` `	,	
V	235	214	236	235	214	236	235	214	236
adj. $R^2$	0.248	0.165	0.218	0.248	0.188	0.219	0.283	0.226	0.259

(3) event: Paris event windows=[0,7] estimation window=[-510,-30]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn								
	ormal_return								
climate_regu	-13.8758***	3.6312	-18.2440***	-2.2536**	-2.2437**	-2.2943**	-2.1841***	-1.2139	-2.7886***
lation_risk									
	(-3.6878)	(0.4565)	(-4.8524)	(-2.2279)	(-2.2442)	(-2.3011)	(-3.1840)	(-1.2664)	(-3.1073)
CRRabsco1	0.9343***								
	(3.4669)								
CRRabsco2		-0.4528							
		(-0.6638)							
CRRabsco3			1.3609***						
			(4.6663)						
CRRgrsco1				0.1335***					
				(6.2007)					
CRRgrsco2					$0.1058^{***}$				
					(3.4878)				
CRRgrsco3						1.3080			
						(0.2561)			
CRRinsco1							$0.0009^{***}$		
							(7.0185)		
CRRinsco2								-0.0034	
								(-0.4700)	
CRRinsco3									0.0091
									(1.5857)
_cons	0.0273	0.0205	0.0240	0.0404	0.0398	0.0402	0.0221	0.0220	0.0202
	(1.6315)	(1.2270)	(1.4706)	(1.6332)	(1.6163)	(1.5593)	(1.3469)	(1.3496)	(1.2388)
Control	Yes								
N	235	236	236	214	216	216	236	236	236
adj. $R^2$	0.023	0.002	0.019	0.012	0.011	0.010	0.040	-0.001	0.010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_ab							
	ormal_return								
CRRabsco1	0.6787			-0.0117			$0.7589^*$		
	(1.5675)			(-0.0287)			(1.8566)		
CRRabsco2	-1.1455***			-0.4915			-0.8271**		
	(-4.3679)			(-1.2753)			(-2.4097)		
CRRabsco3	0.1991			0.3192			$0.9670^{*}$		
	(0.3088)			(0.5595)			(1.6640)		
CRRgrsco1		0.4845***			$0.2903^{*}$			0.3394***	
		(3.2304)			(1.9371)			(2.8616)	
CRRgrsco2		-0.3949**			-0.3132**			-0.1953*	
		(-2.6157)			(-2.0185)			(-1.7049)	
CRRgrsco3		-1.4862			-5.5167**			1.4323	
		(-0.2957)			(-2.2797)			(0.2709)	
CRRinsco1			0.0011***			0.0006			$0.0010^{***}$
			(6.6329)			(0.5702)			(5.4905)
CRRinsco2			-0.0115***			-0.0102**			-0.0060***
			(-3.4035)			(-2.4168)			(-2.7096)
CRRinsco3			-0.0059*			-0.0060*			0.0002
			(-1.7424)			(-1.7553)			(0.0261)
di_319438				0.0022**	$0.0030^{***}$	0.0014			
				(2.3408)	(4.6148)	(0.4774)			
di_319440				-0.0050	-0.0078	0.0006			
				(-0.7596)	(-1.0190)	(0.0844)			
climate_regu							-14.2568**	-2.4110**	-1.8513*
lation_risk									
							(-2.1072)	(-2.4236)	(-1.7431)
_cons	0.0211	0.0180	0.0173	0.0220	0.0206	0.0166	0.0249	0.0417	0.0220
	(1.2495)	(0.8062)	(1.0663)	(1.1903)	(0.8549)	(0.9386)	(1.4550)	(1.6022)	(1.3125)
Control	Yes								
N	235	214	236	235	214	236	235	214	236
adj. $R^2$	0.024	-0.015	0.030	0.030	0.023	0.022	0.032	0.004	0.033

(4) event: Paris event windows=[0,10] estimation window=[-510,-30]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn								
	ormal_return								
climate_regu	-20.8617***	2.7404	-27.6688***	-3.9073***	-3.8742***	-4.2317***	-4.6363***	-3.1541***	-5.2983***
lation_risk									
	(-4.2659)	(0.2587)	(-4.8984)	(-3.8470)	(-3.8188)	(-3.9797)	(-6.4820)	(-2.7820)	(-5.4971)
CRRabsco1	1.2959***								
	(3.5991)								
CRRabsco2		-0.5688							
		(-0.6213)							
CRRabsco3			1.9512***						
			(3.9723)						
CRRgrsco1				0.2228***					
S				(7.7485)					
CRRgrsco2				(,,,,,,,,,	0.1520**				
0144810402					(2.0260)				
CRRgrsco3					(=:0=00)	3.8850			
erargisees						(0.8848)			
CRRinsco1						(0.0010)	0.0013***		
CRRIISCOT							(9.6028)		
CRRinsco2							(9.0028)	-0.0070	
CKKIIISC02									
CDD: 2								(-0.5387)	0.0115
CRRinsco3									0.0115
	0.0050	0.0041	0.0000	0.0017	0.0025	0.0006	0.0021	0.0024	(1.2792)
_cons	0.0050	-0.0041	0.0000	-0.0016	-0.0025	-0.0006	-0.0021	-0.0024	-0.0047
	(0.3133)	(-0.2473)	(0.0018)	(-0.0569)	(-0.0891)	(-0.0226)	(-0.1255)	(-0.1473)	(-0.2717)
Control	Yes								
N	236	237	237	215	217	217	237	237	237
adj. $R^2$	0.129	0.097	0.126	0.103	0.099	0.101	0.153	0.095	0.107

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_a
	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return
CRRabsco1	$0.9118^*$			0.1138			$1.0270^{**}$		
	(1.7039)			(0.2459)			(2.1287)		
CRRabsco2	-1.5909***			-0.8244			-1.0827**		
	(-3.8072)			(-1.3462)			(-2.1942)		
CRRabsco3	0.1780			0.3069			1.3866*		
	(0.1997)			(0.3963)			(1.6789)		
CRRgrsco1		1.1633***			0.9579***			0.9049***	
		(5.4455)			(4.5318)			(6.3442)	
CRRgrsco2		-1.0041***			-0.9244***			-0.6508***	
		(-4.5825)			(-4.2682)			(-4.5563)	
CRRgrsco3		-1.1422			-5.6138**			3.9763	
		(-0.2521)			(-2.3616)			(0.8591)	
CRRinsco1			$0.0016^{***}$			0.0021**			$0.0014^{***}$
			(6.6790)			(1.9982)			(5.4132)
CRRinsco2			-0.0224***			-0.0249***			-0.0110*
			(-3.4853)			(-4.6546)			(-1.8624)
CRRinsco3			-0.0135***			-0.0157***			-0.0014
			(-3.2237)			(-3.6885)			(-0.1742)
di_319438				$0.0026^{**}$	0.0033***	-0.0015			
				(2.3097)	(7.0449)	(-0.4879)			
di_319440				-0.0049	-0.0074	0.0093			
				(-0.7310)	(-0.8532)	(1.4322)			
climate_reg							-22.3316***	-4.3112***	-3.8136***
ulation_risk									
							(-3.0872)	(-4.0102)	(-3.4332)
_cons	-0.0038	-0.0403	-0.0120	-0.0034	-0.0385	-0.0153	0.0018	0.0025	-0.0018
	(-0.2202)	(-1.2849)	(-0.6479)	(-0.1824)	(-1.1610)	(-0.7689)	(0.1087)	(0.0896)	(-0.1114)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	236	215	237	236	215	237	236	215	237
adj. $R^2$	0.128	0.051	0.128	0.136	0.088	0.124	0.148	0.107	0.151

(5) event: Paris event windows=[0,15] estimation window=[-510,-30]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab								
	normal_return								
climate_reg	-28.7608***	0.8969	-31.2115***	-4.1116***	-4.0063***	-4.8262***	-5.3515***	-3.5068**	-5.5138***
ulation_risk									
	(-4.7390)	(0.0643)	(-3.3791)	(-3.4103)	(-3.3652)	(-3.8313)	(-6.1145)	(-2.4122)	(-4.0686)
CRRabsco1	1.8470***								
	(4.2623)								
CRRabsco2		-0.4534							
		(-0.3729)							
CRRabsco3			2.1984***						
			(2.7401)						
CRRgrsco1				0.2566***					
				(5.5059)					
CRRgrsco2					0.1301				
					(1.0170)				
CRRgrsco3						$6.9794^{*}$			
						(1.8017)			
CRRinsco1							0.0015***		
							(7.1192)		
CRRinsco2							,	-0.0103	
								(-0.5042)	
CRRinsco3								,	0.0094
									(0.7044)
_cons	0.0085	-0.0039	0.0000	-0.0220	-0.0233	-0.0196	-0.0020	-0.0025	-0.0045
_	(0.4538)	(-0.1939)	(0.0022)	(-0.6853)	(-0.7222)	(-0.5965)	(-0.1010)	(-0.1284)	(-0.2195)
Control	Yes								
N	235	236	236	214	216	216	236	236	236
adj. $R^2$	0.131	0.079	0.106	0.100	0.094	0.105	0.134	0.080	0.083

CRRabsco1 1.62 (2.4 CRRabsco2 -1.71 (-2.7 CRRabsco3 -0.5	l_return norma 224** 4227) 101*** 7470) 5286 4269) 1.9 (7.9 -1.7 (-6.	lative_ab cumulatival_return normal_re	normal_return	_	_	cumulative_ab normal_return 1.7252*** (2.7158) -1.0788 (-1.5946) 0.9639 (0.7785)	1.6656*** (11.6620) -1.3472*** (-9.6295) 6.8472 (1.6440)	cumulative_ab normal_return
CRRabsco1 1.62 (2.4 CRRabsco2 -1.71 (-2.7 CRRabsco3 -0.5 (-0.4 CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	224** 4227) 101*** 7470) 5286 4269) 1.9- (71.7 (-6.	9426*** 9470) 7299*** .9258) .1592 2633) 0.0019	0.9292* (1.6993) -1.0308 (-1.1280) -0.4304 (-0.3820)	1.7552*** (6.8964) -1.6778*** (-6.3905) -3.5890	_	1.7252*** (2.7158) -1.0788 (-1.5946) 0.9639	1.6656*** (11.6620) -1.3472*** (-9.6295) 6.8472	normal_return
CRRabsco2 -1.71 (-2.7 CRRabsco3 -0.5 (-0.4 CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	1227) 101*** 7470) 5286 4269) 1.9 (7.9 -1.7 (-6.1	9470) 7299*** .9258) .1592 .2633) 0.0019	(1.6993) -1.0308 (-1.1280) -0.4304 (-0.3820)	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*	(2.7158) -1.0788 (-1.5946) 0.9639	(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRabsco2 -1.71 (-2.7 CRRabsco3 -0.5 (-0.4 CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	101*** 7470) 5286 4269) 1.9 (71.7 (-6.	9470) 7299*** .9258) .1592 .2633) 0.0019	-1.0308 (-1.1280) -0.4304 (-0.3820)	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*	-1.0788 (-1.5946) 0.9639	(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRabsco3 (-2.7 CRRabsco3 -0.5 (-0.4 CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	7470) 5286 4269) 1.9 (7. -1.7 (-6.	9470) 7299*** .9258) .1592 .2633) 0.0019	(-1.1280) -0.4304 (-0.3820)	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*	(-1.5946) 0.9639	(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRabsco3 -0.5 (-0.4 CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	5286 4269) 1.9- (7 -1.7 (-6. 1.	9470) 7299*** .9258) .1592 .2633) 0.0019	-0.4304 (-0.3820)	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*	0.9639	(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	4269) 1.9- (7.9- -1.7- (-6.9- 1.0- 1.0- 1.0- 1.0- 1.0- 1.0- 1.0- 1.0	9470) 7299*** .9258) .1592 .2633) 0.0019	(-0.3820)	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*		(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRgrsco1 CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	1.9- (7. -1.7 (-6. 1.	9470) 7299*** .9258) .1592 .2633) 0.0019	***	(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*	(0.7785)	(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRgrsco2 CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	(7.5 -1.7 (-6. 1.	9470) 7299*** .9258) .1592 .2633) 0.0019		(6.8964) -1.6778*** (-6.3905) -3.5890	0.0027*		(11.6620) -1.3472*** (-9.6295) 6.8472	
CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	-1.7 (-6. 1.	7299*** .9258) .1592 .2633) 0.0019		-1.6778*** (-6.3905) -3.5890	0.0027*		-1.3472*** (-9.6295) 6.8472	
CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 di_319438	(-6. 1.	.9258) .1592 .2633) 0.0019		(-6.3905) -3.5890	0.0027*		(-9.6295) 6.8472	
CRRinsco1 CRRinsco2 CRRinsco3 di_319438	1.	1592 2633) 0.0019		-3.5890	0.0027*		6.8472	
CRRinsco1 CRRinsco2 CRRinsco3 di_319438		2633) 0.0019			0 0027*			
CRRinsco2 CRRinsco3 di_319438	(0.	0.0019		(-1.2825)	0.0027*		(1.6440)	
CRRinsco2 CRRinsco3 di_319438					0.0027*			
CRRinsco3 di_319438		(4.000			0.002/			$0.0017^{***}$
CRRinsco3 di_319438		(4.983)	8)		(1.9248)			(4.2182)
di_319438		-0.0269	9**		-0.0308***			-0.0164
di_319438		(-2.206	56)		(-2.7324)			(-1.3069)
_		-0.0186	5***		-0.0220***			-0.0073
_		(-2.661	11)		(-3.0834)			(-0.6431)
di_319440			$0.0022^{*}$	0.0035***	-0.0022			
di_319440			(1.6702)	(5.0497)	(-0.5454)			
			-0.0024	-0.0063	$0.0152^{**}$			
			(-0.2696)	(-0.5677)	(2.3601)			
climate_reg						-27.0207***	-4.7552***	-3.4699**
ulation_risk								
						(-2.7477)	(-4.1040)	(-2.6089)
_cons -0.0	0009 -0.	.0615 -0.009	-0.0018	-0.0606	-0.0147	0.0055	-0.0141	-0.0004
(-0.0	0463) (-1.	.6506) (-0.438	(-0.0853)	(-1.5873)	(-0.6913)	(0.2873)	(-0.4505)	(-0.0195)
Control Y	( )	Yes Yes	Yes	Yes	Yes	Yes	Yes	Yes
N 23	,		235	214	236	235	214	236
adj. $R^2$ 0.1	les '	214 236		0.102	0.123	0.138	0.123	0.136

(6) event: Paris, event windows=[0,x] estimation window=[-510,-30], keep all samples on event window.

	[0,3]	[0,5]	[0,7]	[0,10]	[0,15]
	cumulative_abnormal_re	cumulative_abnormal_re	cumulative_abnormal_re	cumulative_abnormal_re c	umulative_abnormal_re
	turn	turn	turn	turn	turn
climate_regulation_	<b>-2.4997</b> **	-3.6313***	0.6348	-0.7980	-0.4406
risk			<b>幸化 田郷はみ</b>		
	(-2.4556)	(-2.7878)	事件: 巴黎协定		0.4314)
me	-0.0000	-0.0000	   结论: 在只包含基本面	和 CRR 的回归中,在窗口[0,3]	和 0.0000
	(-1.0105)	(-1.4488)		5]两个窗口期中,CRR 系数为负且显著。	
wt	$-0.0000^*$	-0.0000**		·····································	.0000
	(-1.7466)	(-2.0280)	(-1.6740)	(-1.6680)	(0.2001)
cumretx	$0.0033^{**}$	0.0024	-0.0006	0.0003	-0.0063***
	(2.1432)	(1.2178)	(-0.3688)	(0.1479)	(-2.6174)
mebase	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000**
	(-7.4485)	(-4.5020)	(-2.7682)	(-3.6925)	(-2.2478)
lme	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(-0.1221)	(-0.3699)	(-1.1300)	(-1.3424)	(-1.6154)
dec_me	$0.0000^{***}$	$0.0000^{**}$	$0.0000^{**}$	$0.0000^{**}$	$0.0000^*$
	(2.6973)	(2.0697)	(2.3846)	(2.3156)	(1.8918)
be	-0.0000	0.0000	0.0000	0.0000	-0.0000
	(-0.7812)	(0.0516)	(0.4875)	(0.1884)	(-0.3828)
_cons	-0.0043	0.0047	0.0043	0.0020	0.0118
	(-1.2146)	(0.9033)	(0.8501)	(0.4430)	(1.5836)
N	3589	3589	3589	3589	3589
adj. $R^2$	0.100	0.124	0.015	0.033	0.024

(7) event: Paris event windows=[0,3] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab
	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return
climate_reg	-18.2974**	-2.7430	-31.6170***	-3.9773***	-3.8675***	<b>-3.5216</b> ***	<b>-4.8768</b> ***	-3.7358***	-6.2657***
ulation_risk									
	(-2.6105)	(-0.4505)	(-3.4705)	(-4.4529)	(-4.4870)	(-3.3961)	(-6.0391)	(-5.0206)	(-7.5717)
CRRabsco1	1.0339**								
	(2.0804)				事件:	巴黎协定			
CRRabsco2		-0.1597							
cpp 1 a		(-0.3027)	2 10 = = ***		窗口期	: event windows	=[0,3] estimation	n window=[-510,-	30]
CRRabsco3			2.1977***						
CDD 1			(2.9964)	0.1758***		通过比较 18 个[		•	
CRRgrsco1					CRR 系	数为负且显著;	如果三个 scope	的 carbon 同时出	出现在回归时,
CRRgrsco2				(7.1675)	0.0 CRR 仍	为负且显著,但	三个 scope 中,	只有 scope2 和 3	表现比较好。值
CKKgrsco2					(0.3) 得注意	的是,在回归1	~9 中,仅(2)「	中 CRR 不显著,而	页(2)又是对
CRRgrsco3						2 的回归,可以推	註测,scope2*CR	R 解释力度较好。	
Crtrg13003									
CRRinsco1						( 0.025 .)	0.0004		
							(1.4430)		
CRRinsco2							,	-0.0126	
								(-0.9409)	
CRRinsco3									0.0118***
									(3.1041)
_cons	-0.0058	-0.0124	-0.0091	-0.0213	-0.0221	-0.0235	-0.0118	-0.0119	-0.0144
	(-0.3592)	(-0.7050)	(-0.5184)	(-0.8055)	(-0.8361)	(-0.8541)	(-0.6706)	(-0.6898)	(-0.7594)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	943	947	947	859	867	867	947	947	947
adj. $R^2$	0.222	0.199	0.242	0.192	0.188	0.189	0.205	0.206	0.214

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
CRRabsco1	0.3304			0.4434			0.4706		
	(0.7302)			(1.2140)			(0.8609)		
CRRabsco2	-1.2585***			-1.3611***			-0.6125**		
	(-3.2121)			(-2.8581)			(-2.3714)		
CRRabsco3	0.4356			0.4109			1.9694***		
	(0.8154)			(0.7556)			(2.6979)		
CRRgrsco1		1.9340***			1.8709***			1.7454***	
		(9.1157)			(9.2767)			(18.6429)	
CRRgrsco2		-1.7965***			-1.7839***			-1.5362***	
		(-8.2570)			(-9.3563)			(-16.6707)	
CRRgrsco3		<b>-6.1706</b> **			<del>-7.8416***</del>			-2.3327	
		(-2.0192)			(-3.6400)			(-0.6755)	
CRRinsco1			0.0005			0.0008			0.0003
			(1.0925)			(0.4652)			(0.6384)
CRRinsco2			-0.0276**			-0.0296***			-0.0117
			(-2.3289)			(-2.7370)			(-1.0247)
CRRinsco3			-0.0082*			-0.0111**			$0.0086^{**}$
			(-1.7583)			(-2.1692)			(2.6017)
di_319438				-0.0004	$0.0013^*$	-0.0007			
				(-0.2721)	(1.6972)	(-0.1559)			
di_319440				0.0013	-0.0013	0.0126			
				(0.2255)	(-0.1940)	(1.5994)			
climate_regu							-28.2537***	-3.2307***	-5.2657***
lation_risk									
							(-2.6348)	(-3.2027)	(-6.1167)
_cons	-0.0159	-0.0510*	-0.0275	-0.0164	-0.0516*	-0.0324	-0.0086	-0.0189	-0.0137
	(-0.8386)	(-1.8492)	(-1.2297)	(-0.8076)	(-1.6718)	(-1.3597)	(-0.4985)	(-0.7300)	(-0.7517)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	943	859	947	943	859	947	943	859	947
adj. $R^2$	0.211	0.189	0.169	0.209	0.194	0.173	0.248	0.224	0.220

(8) event: Paris event windows=[0,5] estimation window=[-510,-30], keep all samples during event windows.

	(1) cumulative_abn ormal_return	(2) cumulative_abn ormal_return	(3) cumulative_abn ormal_return	(4) cumulative_abn ormal_return	(5) cumulative_abn ormal_return	(6) cumulative_abn ormal_return	(7) cumulative_abn ormal_return	(8) cumulative_abn ormal_return	(9) cumulative_abn ormal_return
climate_regul ation_risk	-23.5072***	0.8466	-36.6078***	<b>-4.8756***</b>	<b>-4.7697***</b>	<b>-5.0238</b> ***	-6.3652***	-4.5185***	-7.3487***
CRRabsco1	(-3.9355) 1.3543*** (3.1226)	(0.0801)	(-3.6192)	(-5.2961)	(-5.1499)	(-4.6785)	(-10.7214)	(-4.4606)	(-8.8577)
CRRabsco2		-0.5662 (-0.6167)			事件:	巴黎协定			
CRRabsco3			2.5256*** (2.9985)		窗口期	別: event window	rs=[0,5] estimation	on window=[-510,-	30]
CRRgrsco1			,	0.2035*** (8.0548)		通过比较 18 个 RR 系数为负且显			
CRRgrsco2				,	0.08 归时,	CRR 仍为负且显	著,但三个 sco	pe 中,只有 scor	e2 和 3 表现
CRRgrsco3					比较处	子。值得注意的是 又是对 scope2 的			
CRRinsco1					好。				
CRRinsco2							,	-0.0151 (-0.9683)	
CRRinsco3									0.0128*
_cons	0.0065	-0.0032	0.0017	-0.0102	-0.0111	-0.0099	-0.0012	-0.0015	(1.8519)
			(0.0021)	(-0.3517)	(-0.3789)	(-0.3229)	(-0.0638)		-0.0041
	(0.3827)	(-0.1767)	(0.0931)	• • • • • • • • • • • • • • • • • • • •	. ,		• • • • • • • • • • • • • • • • • • • •	(-0.0819)	-0.0041 (-0.2032)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	(-0.0819) Yes	-0.0041 (-0.2032) Yes
Control $N$ adj. $R^2$			· · · · · · · · · · · · · · · · · · ·	• • • • • • • • • • • • • • • • • • • •	. ,		• • • • • • • • • • • • • • • • • • • •		-0.0041 (-0.2032)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
CRRabsco1	0.6813			0.1178			$0.8347^{*}$		
	(1.3410)			(0.2728)			(1.7341)		
CRRabsco2	-1.8439***			-1.3012**			-1.1523***		
	(-4.7896)			(-2.0647)			(-2.9008)		
CRRabsco3	0.5101			0.5988			2.1430**		
	(0.6072)			(0.7769)			(2.0006)		
CRRgrsco1		1.9429***			1.7662***			1.6665***	
		(6.9016)			(6.4124)			(17.9021)	
CRRgrsco2		-1.8015***			-1.7330***			<b>-1.4161</b> ***	
		(-6.4313)			(-6.4920)			(-16.7148)	
CRRgrsco3		-3.4736			<b>-7.4050</b> ***			2.2692	
		(-0.7067)			(-3.0080)			(0.4194)	
CRRinsco1			$0.0014^{***}$			0.0016			0.0011***
			(4.0706)			(0.9622)			(3.8792)
CRRinsco2			-0.0343***			-0.0364***			-0.0179*
			(-3.3236)			(-3.8997)			(-1.8646)
CRRinsco3			-0.0163***			-0.0199***			0.0012
			(-4.3567)			(-5.2492)			(0.1842)
di_319438				0.0018	$0.0029^{***}$	-0.0004			
				(1.3428)	(4.8457)	(-0.0936)			
di_319440				-0.0032	-0.0071	0.0159**			
				(-0.5061)	(-0.8965)	(2.2032)			
climate_regu							-30.1864**	-4.8393***	-5.4645***
lation_risk									
							(-2.3172)	(-4.3689)	(-5.0546)
_cons	-0.0054	-0.0531	-0.0156	-0.0053	-0.0512	-0.0220	0.0023	-0.0051	-0.0016
	(-0.2586)	(-1.5988)	(-0.6638)	(-0.2470)	(-1.4348)	(-0.8872)	(0.1283)	(-0.1824)	(-0.0838)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1414	1288	1420	1414	1288	1420	1414	1288	1420
adj. $R^2$	0.275	0.197	0.246	0.280	0.226	0.253	0.310	0.263	0.290

(9) event: Paris event windows=[0,7] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	-13.8787***	3.6549	<b>-18.6912***</b>	-2.2574**	-2.2466**	-2.3003**	-2.1858***	-1.1995	-2.7727***
lation_risk									
	(-3.7480)	(0.4666)	(-4.9666)	(-2.2634)	(-2.2783)	(-2.3149)	(-3.2385)	(-1.2662)	(-3.1937)
CRRabsco1	0.9348***								
	(3.5437)				+ M				
CRRabsco2		-0.4550			事件: 巴黎	协定			
		(-0.6772)					_		
CRRabsco3			1.3995***		窗口期: eve	ent windows=[0,	7] estimation wind	dow=[-510,-30]	
			(4.7549)	***					
CRRgrsco1				0.1317***	'''-		吉果,在 CRR、Ca	— , , , , , ,	
				(6.4691)	亥粉-4-6-1	日本 加田一人	<i>LL</i> 1		14 th can 1 the
				(0051)	尔致乃贝且	亚者; 如果二个	scope 的 carbon	同时出现在回归	时,CRR 仍为
CRRgrsco2				(0.1051)			scope 的 carbon ,scope2 表现比		
C				(01.103.2)	<b>负且显著,</b>	但三个 scope 中		较突出。值得注	意的是,在回
CRRgrsco2 CRRgrsco3				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 「显著,而(2)	较突出。值得注	意的是,在回
CRRgrsco3				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中	,scope2 表现比 「显著,而(2) 「较好。	较突出。值得注	意的是,在回
C				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 下显著,而(2) 较好。 0.0009***	较突出。值得注	意的是,在回
CRRgrsco3 CRRinsco1				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 「显著,而(2) 「较好。	较突出。值得注 又是对 scope2 的	意的是,在回
CRRgrsco3				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 下显著,而(2) 较好。 0.0009***	· 较突出。值得注 又是对 scope2 的	意的是,在回
CRRgrsco3 CRRinsco1 CRRinsco2				(0.105.1)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 下显著,而(2) 较好。 0.0009***	较突出。值得注 又是对 scope2 的	意的是,在回 的回归,可以
CRRgrsco3 CRRinsco1				(0.105.2)	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 下显著,而(2) 较好。 0.0009***	· 较突出。值得注 又是对 scope2 的	意的是,在回 的回归,可以 0.0091
CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3	$0.0280^*$	0.0210	0.0244	0.0410*	负且显著, 归 1 <sup>~</sup> 9 中,	但三个 scope 中 仅(2)中 CRR 7	,scope2 表现比 下显著,而(2) 较好。 0.0009***	· 较突出。值得注 又是对 scope2 的	意的是,在回 的回归,可以
CRRgrsco3 CRRinsco1 CRRinsco2	0.0280* (1.6829)	0.0210 (1.2688)	0.0244 (1.5078)		负且显著, 归 1~9 中, 推测,scop	但三个 scope 中 仅(2)中 CRR 7 e2*CRR 解释力度	,scope2 表现比 下显著,而(2) 较好。 0.0009*** (7.1508)	·较突出。值得注 又是对 scope2 的 -0.0035 (-0.4915)	意的是,在回 的回归,可以 0.0091 (1.6179)
CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3				0.0410*	负且显著, 归 1~9 中, 推测,scop	但三个 scope 中 仅(2)中 CRR 7 e2*CRR 解释力度 0.0409	,scope2 表现比 下显著,而(2) 较好。 0.0009*** (7.1508)	·较突出。值得注 又是对 scope2 的 -0.0035 (-0.4915)	意的是,在回 的回归,可以 0.0091 (1.6179) 0.0206
CRRgrsco3 CRRinsco1 CRRinsco2 CRRinsco3 _cons	(1.6829)	(1.2688)	(1.5078)	0.0410* (1.6758)	负且显著, 归 1~9 中, 推测,scop 0.0405 (1.6585)	但三个 scope 中 仅(2)中 CRR 不 e2*CRR 解释力度 0.0409 (1.5988)	,scope2 表现比 下显著,而(2) 较好。 0.0009*** (7.1508) 0.0227 (1.3960)	·较突出。值得注 又是对 scope2 的 -0.0035 (-0.4915) 0.0225 (1.3918)	0.0091 (1.6179) 0.0206 (1.2727)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
CRRabsco1	0.6718			-0.0161			$0.7496^{*}$		
	(1.5799)			(-0.0403)			(1.8817)		
CRRabsco2	-1.1576***			-0.5074			-0.8282**		
	(-4.5332)			(-1.3452)			(-2.4809)		
CRRabsco3	0.2167			0.3382			$1.0031^{*}$		
	(0.3418)			(0.6072)			(1.7386)		
CRRgrsco1		0.4838***			0.2925**			0.3413***	
		(3.2667)			(1.9894)			(2.9738)	
CRRgrsco2		-0.3952***			-0.3156**			-0.1991 <sup>*</sup>	
		(-2.6319)			(-2.0665)			(-1.7868)	
CRRgrsco3		-1.4689			<b>-</b> 5.5239**			1.4238	
		(-0.3019)			(-2.3664)			(0.2767)	
CRRinsco1			0.0011***			0.0006			$0.0010^{***}$
			(6.6370)			(0.5790)			(5.4807)
CRRinsco2			<b>-</b> 0.0116***			-0.0102**			<b>-</b> 0.0060***
			(-3.5103)			(-2.4870)			(-2.7946)
CRRinsco3			-0.0057*			-0.0058*			0.0002
			(-1.6867)			(-1.6892)			(0.0398)
di_319438				$0.0022^{**}$	$0.0030^{***}$	0.0014			
				(2.3789)	(4.7405)	(0.4790)			
di_319440				-0.0052	-0.0078	0.0003			
				(-0.8306)	(-1.0544)	(0.0452)			
climate_regu							-14.5606**	-2.4143**	-1.8593*
lation_risk									
							(-2.1788)	(-2.4363)	(-1.8106)
_cons	0.0217	0.0185	0.0178	0.0227	0.0209	0.0172	0.0255	0.0424	0.0226
	(1.2902)	(0.8449)	(1.1017)	(1.2413)	(0.8862)	(0.9880)	(1.5027)	(1.6487)	(1.3637)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1882	1714	1890	1882	1714	1890	1882	1714	1890
adj. $R^2$	0.061	0.027	0.066	0.074	0.071	0.065	0.073	0.049	0.073

(10) event: Paris event windows=[0,10] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab
	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return
climate_reg	-20.8494***	2.7983	-27.5628***	<b>-3.8691</b> ***	-3.8361***	<b>-4.1944</b> ***	<b>-4</b> .6203***	-3.1409***	<b>-5.3002</b> ***
ulation_risk									
	(-4.3415)	(0.2694)	(-5.0454)	(-3.9120)	(-3.8859)	(-4.0547)	(-6.7242)	(-2.8468)	(-5.6472)
CRRabsco1	1.2964***				_				
	(3.6625)					事件: 巴黎协定			
CRRabsco2		-0.5721							
		(-0.6379)				窗口期: event wi	ndows=[0, 10] e	estimation window	=[-51030]
CRRabsco3			1.9431***			Z - /y, event wi	10,10,10	water william	[ 510, 50]
CDD - · · · · · · 1			(4.0956)	0.2222***		结论:通过比较	18 个回归结果,	在 CRR、Carbon、	基本面的回归
CRRgrsco1				0.2222***		中,CRR 系数为负	5. 且显著: 如果三	三个 scope 的 car	bon 同时出现在
CRRgrsco2				(7.9179)	0.1521**	回归时,CRR 仍为		- · · ·	
CKKgrsc02					(2.0983)	稳健。值得注意的			-
CRRgrsco3					(2.0703)			ジャ, C (2) キャ 以猜测, scope2 f	
erargise03					L	(2) <b>文定</b> 例 SCO <sub>2</sub>	pez դյ <u>ա</u> յել, ելկ	久須例, SCOPEZ F	16月午7年 しんれ。
CRRinsco1						(0.0332)	0.0013***		
							(9.7204)		
CRRinsco2							,	-0.0070	
								(-0.5471)	
CRRinsco3									0.0116
									(1.3162)
_cons	0.0045	-0.0048	-0.0004	-0.0025	-0.0035	-0.0017	-0.0028	-0.0030	-0.0054
	(0.2920)	(-0.2971)	(-0.0268)	(-0.0930)	(-0.1266)	(-0.0602)	(-0.1750)	(-0.1892)	(-0.3195)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2591	2602	2602	2362	2384	2384	2602	2602	2602
adj. $R^2$	0.159	0.128	0.156	0.136	0.133	0.134	0.182	0.126	0.138

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
CRRabsco1	$0.9058^{*}$			0.1097			1.0264**		
	(1.7274)			(0.2430)			(2.1849)		
CRRabsco2	-1.5969***			-0.8323			-1.0896**		
	(-3.8828)			(-1.3846)			(-2.2550)		
CRRabsco3	0.1919			0.3197			1.3895*		
	(0.2191)			(0.4223)			(1.7420)		
CRRgrsco1		1.1434***			0.9396***			0.8916***	
		(5.3945)			(4.5091)			(6.5602)	
CRRgrsco2		-0.9844***			-0.9064***			-0.6379***	
		(-4.5520)			(-4.2463)			(-4.7033)	
CRRgrsco3		-1.1768			<b>-</b> 5.6571**			3.9441	
		(-0.2663)			(-2.4958)			(0.8744)	
CRRinsco1			$0.0016^{***}$			0.0021**			0.0013***
			(6.7786)			(2.0266)			(5.5074)
CRRinsco2			-0.0224***			-0.0249***			-0.0109*
			(-3.5566)			(-4.7925)			(-1.9111)
CRRinsco3			-0.0135***			-0.0156***			-0.0012
			(-3.3104)			(-3.7836)			(-0.1569)
di_319438				$0.0026^{**}$	0.0034***	-0.0015			
				(2.3514)	(7.3041)	(-0.4978)			
di_319440				-0.0047	-0.0077	0.0093			
				(-0.7151)	(-0.9055)	(1.4485)			
climate_regu							-22.2648***	<b>-4</b> .2806***	-3.8245***
lation_risk									
							(-3.1840)	(-4.1199)	(-3.5708)
_cons	-0.0046	-0.0409	-0.0124	-0.0043	-0.0391	-0.0157	0.0012	0.0016	-0.0026
	(-0.2711)	(-1.3253)	(-0.6899)	(-0.2374)	(-1.2053)	(-0.8166)	(0.0761)	(0.0575)	(-0.1633)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2591	2362	2602	2591	2362	2602	2591	2362	2602
adj. $R^2$	0.162	0.091	0.161	0.176	0.134	0.164	0.184	0.147	0.187

(11) event: Paris event windows=[0,15] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	-29.1602***	-0.8696	-30.3279***	<b>-4.2406***</b>	<b>-4</b> .1684***	<b>-4</b> .1620***	-5.3629***	-3.5658***	-5.5977***
lation_risk									
	(-5.3107)	(-0.0665)	(-3.8468)	(-3.8360)	(-3.8039)	(-3.7243)	(-6.3503)	(-2.9024)	(-4.1988)
CRRabsco1	1.8890***								
	(4.8081)								
CRRabsco2		-0.3010			事件:	巴黎协定			
		(-0.2618)							
CRRabsco3			2.1350***		窗口期:	event windows	=[0, 15] estimation	on window=[-510	301
			(3.0681)		<b>24</b> , 7, 7, 7, 4	•	[		, ]
CRRgrsco1				0.2696***	结论:	通过比较 18 个回	可归结果,在 CRR	、Carbon、基本	面的回归中,
				(5.1883)	CRR 系数	数为负目显 <b>著</b> 。 t	如果三个 scope 的	n carbon 同时出	现在同归时.
CRRgrsco2					0.1		三个 scope 中,s		
					(1.)		- ·		
CRRgrsco3							仅(2)中 CRR 不		く 定刈 scope 2 的
					回归,	可以推测,scope	e2*CRR 解释力度	较好。	
CRRinsco1							0.001.		
							(6.9222)		
CRRinsco2								-0.0100	
								(-0.6730)	
CRRinsco3									0.0095
									(0.7530)
_cons	0.0080	-0.0038	-0.0001	-0.0149	-0.0158	-0.0146	-0.0026	-0.0027	-0.0048
	(0.4370)	(-0.1923)	(-0.0045)	(-0.5810)	(-0.6107)	(-0.5673)	(-0.1359)	(-0.1423)	(-0.2350)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3771	3787	3787	3494	3522	3522	3787	3787	3787
adj. $R^2$	0.170	0.113	0.143	0.132	0.127	0.134	0.167	0.117	0.119

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab
	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return
CRRabsco1	1.5811**			0.8711			1.7467***		
	(2.3815)			(1.6295)			(2.8439)		
CRRabsco2	<b>-1.6689</b> ***			-0.9720			-1.0155		
	(-2.6516)			(-1.0733)			(-1.5258)		
CRRabsco3	-0.5210			-0.4225			0.9603		
	(-0.4237)			(-0.3749)			(0.8395)		
CRRgrsco1		2.0859***			1.8785***			1.8345***	
		(11.3767)			(8.9676)			(13.9355)	
CRRgrsco2		-1.8608***			-1.7530***			-1.5319***	
		(-9.7045)			(-8.1866)			(-11.1993)	
CRRgrsco3		$4.0739^*$			$2.1688^*$			4.5313*	
		(1.7635)			(1.6958)			(1.7624)	
CRRinsco1			$0.0018^{***}$			$0.0023^{*}$			$0.0016^{***}$
			(5.3015)			(1.8954)			(4.2568)
CRRinsco2			-0.0219**			-0.0253***			-0.0135
			(-2.4889)			(-2.9865)			(-1.4459)
CRRinsco3			-0.0183***			-0.0220***			-0.0058
			(-2.7435)			(-3.2692)			(-0.5306)
di_319438				$0.0022^{*}$	0.0027***	-0.0014			
				(1.7773)	(5.6567)	(-0.3898)			
di_319440				-0.0020	-0.0060	0.0162**			
				(-0.2417)	(-0.6528)	(2.5996)			
climate_reg							-27.8419***	-4.0387***	-3.8155***
ulation_risk									
							(-3.4653)	(-3.8209)	(-3.2686)
_cons	-0.0025	-0.0528	-0.0120	-0.0035	-0.0556	-0.0182	0.0051	-0.0114	-0.0013
	(-0.1259)	(-1.4861)	(-0.5603)	(-0.1700)	(-1.5601)	(-0.8307)	(0.2716)	(-0.4660)	(-0.0707)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3771	3494	3787	3771	3494	3787	3771	3494	3787
adj. $R^2$	0.154	0.110	0.157	0.162	0.134	0.164	0.182	0.157	0.177

(12) event: Trump, event windows=[0,x] estimation window=[-510,-30], keep all samples on event window.

	[0,3]	[0,5]	[0,7]	[0,10]	[0,13]	[0,15]
	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor	cumulative_abnor
	mal return	mal return	mal return	mal return	mal return	mal_return
climate_regula	-0.6838	-0.0058	0.4975	2.2858***	-0.4604	6.4657***
tion_risk						
_	(-1.0473)	(-0.0095)	(0.7643)	(3.7122)	(-0.5998)	(7.9090)
me	-0.0000	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000
	(-1.6000)	(-1.5851)	(-1.6987)	(-1.2715)	(-0.8288)	(-1.1780)
wt	$0.0000^{***}$	$0.0000^{*}$	$0.0000^{*}$	$0.0000^{*}$	$0.0000^{*}$	0.0000**
	(2.6537)	(1.7872)	(1.929	(1.0204)	(1.7462)	(2 2765)
cumretx	-0.0088**	-0.0091*	-0.007 事件:	特朗普上台		
	(-2.3169)	(-1.9477)	(-1.796			
mebase	0.0000	0.0000	0.0000 给论:		RR 的回归中,在窗口	
	(0.7055)	(1.0907)	(1.765 口期中	ī,CRR 系数为负且显	著。但同时截距项也	显著,说明变量不足!
lme	-0.0000	0.0000	-0.000 释 CAI	2°		
	(-0.2516)	(0.1797)	$(-0.248\frac{1}{2})$	(-0.7733)	(-0.2737)	(-0.3302)
dec_me	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
_	(1.3239)	(0.3957)	(0.1095)	(0.0974)	(0.5839)	(-1.4797)
be	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.4977)	(0.5018)	(0.3650)	(0.3531)	(0.3214)	(1.3719)
_cons	0.0665***	0.0652***	0.0673***	0.0686***	0.0695***	0.0538***
	(7.2169)	(7.2141)	(6.8936)	(6.9538)	(6.2205)	(4.2876)
N	3395	3395	3395	3395	3395	3395
adj. $R^2$	0.039	0.027	0.031	0.041	0.023	0.082

(13) event: Trump event windows=[0,3] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	6.9355	-1.8208	-2.5758	-1.1677	-0.9491	-0.3890	-1.1288	-1.2059	-1.4848
lation_risk									
	(1.6054)	(-0.3088)	(-0.4398)	(-1.4881)	(-1.0295)	(-0.3830)	(-1.1016)	(-1.1678)	(-1.0185)
CRRabsco1	-0.6574**								
	(-2.2849)				事件:特朗普	<b></b>			
CRRabsco2		0.0410							
		(0.0790)			   窗口期. ever	nt windows= $[0,3]$	l estimation windo	ow=[-510 -30]	
CRRabsco3			0.0978		Z 1 7/31. CVCI	it windows [0,2]	community winds	5w [ 510, 50]	
			(0.2188)	***	   结论: 通过日	比较 18 个回归结:	果,极少能找到	系数为正且显著的	的变量,而且截距
CRRgrsco1				0.0053***		直得注意的是,CI			
				(9.8968)			di Boopoi ( oddi	. воороо нажина	~>u~~~
CRRgrsco2					0.7505				
CDD 2					(0.4762)	2.0744			
CRRgrsco3						2.8744			
CDD: 1						(1.2725)	0.0002***		
CRRinsco1							-0.0003***		
CDD: 2							(-4.2577)	0.0021	
CRRinsco2								-0.0031	
CDD: 2								(-1.1343)	0.0005
CRRinsco3									0.0005
	0.1118***	0.1137***	0.1139***	0.1036***	0.1049***	0.1075***	0.1140***	0.1139***	(0.0970) 0.1137***
_cons									
Control	(7.0485)	(7.1920)	(7.2193)	(5.2161)	(5.4913)	(5.9168)	(7.2406)	(7.2172)	(7.2096)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1067	1067	1067	751	751	751	1067	1067	1067
adj. $R^2$	0.204	0.193	0.193	0.198	0.192	0.197	0.198	0.194	0.193

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn								
	ormal_return								
CRRabsco1	-1.2910***			-1.4701***			-1.2840***		
	(-4.9866)			(-4.2524)			(-4.6384)		
CRRabsco2	0.1115			0.2435			0.1468		
	(0.4756)			(0.9188)			(0.4921)		
CRRabsco3	1.1376***			1.2302***			1.2173***		
	(3.0339)			(3.2618)			(3.8130)		
CRRgrsco1		0.0054***			0.0052***			0.0054***	
		(9.9446)			(8.4902)			(9.7864)	
CRRgrsco2		-2.7204*			-1.4029			-2.6961*	
		(-1.7306)			(-0.8148)			(-1.7666)	
CRRgrsco3		6.3818**			5.1186*			5.8389**	
		(2.4042)			(1.8946)			(2.0012)	
CRRinsco1			-0.0003***			0.0003			-0.0004***
			(-3.2823)			(0.6113)			(-4.7629)
CRRinsco2			-0.0051**			-0.0029			-0.0032
			(-2.3999)			(-1.2772)			(-1.0479)
CRRinsco3			-0.0014			0.0009			0.0039
			(-0.3699)			(0.1727)			(0.7594)
di_319438				0.0005	-0.0009***	-0.0022			
				(1.1418)	(-4.4433)	(-1.3248)			
di_319440				-0.0152**	-0.0074	-0.0128			
				(-2.3896)	(-1.0398)	(-1.5182)			
climate_regu							-1.4545	-0.3537	-1.5669
lation_risk									
							(-0.2949)	(-0.3517)	(-0.9788)
_cons	0.1135***	0.1062***	0.1118***	0.1218***	0.1143***	0.1181***	0.1139***	0.1071***	0.1150***
	(7.2003)	(5.8746)	(6.9481)	(7.0887)	(5.6895)	(6.4637)	(7.1932)	(5.9485)	(7.3324)
Control	Yes								
N	1067	751	1067	1067	751	1067	1067	751	1067
adj. $R^2$	0.215	0.205	0.196	0.226	0.214	0.204	0.215	0.204	0.199

(14) event: Trump event windows=[0,5] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	8.0285**	-1.3101	-0.3288	-0.2327	-0.1908	0.2478	-0.2490	-0.2903	-0.2441
lation_risk									
	(2.1788)	(-0.2285)	(-0.0669)	(-0.3698)	(-0.2367)	(0.2621)	(-0.3356)	(-0.3783)	(-0.2200)
CRRabsco1	-0.6732**				事件:特朗普				
	(-2.6059)				<del>ず</del> に 1700日-	<u>_                                    </u>			
CRRabsco2		0.0773			ada Pite				
		(0.1506)			窗口期: event	windows= $[0,5]$	estimation windov	v=[-510,-30]	
CRRabsco3			-0.0137		作:(V )鬼:(4) (A)	餃 18 个回归结果	权小化铅列系	粉尘工口目蒸炉	水县 五日恭明
			(-0.0354)						
CRRgrsco1				0.0037***		得注意的是,CRR	*scopel、CKK*s	cope3 的数据表达	<b>见</b> 牧好。
CDD 2				(6.9168)	0.1220				
CRRgrsco2					0.1230				
CRRgrsco3					(0.0881)	1.7592			
CKKgisco3						(0.8494)			
CRRinsco1						(0.8494)	-0.0003***		
Cicinisco							(-3.5962)		
CRRinsco2							(3.5702)	-0.0035	
ordenis <b>c</b> o2								(-1.5201)	
CRRinsco3								()	-0.0014
									(-0.2996)
_cons	0.1024***	0.1044***	0.1042***	0.0979***	0.0981***	0.1002***	0.1046***	0.1045***	0.1040***
_	(6.7150)	(6.8924)	(6.8418)	(4.4226)	(4.3613)	(4.4914)	(6.9260)	(6.8964)	(6.8776)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1597	1597	1597	1123	1123	1123	1597	1597	1597
adj. $R^2$	0.173	0.161	0.161	0.169	0.166	0.168	0.166	0.162	0.161

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn								
	ormal_return								
CRRabsco1	-1.2244***			-1.5205***			-1.2262***		
	(-4.4310)			(-4.4800)			(-4.3063)		
CRRabsco2	0.2580			0.5271			0.2496		
	(1.2182)			(1.6252)			(0.8920)		
CRRabsco3	1.0118***			1.0987***			0.9928***		
	(2.6912)			(3.0270)			(3.0453)		
CRRgrsco1		0.0037***			0.0036***			0.0038***	
		(7.0059)			(6.1122)			(6.9904)	
CRRgrsco2		-2.5960*			-1.4022			-2.6163*	
		(-1.8698)			(-0.9222)			(-1.8614)	
CRRgrsco3		$4.2036^*$			3.0026			4.6247*	
		(1.8632)			(1.3687)			(1.6707)	
CRRinsco1			-0.0003***			0.0002			-0.0003***
			(-3.1573)			(0.2919)			(-3.1380)
CRRinsco2			-0.0040**			-0.0017			-0.0038
			(-2.3792)			(-0.8867)			(-1.5024)
CRRinsco3			0.0005			0.0029			0.0013
			(0.1689)			(0.7884)			(0.2673)
di_319438				$0.0008^*$	-0.0006**	-0.0019			
				(1.7796)	(-2.5363)	(-0.7224)			
di_319440				-0.0149***	-0.0076	-0.0132*			
				(-2.7201)	(-1.2568)	(-1.8838)			
climate_regu							0.3483	0.2767	-0.2272
lation_risk									
							(0.0762)	(0.3000)	(-0.1821)
_cons	0.1044***	0.1007***	0.1047***	0.1124***	$0.1080^{***}$	0.1112***	0.1042***	$0.1000^{***}$	0.1051***
	(6.9216)	(4.5521)	(7.0262)	(6.9667)	(4.5556)	(6.8919)	(6.8510)	(4.4922)	(6.9779)
Control	Yes								
N	1597	1123	1597	1597	1123	1597	1597	1123	1597
adj. $R^2$	0.183	0.173	0.167	0.195	0.179	0.176	0.183	0.172	0.166

(15) event: Trump event windows=[0,7] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	10.5844**	-0.3240	2.0688	-0.4812	-0.3330	-0.0201	-0.2554	-0.3678	-0.2473
lation_risk									
	(2.6006)	(-0.0532)	(0.3948)	(-0.7220)	事件:特朗普_	上台			
CRRabsco1	-0.8751***								
	(-2.9548)				窗口期: event	windows= $[0,7]$	estimation windov	v=[-510,-30]	
CRRabsco2		-0.0160							
		(-0.0294)			结论:通过比较	铰 18 个回归结果	l,极少能找到系	数为正且显著的	变量,而且截距
CRRabsco3			-0.2112		项均显著。值往	得注意的是,CRI	R*scope1、CRR*s	cope3 的数据表现	现较好。
			(-0.5183)						
CRRgrsco1				0.0015***					
CDD A				(2.9122)	0.5105				
CRRgrsco2					0.5197				
CDD amaga 2					(0.3614)	1.7072			
CRRgrsco3									
CRRinsco1						(0.8123)	-0.0003**		
CKKIIISCOI							-0.0003 (-2.5215)		
CRRinsco2							(-2.3213)	-0.0021	
CICICIIISCO2								(-1.0393)	
CRRinsco3								(1.0373)	-0.0014
CRRIIISCOS									(-0.2654)
_cons	0.0933***	0.0955***	0.0949***	0.0995***	0.1003***	0.1018***	0.0959***	0.0957***	0.0953***
	(5.5997)	(5.7074)	(5.6212)	(4.5478)	(4.4342)	(4.4291)	(5.7696)	(5.7282)	(5.7091)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2125	2125	2125	1493	1493	1493	2125	2125	2125
adj. $R^2$	0.129	0.111	0.112	0.152	0.152	0.153	0.115	0.112	0.112

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abi							
	ormal_return								
CRRabsco1	-1.4077***			-1.9348***			-1.4229***		
	(-3.9960)			(-4.7670)			(-3.8899)		
CRRabsco2	0.3342**			0.8582***			0.2619		
	(2.3570)			(2.8962)			(1.1926)		
CRRabsco3	1.1333***			1.2314***			$0.9717^{***}$		
	(2.6939)			(2.9030)			(2.6420)		
CRRgrsco1		0.0016***			$0.0014^{**}$			$0.0016^{***}$	
		(3.0515)			(2.4416)			(3.0137)	
CRRgrsco2		-1.4188			-0.1992			-1.4185	
		(-0.8425)			(-0.1106)			(-0.8384)	
CRRgrsco3		3.2617			2.0347			3.2539	
		(1.4583)			(0.9186)			(1.1190)	
CRRinsco1			-0.0003**			0.0003			-0.0003**
			(-2.2542)			(0.2952)			(-2.2476)
CRRinsco2			-0.0028*			0.0002			-0.0024
			(-1.8450)			(0.0855)			(-1.0591)
CRRinsco3			0.0002			0.0033			0.0014
			(0.0731)			(0.8334)			(0.2565)
di_319438				0.0016***	-0.0006**	-0.0019			
				(3.0575)	(-2.2339)	(-0.7135)			
di_319440				-0.0179***	-0.0076	-0.0166**			
				(-2.9145)	(-1.1973)	(-2.1912)			
climate_regu							2.9698	-0.0051	-0.3322
lation_risk									
							(0.5723)	(-0.0050)	(-0.2527)
_cons	0.0959***	0.1016***	0.0957***	0.1051***	0.1090***	0.1038***	0.0950***	0.1016***	0.0963***
	(5.8377)	(4.3857)	(5.9507)	(6.0122)	(4.5046)	(6.1228)	(5.6817)	(4.4149)	(5.7566)
Control	Yes								
N	2125	1493	2125	2125	1493	2125	2125	1493	2125
adj. $R^2$	0.137	0.154	0.115	0.152	0.160	0.127	0.137	0.153	0.115

(16) event: Trump event windows=[0,10] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	13.2474***	2.1479	4.4206	0.7798	0.9678	1.2944	0.9251	0.6977	0.7631
lation_risk									
	(3.1755)	(0.2979)	(0.6592)	(0.8930)	(0.8551)	(0.9970)	(1.0400)	(0.7299)	(0.5826)
CRRabsco1	-1.0007***			_					
	(-3.3636)				事件:特朗普上	台			
CRRabsco2		-0.1490			411. 14.93 ET	. Н			
		(-0.2338)			☆ □ ₩		estimation windo	F 510 201	
CRRabsco3			-0.3169		窗口别: event w	vindows=[0, 10]	estimation windo	w=[-510,-30]	
			(-0.5897)		体孙 海州中郊	: 10 人同心法用	极少能找到系数	- - - - - - - - - - - - - - - - - - -	1111年日本 412年
CRRgrsco1				0.0018***					
				(2.8085)	<b>坝</b> 以	注思的定,URR*	scope1、CRR*sc	ope3 的致据表现	.牧好。
CRRgrsco2				L					
					(0.3909)				
CRRgrsco3						1.9044			
						(0.7406)			
CRRinsco1							-0.0004***		
							(-3.8793)		
CRRinsco2								-0.0021	
								(-0.7696)	
CRRinsco3									-0.0011
	***	***	***			***	***		(-0.1500)
_cons	0.1030***	0.1053***	0.1047***	0.1055***	0.1065***	0.1080***	0.1062***	0.1058***	0.1055***
	(5.8837)	(6.0519)	(5.9672)	(4.4319)	(4.4011)	(4.4389)	(6.1239)	(6.0706)	(6.0586)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2924	2924	2924	2055	2055	2055	2924	2924	2924
adj. $R^2$	0.145	0.125	0.126	0.167	0.167	0.168	0.132	0.126	0.125

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn								
	ormal_return								
CRRabsco1	-1.5213***			-1.7762***			-1.5505***		
	(-4.2367)			(-3.7058)			(-4.3796)		
CRRabsco2	0.3030			0.4992			0.1604		
	(1.0214)			(0.9531)			(0.4377)		
CRRabsco3	1.3630***			1.4830***			1.0438*		
	(2.7458)			(2.8614)			(1.9663)		
CRRgrsco1		0.0018***			$0.0016^{**}$			0.0018***	
		(2.8926)			(2.3838)			(2.9944)	
CRRgrsco2		-1.2699			-0.1529			-1.3526	
		(-0.7142)			(-0.0748)			(-0.7384)	
CRRgrsco3		1.3801			0.3361			3.3819	
		(0.4849)			(0.1137)			(0.9783)	
CRRinsco1			-0.0005***			-0.0001			-0.0005***
			(-3.5480)			(-0.1305)			(-3.0596)
CRRinsco2			-0.0017			0.0025			-0.0023
			(-0.9129)			(1.0730)			(-0.8274)
CRRinsco3			0.0052			0.0095**			0.0034
			(1.3026)			(2.1845)			(0.5258)
di_319438				0.0007	-0.0008***	-0.0013			
				(0.9095)	(-2.8693)	(-0.4987)			
di_319440				-0.0195***	-0.0060	-0.0228***			
				(-2.8123)	(-0.7590)	(-2.8370)			
climate_regu							5.8539	1.3093	0.5249
lation_risk									
							(1.0072)	(1.0174)	(0.3663)
_cons	0.1066***	0.1111***	0.1080***	0.1171***	0.1181***	0.1189***	0.1048***	0.1079***	0.1070***
	(6.1038)	(4.5454)	(6.3683)	(6.3707)	(4.5415)	(6.6722)	(5.9340)	(4.4287)	(6.1200)
Control	Yes								
N	2924	2055	2924	2924	2055	2924	2924	2055	2924
adj. $R^2$	0.150	0.164	0.133	0.163	0.170	0.149	0.151	0.168	0.133

(17) event: Trump event windows=[0,15] estimation window=[-510,-30], keep all samples during event windows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn	cumulative_abn
	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return	ormal_return
climate_regu	24.2927***	3.1993	11.9564	4.8850***	5.2553**	5.6520**	5.5506***	4.1942**	5.1440***
lation_risk									
	(3.2899)	(0.2452)	(1.1018)	(3.1580)	(2.2199)	(2.0973)	(3.8713)	(2.4549)	(2.9605)
CRRabsco1	-1.5503***								
	(-2.7766)				事件:特朗普	LA			
CRRabsco2		0.1386			事件: 特別百 	<b>一一</b>			
		(0.1193)				1.6	-		
CRRabsco3			-0.6012		│ 窗口期: even	t windows= $[0, 15]$	] estimation wind	dow=[-510,-30]	
			(-0.6456)			<del>~</del>			
CRRgrsco1				0.0029***					3分 CRR 都显著且
				(3.6718)	为正,是以上	模型表现最好的	。值得注意的是	,CRR*scope1的	数据表现较好。
CRRgrsco2									
						20120			
CRRgrsco3						2.8439			
cp.p.!						(0.5071)	0.0044***		
CRRinsco1							-0.0011***		
CDD' A							(-6.9533)	0.0000	
CRRinsco2								0.0080	
CDD: 2								(1.2077)	0.0020
CRRinsco3									-0.0028
	0.1071***	O 1115***	0.1005***	0.1105***	0.1215***	0 1222***	0.1137***	0.1104***	(-0.1966) 0.1109***
_cons		0.1115***	0.1095***	0.1195***	0.1215***	0.1233***	0.1126***		
- C 1	(4.8251)	(5.1825)	(4.9518)	(3.8452)	(3.8736)	(3.8159)	(5.2158)	(5.0176)	(5.0317)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4254	4254	4254	2988	2988	2988	4254	4254	4254
adj. $R^2$	0.210	0.182	0.184	0.253	0.253	0.254	0.209	0.185	0.182

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab	cumulative_ab
	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return	normal_return
CRRabsco1	-2.2975***			-1.8444**			-2.3587***		
	(-3.3112)			(-2.3692)			(-3.6976)		
CRRabsco2	1.0814			0.4984			0.7897		
	(1.3506)			(0.4146)			(0.9069)		
CRRabsco3	1.8235*			1.9065*			1.1686		
	(1.6952)			(1.8010)			(1.0356)		
CRRgrsco1		0.0028***			0.0030***			$0.0030^{***}$	
		(3.4918)			(3.5040)			(4.0669)	
CRRgrsco2		-0.7572			-1.0493			-1.1138	
		(-0.2349)			(-0.3192)			(-0.2329)	
CRRgrsco3		-4.5287			-3.4451			4.0811	
		(-1.2572)			(-0.8118)			(0.6488)	
CRRinsco1			-0.0014***			-0.0014			-0.0012***
			(-5.5805)			(-1.0384)			(-4.2586)
CRRinsco2			$0.0116^{**}$			0.0171***			0.0075
			(2.3367)			(3.1241)			(1.1517)
CRRinsco3			$0.0220^{***}$			0.0275***			0.0101
			(2.7844)			(3.4502)			(0.8536)
di_319438				-0.0015	-0.0022***	0.0003			
				(-1.0422)	(-3.7935)	(0.0747)			
di_319440				-0.0099	0.0113	-0.0284***			
				(-0.8829)	(0.7039)	(-2.9470)			
climate_reg							12.0157	5.6675**	$3.4738^*$
ulation_risk									
							(1.2596)	(2.1192)	(1.8288)
_cons	0.1136***	0.1381***	0.1205***	0.1201***	0.1380***	0.1336***	0.1099***	0.1232***	0.1133***
	(5.0940)	(4.0805)	(5.6066)	(5.0102)	(4.0672)	(6.0608)	(4.9473)	(3.8158)	(5.1303)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\overline{N}$	4254	2988	4254	4254	2988	4254	4254	2988	4254
adj. $R^2$	0.216	0.211	0.206	0.220	0.226	0.220	0.220	0.255	0.214

#### Code:

# 1) To merge CRSP stock return and CompStat Fundamental Information<sup>5</sup>(Python version)

```
# Daily Stock Return & CompStat Fundamental #
# Shengjie SONG
# Date: Sep 2024
                                         #
import pandas as pd
import numpy as np
import datetime as dt
import matplotlib.pyplot as plt
from dateutil.relativedelta import *
from pandas.tseries.offsets import *
from scipy import stats
####################
# Compustat Block #
#####################
comp = pd.read_csv('20240912\\Compustat_Fundamental.csv', low_memory=False)
comp.columns = comp.columns.str.lower()
comp['datadate'] = pd.to_datetime(comp['datadate'])
comp['year']=comp['datadate'].dt.year
# create preferrerd stock
comp['ps']=np.where(comp['pstkrv'].isnull(), comp['pstkl'], comp['pstkrv'])
comp['ps']=np.where(comp['ps'].isnull(),comp['pstk'], comp['ps'])
comp['ps']=np.where(comp['ps'].isnull(),0,comp['ps'])
comp['txditc']=comp['txditc'].fillna(0)
# create book equity
comp['be']=comp['seq']+comp['txditc']-comp['ps']
comp['be']=np.where(comp['be']>0, comp['be'], np.nan)
# number of years in Compustat
comp=comp.sort values(by=['gvkey','datadate'])
comp['count']=comp.groupby(['gvkey']).cumcount()
filtered_data = []
chunksize = 1 * 10000
num = 0
```

<sup>&</sup>lt;sup>5</sup> Source: This code quote is from Qingyi (Freda) Song Drechsler, rewritten for database merging. (<a href="https://www.fredasongdrechsler.com/data-crunching/fama-french">https://www.fredasongdrechsler.com/data-crunching/fama-french</a>)

```
# 可以根据实际情况调整分块大小
for chunk in pd.read csv('CRSP Daily Stock Return.csv',
chunksize=chunksize, low_memory=False):
   chunk.columns = chunk.columns.str.lower()
   chunk = chunk[['permno', 'permco', 'date', 'ret', 'retx', 'shrout',
'prc']]
    chunk['datadate'] = pd.to datetime(comp['datadate'])
   filtered_chunk = chunk[(chunk['date'] >= '2014-06-01') &
(chunk['date'] <= '2014-06-30')]
    num += 1
     print(num, filtered chunk.count)
   # 替换为实际筛选条件
   filtered_data.append(filtered_chunk)
filtered df = pd.concat(filtered data)
####################
# CRSP Block
#####################
# df a = pd.read csv('20240912\\CRSP Daily Stock Return.csv',
Low memory=False, nrows=500000)
df b = pd.read csv('NAME.csv', low memory=False)
df_b.columns = df_b.columns.str.lower()
df b = df b[['permno', 'shrcd', 'exchcd']]
\# df_a = df_a[(df_a['date'] >= '2014-01-01') \& (df_a['date'] <= '2019-
06-30')7
df c = df b[(df b['exchcd'] \geq 1) & (df b['exchcd'] \leq 3)]
merged_df = pd.merge(df_a, df_c, on='permno')
crsp_m = merged_df
print(crsp_m.columns)
# crsp_m = merged_df[merged_df['date'] <= merged_df['nameendt']]</pre>
# change variable format to int
crsp_m[['permco','permno','shrcd','exchcd']]=crsp_m[['permco','permno',
'shrcd','exchcd']].astype(int)
# Line up date to be end of month
crsp_m['jdate'] = pd.to_datetime(crsp_m['date']) # 日期对齐到每天
#crsp_m['jdate']=pd.to_datetime(crsp_m['date'])+ MonthEnd(0)
# add delisting return
dlret = pd.read_csv('20240912\\Delisted Stocks.csv', low_memory=False)
dlret.columns = dlret.columns.str.lower()
dlret['dlstdt']=pd.to datetime(dlret['dlstdt'])
dlret['jdate']=dlret['dlstdt']+MonthEnd(0)
crsp = pd.merge(crsp_m, dlret, how='left',on=['permno','jdate'])
crsp['dlret']=crsp['dlret_x'].fillna(0)
```

```
crsp['ret']=crsp['ret'].fillna(0)
# retadj factors in the delisting returns
crsp['ret'] = pd.to_numeric(crsp['ret'], errors='coerce')
crsp['dlret'] = pd.to_numeric(crsp['dlret'], errors='coerce')
crsp['retadj']=(1+crsp['ret'])*(1+crsp['dlret'])-1
# calculate market equity
crsp['me']=crsp['prc'].abs()*crsp['shrout']
crsp=crsp.drop(['dlret','dlstdt','prc','shrout'], axis=1)
crsp=crsp.sort_values(by=['jdate','permco','me'])
### Aggregate Market Cap ###
# sum of me across different permno belonging to same permco a given date
crsp_summe = crsp.groupby(['jdate','permco'])['me'].sum().reset_index()
# largest mktcap within a permco/date
crsp_maxme = crsp.groupby(['jdate','permco'])['me'].max().reset_index()
# join by jdate/maxme to find the permno
crsp1=pd.merge(crsp, crsp_maxme, how='inner', on=['jdate','permco','me'])
# drop me column and replace with the sum me
crsp1=crsp1.drop(['me'], axis=1)
# join with sum of me to get the correct market cap info
crsp2=pd.merge(crsp1, crsp_summe, how='inner', on=['jdate','permco'])
# sort by permno and date and also drop duplicates
crsp2=crsp2.sort_values(by=['permno','jdate']).drop_duplicates()
# keep December market cap
crsp2['year']=crsp2['jdate'].dt.year
crsp2['month']=crsp2['jdate'].dt.month
# decme=crsp2[crsp2['month']==12]
decme=decme[['permno','date','jdate','me','year']].rename(columns={'me':'de
c_me'})
### July to June dates
crsp2['ffdate']=crsp2['jdate']+MonthEnd(-6)
crsp2['ffyear']=crsp2['ffdate'].dt.year
crsp2['ffmonth']=crsp2['ffdate'].dt.month
crsp2['retx'] = pd.to_numeric(crsp2['retx'], errors='coerce')
crsp2['1+retx']=1+crsp2['retx']
crsp2=crsp2.sort_values(by=['permno','date'])
# cumret by stock
crsp2['cumretx']=crsp2.groupby(['permno','ffyear'])['1+retx'].cumprod()
# lag cumret
crsp2['lcumretx']=crsp2.groupby(['permno'])['cumretx'].shift(1)
# lag market cap
crsp2['lme']=crsp2.groupby(['permno'])['me'].shift(1)
# if first permno then use me/(1+retx) to replace the missing value
```

```
crsp2['count']=crsp2.groupby(['permno']).cumcount()
crsp2['lme']=np.where(crsp2['count']==0, crsp2['me']/crsp2['1+retx'],
crsp2['lme'])
# baseline me
mebase=crsp2[crsp2['ffmonth']==1][['permno','ffyear',
'lme']].rename(columns={'lme':'mebase'})
# merge result back together
crsp3=pd.merge(crsp2, mebase, how='left', on=['permno','ffyear'])
crsp3['wt']=np.where(crsp3['ffmonth']==1, crsp3['lme'],
crsp3['mebase']*crsp3['lcumretx'])
decme['year']=decme['year']+1
decme=decme[['permno','year','dec_me']]
# Info as of June
crsp3_jun = crsp3[crsp3['month']==6]
crsp_jun = pd.merge(crsp3_jun, decme, how='inner', on=['permno','year'])
crsp_jun = crsp_jun[['permno','date', 'jdate',
'shrcd','exchcd','retadj','me','wt','cumretx','mebase','lme','dec_me']]
crsp_jun = crsp_jun.sort_values(by=['permno','jdate']).drop_duplicates()
############################
# CCM Block
#############################
ccm = pd.read csv('20240912\\CCM CRSP Link Table CRSP.csv',
low_memory=False)
ccm.columns = ccm.columns.str.lower()
# if linkenddt is missing then set to today date
ccm['linkenddt']=ccm['linkenddt'].fillna(pd.to_datetime('today'))
# ccm1=pd.merge(comp[['gvkey', 'datadate', 'be',
'count']],ccm,how='left',on=['gvkey'])
ccm1=pd.merge(comp[['gvkey', 'datadate', 'be', 'count']], ccm, how='left',
on=['gvkey'])
ccm1['yearend']=ccm1['datadate']+YearEnd(0)
ccm1['jdate']=ccm1['yearend']+MonthEnd(6)
# set link date bounds
ccm1['jdate'] = pd.to_datetime(ccm1['jdate'], errors='coerce')
ccm1['linkdt'] = pd.to_datetime(ccm1['linkdt'], errors='coerce')
ccm1['linkenddt'] = pd.to_datetime(ccm1['linkenddt'], errors='coerce')
# Drop rows with NaT values if necessary
ccm1.dropna(subset=['jdate', 'linkdt', 'linkenddt'], inplace=True)
ccm2=ccm1[(ccm1['jdate']>=ccm1['linkdt'])&(ccm1['jdate']<=ccm1['linkenddt']</pre>
)]
ccm2['permno'] = ccm2['lpermno']
ccm2=ccm2[['gvkey','permno','datadate','yearend', 'jdate','be', 'count']]
# link comp and crsp
```

```
ccm_jun=pd.merge(crsp_jun, ccm2, how='inner', on=['permno', 'jdate'])
ccm_jun['beme']=ccm_jun['be']*1000/ccm_jun['dec_me']
```

## 2) Merge the fundamental data to CER and Carbon Emission (Stata version)

```
cd D:\Users\Desktop\HKUST-RA\0913
* ssc install rangejoin
* ssc install rangestat
```

1. Read stock data and CRE data and convert dates to Stata date format. 读取股票数据和 CRE 数据,并将日期转换为 Stata 日期格式

```
use CRE.dta, replace
gen filedate = substr(file_name, 1, 8)
gen cre_date = date(filedate, "YMD")
format cre_date %td
tempfile cre_data
save CRE_process.dta, replace
```

2. Read the stock data and use the rangejoin command to merge the stock data with the CRE data, matching the nearest neighbouring CRE date. 读取股票数据并使用 rangejoin 命令合并股票数据和 CRE 数据,匹配最邻近的 CRE 日期。

```
use test_stock.dta, clear
gen stock_date = date(date, "YMD")
format stock_date %td
save test_stock_process.dta, replace
```

3. Adding cik values to stock daily frequency data. 给股票日频数据加上 cik 值

```
use link_table.dta, clear
rename lpermno permno
bysort permno: keep if _n == 1
save link_table_process.dta, replace

use test_stock_process.dta,clear
merge m:1 permno using link_table_process.dta
save test_stock_process.dta, replace
drop _merge * Since two merges were performed, a column indicating a
merge has to be deleted or the merge command will not work.
```

4. Use the joinby command to match all possible combinations and calculate the date difference, keeping the record with the smallest date difference. 使用 joinby 命令匹配所有可能的组合,并计算日期差值,保留日期差值最小的记录。

```
joinby cik using CRE_process.dta
keep if stock_date_stata >= cre_date_stata
gen date_diff = stock_date - cre_date
bysort cik stock_date (date_diff): keep if _n == 1
```

# 3) Compute CER and Cross-sectional regression<sup>6</sup>

#### Data Preparation: Security\_id, Market return, Security return

Before experiment, we have already collect a data set including three main variables in event study: Security\_id: permno, event occurrence's date(date), markettype(exchcd). Market return: vwretx. Security return: Value-Weighted Return (excluding dividends) (retx)

In our case, we already have data with a data variable, which we call "stock\_date", and a company identifier, which we called "permno".

#### Cleaning the data and Calculating the Event and Estimation Windows

We need to create a variable, **dif**, that will count the number of days from the observation to the event date. Note that when using trading days, Saturday and Sunday are excluded, however dif needs to be a continuous uninterrupted variable.

```
drop if vwretx==.
gen event_date = date("14dec2015", "DMY")
format event_date %td
save test_process.dta,replace *Adding this line and above if you need.
use test_process.dta,replace
sort cik stock_date
```

For trading days, we first need to create a variable that counts the number of days within each company id.

```
by cik: gen datenum=_n
```

Then we determine which observation occurs on the event date. We create a variable with the event date's day number on all of the observations within that company id.

```
by cik: gen target=datenum if stock_date==event_date
egen td=min(target), by(cik)
drop target
```

Finally, we simply take the difference between the two, creating a variable, dif, that counts the number of days between each individual observation and the event day.

```
gen dif=datenum-td
```

Next, we need to make sure that we have the minimum number of observations before and after the event date, as well as the minimum number of observation: before the event window for the estimation window, Let's say we want 2 days before and after the event date (a total of 5 days in the event window) and 30 days for the estimation window. (You can of course change these numbers to suit your analysis.)

<sup>&</sup>lt;sup>6</sup> Source and Cite: https://mp.weixin.qq.com/s/VXxkQ2jlJFFQlGETfStT0Q

```
by cik: gen event_window=1 if dif>=-2 & dif<=2
egen count_event_obs=count(event_window) ,by(cik)
by cik: gen estimation_window=1 if dif<-30 & dif>=-60
egen count_est_obs=count(estimation_window), by(cik)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.
```

## **Estimating Normal Performance**<sup>7</sup>

We will run a seperate regression for each company using the data within the estimation window and save the alphas (the intercept) and betas (the coeffcient of the independent variable).

Before this process, maybe you need to filter data.

```
drop if dif==.
           local threshold = date("event date", "YMD")
           bysort id: egen min_date = min(date)
           drop if min_date > `threshold'
           drop min date
           drop if retx==.b
            replace retx = 0 if retx == .c
set more off
gen predicted return=.
egen id=group(cik)
*drop if dif==.
forvalues i=1(1)280{
   count if id == `i' & dif == 0
   if r(N) > 0 {
   l id cik if id==`i' & dif==0
    reg retx vwretx if id==`i' & estimation_window==1
   predict p if id==`i'
   replace predicted return=p if id==`i' & event window==1
   drop p
    }
```

# **Abnormaland Cumulative Abnormal Returns**

The daily abnormal return is computed by subtracting the predicted normal return from the actual return for each day in the event window. The sum of the abnormal returns over the event window is the cumulative abnormal return.

```
sort cik stock_date
```

\_

<sup>&</sup>lt;sup>7</sup> Note that it is necessary to first observe whether there are missing variables and whether they need to be excluded. The code here does not include this processing.

```
gen abnormal_return= retx-predicted_return if event_window==1
by cik:egen cumulative_abnormal_return = total(abnormal_return)
```

#### **Testing for Significance**

We are going to compute a test statistic, test, to check whether the average abnormal return for each stock is statistically different from zero. Note that the difference between sample standard deviation and the population standard deviation.

```
sort cik stock_date
by cik: egen ar_sd=sd(abnormal_return)
gen test=(1/sqrt(5))*(cumulative_abnormal_return / ar_sd)
list cik cumulative_abnormal_return test if dif==0

export excel cik event_date cumulative_abnormal_return
"stats.xls" if dif==0, firstrow(variables) replace
```

#### **Testing Across All Events**

```
reg cumulative_abnormal_return if dif==0, robust
```

# 4) Graphing and cross-sectional regression<sup>8</sup>

```
gen esg=.
replace esg=1 if climate__risk!=0
replace esg=0 if climate__risk==0
* 按 climate_regulation_risk 分组并累加收益
bysort esg dif: egen cum_return = total(abnormal_return)
* 创建两个新的变量,分别存储 climate regulation risk 为 1 和 0 的累加收益
gen esg_car = cum_return if esg == 1
gen nesg_car = cum_return if esg == 0
twoway (line esg car dif, lcolor(blue) lpattern(solid)) ///
      (line nesg_car dif, lcolor(red) lpattern(dash)), ///
      title("CAR by Day") ///
      xlabel(-5(1)5) ///
      ylabel(-2(0.5)2) ///
      legend(order(1 "ESG" 2 "NESG")) ///
      xline(0, lcolor(green) lpattern(dash))
reg cumulative_abnormal_return climate__risk company_features
esttab m1 using regression.rtf, replace b(%6.4f) t(%6.4f) nogap ar2
star(* 0.1 ** 0.05 *** 0.01)
```

-

<sup>&</sup>lt;sup>8</sup> The regression commands are simple and can be debugged to suit your needs.

#### 5) Regression in detail

```
use Computsat data.dta, clear
gen comp_date = date(date, "YMD")
gen year merge = year(comp date)
save Computsat data 1.dta, replace
import delimited trucost_environmental_Liying.csv, clear
gen year_merge = fiscalyear
gen carbon date = date(periodenddate, "YMD")
format carbon_date %td
gen year = year(carbon_date)
gen month = month(carbon_date)
by gvkey month (year), sort: gen lag di 319413 = di 319413[ n-1]
gen growth_rate_scope1 = (di_319413 - lag_di_319413) / lag_di_319413
by gvkey month (year), sort: gen lag_di_319414 = di_319414[_n-1]
gen growth_rate_scope2 = (di_319414 - lag_di_319414) / lag_di_319414
by gvkey month (year), sort: gen lag_di_319415 = di_319415[_n-1]
gen growth_rate_scope3 = (di_319415 - lag_di_319415) / lag_di_319415
save trucost process.dta, replace
use trucost process.dta, clear
keep if year(carbon_date)==2015 | year(carbon_date)==2014 |
year(carbon date)==2013
save Ptrucost_process.dta, replace
use experimentP15.dta, clear
gen year_merge = year(date)
replace year_merge = year_merge - 1 if month(date) <= 6</pre>
joinby gvkey year merge using Computsat data 1.dta, unmatched(master)
*merge m:1 gvkey year_merge using Computsat_data_1.dta, keep(match)
nogenerate force
keep if dif>=0 & dif<=15
drop _merge
joinby gvkey using Ptrucost process.dta, unmatched(master)
keep if date >= carbon_date
gen cdate diff = date - carbon date
bysort gvkey date (cdate_diff): keep if _n == 1
gen CRRabsco1=climate_regulation_risk*log(di_319413)
gen CRRabsco2=climate regulation risk*log(di 319414)
gen CRRabsco3=climate_regulation_risk*log(di_319415)
```

```
gen CRRgrsco1=climate_regulation_risk*growth_rate_scope1
gen CRRgrsco2=climate_regulation_risk*growth_rate_scope2
gen CRRgrsco3=climate_regulation_risk*growth_rate_scope3
gen CRRinsco1=climate regulation risk*di 319407
gen CRRinsco2=climate_regulation_risk*di_319408
gen CRRinsco3=climate regulation risk*di 319409
reg cumulative abnormal return climate regulation risk me wt cumretx
mebase lme dec me be, vce(cluster industry)
reg cumulative_abnormal_return climate_regulation_risk CRRabsco1 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m1
reg cumulative abnormal return climate regulation risk CRRabsco2 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m2
reg cumulative_abnormal_return climate_regulation_risk CRRabsco3 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m3
reg cumulative abnormal return climate regulation risk CRRgrsco1 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m4
reg cumulative_abnormal_return climate_regulation_risk CRRgrsco2 me wt
cumretx mebase lme dec me be, vce(cluster industry)
est store m5
reg cumulative_abnormal_return climate_regulation_risk CRRgrsco3 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m6
reg cumulative_abnormal_return climate_regulation_risk CRRinsco1 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m7
reg cumulative_abnormal_return climate_regulation_risk CRRinsco2 me wt
cumretx mebase lme dec me be, vce(cluster industry)
est store m8
reg cumulative abnormal return climate regulation risk CRRinsco3 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m9
esttab m1 m2 m3 m4 m5 m6 m7 m8 m9 using regression1.rtf ,replace
b(%6.4f) t(%6.4f) nogap ar2 star(* 0.1 ** 0.05 *** 0.01)
```

```
reg cumulative_abnormal_return CRRabsco1 CRRabsco2 CRRabsco3 me wt
cumretx mebase lme dec me be, vce(cluster industry)
est store m1
reg cumulative abnormal return CRRgrsco1 CRRgrsco2 CRRgrsco3 me wt
cumretx mebase lme dec me be, vce(cluster industry)
est store m2
reg cumulative abnormal return CRRinsco1 CRRinsco2 CRRinsco3 me wt
cumretx mebase lme dec_me be, vce(cluster industry)
est store m3
reg cumulative abnormal return CRRabsco1 CRRabsco2 CRRabsco3 di 319438
di_319440 me wt cumretx mebase lme dec_me be, vce(cluster industry)
est store m4
reg cumulative abnormal return CRRgrsco1 CRRgrsco2 CRRgrsco3 di 319438
di_319440 me wt cumretx mebase lme dec_me be, vce(cluster industry)
est store m5
reg cumulative_abnormal_return CRRinsco1 CRRinsco2 CRRinsco3 di_319438
di_319440 me wt cumretx mebase lme dec_me be, vce(cluster industry)
est store m6
reg cumulative abnormal return climate regulation risk CRRabsco1
CRRabsco2 CRRabsco3 me wt cumretx mebase lme dec_me be, vce(cluster
industry)
est store m7
reg cumulative abnormal return climate regulation risk CRRgrsco1
CRRgrsco2 CRRgrsco3 me wt cumretx mebase lme dec_me be, vce(cluster
industry)
est store m8
reg cumulative_abnormal_return climate_regulation_risk CRRinsco1
CRRinsco2 CRRinsco3 me wt cumretx mebase lme dec me be, vce(cluster
industry)
est store m9
esttab m1 m2 m3 m4 m5 m6 m7 m8 m9 using regression2.rtf ,replace
b(%6.4f) t(%6.4f) nogap ar2 star(* 0.1 ** 0.05 *** 0.01)
```