Climate Change Shareholder Engagement and Systemic Downside Risk

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Smurfit PhD Symposium - 19th Semptember 2022

Introduction I

This paper studies the effects of shareholder engagement regarding Climate Change issues on the Systemic and Idiosyncratic risk trends of the approached firms.

We build on Hoepner, Oikonomou, Sautner, Starks and Zhou (2022) who demonstrate that successful ESG shareholder activism reduces firms downside risk.

With an updated version of the database of investor engagement used in the paper above, we focus on Climate Change activism and split downside risk into Systemic and Idiosyncratic using a definition of Beta that only looks at the negative side of the returns distribution.

Brief Literature Review I

Besides Hoepner, Oikonomou, Sautner, Starks and Zhou (2022), there are relevant investor activism papers to our work. Smith (1996) finds, using CalPERS data, finds that successful engagements increase shareholders wealth. Chu and Zhao (2019) find that Hedge Fund activism influences firms to reduce toxic chemical emissions. Akey and Appel (2020) find the same result on a similar study, noting that the reduction is higher for chemicals released into the air than emissions into the water or ground. Using data from New York City Pension System, Naaraayanan, Lakshmi and Sharma (2021) find a similar reduction in emissions as in Akey and Appel (2020).

Brief Literature Review II

Regarding climate risks, Krueger, Sautner, and Starks (2019) find that institutional investors consider them for both financial and non-financial reasons. Kim, Li and Li (2014) find that good CSR practices reduce stock market crash risk. Similarly, Krueger (2015) finds that negative news about different ESG topics implies negative returns for the firm.

Bolton and Kacperczyk (2021) find that firms with higher exposure to climate risks, measured as total and changes in Scope 1, 2 and 3 emissions, carry a carbon premium. Hsu, Li and Tsou (2022) find a similar result using plant-based pollution (chemicals emissions) data, however, opposed to Bolton and Kacperczyk (2021), the pollution premium is explained by pollution intensity rather than absolutes or changes in absolutes.

Data I

The engagement database is an updated version of Hoepner, Oikonomou, Sautner, Starks and Zhou (2022) sample. Data is obtained from a large asset manager which is regarded as an influential activist. The asset manager engages with firms of their own portfolio as well as on behalf of clients with the objective of promoting better ESG standards.

The sample runs from January 2005 to today, although we restrict the sample to December 2020 to have enough post-engagement observations to estimate the effects.

Data II

The investor engaged with 370 firms regarding Climate Change issues for a total of 573 engagements. On the whole picture, this means that the 39% of firms in the sample have been subject of at least on Climate engagement, while 18% of all engagements are part of this topic.

This is an international sample that contains firms from 44 countries, where 32 countries have at least 2 firms in the sample. US firms represent 27% of the sample.

Engagement Process I

The investor identifies issues on firms and targets them on a 4-stage process consisting of the following milestones:

- Milestone 1: The investor shares their concern with the firm.
- Milestone 2: The firm acknowledges that there is an issue.
- Milestone 3: The firm implements changes to solve the issue.
- Milestone 4: The investor evaluates the actions and results and considers the issue solved.

We use these milestones to calculate a Success Rate for every engagement and firm. 10% of the engagements did not pass the first milestone. In 33% of the cases the firm acknowledged the issue but did not take action. In the remaining cases the firm took action and the investor considered it enough in 56% of the cases (in other words, 32% of the engagements reached milestone 4).

Risk Measures I

We estimate monthly Systemic and Specific risk measures using the beta decomposition method proposed by Bollerslev, Patton and Quaedvlieg (2022). The authors decompose the traditional market beta into four "semi-betas" that add up to the standard market beta. Each of them considers only one side of the returns for both the asset and the market, thus obtaining negative-negative, positive-positive, negative-positive and positive-negative semi-betas.

Risk Measures II

Our semibeta of interest is the negative-negative semibeta, which is defined for firm i at month t by:

$$\widehat{\beta_{i,t}^{N}} = \frac{\sum_{k=1}^{m} min(r_{k,i}^{-}, 0) min(r_{k,m}^{-}, 0)}{\sum_{k=1}^{m} r_{k,m}^{2}} \tag{1}$$

Where m is the number of days in the month, k is the day number, $r_{k,i}$ is the asset return at day k and $r_{k,m}$ is the market return at time k.

The choice of the negative-negative beta is motivated by the conclusion of Bollerslev et al. (2022), who find that the negative-negative beta can better explain asset's risk premia than the standard market beta and the downside beta proposed by Ang et al. (2006).

Risk Measures III

We obtain three monthly negative-negative semibetas for each firm; one against a global market index (FTSE All World), a country specific index and a sector specific index, both being value weighted indices with monthly re-weighting self-calculated using FTSE Industry Classification Benchmark (ICB) data.

Bollerslev et al. (2022) only define semibetas for the univariate case, thus, to avoid having to derive a multi-factor model, we simply orthogonalize the country (against the global indices) and sector (against the global and country indices) indices.

Risk Measures IV

We then calculate the negative-negative betas and obtain monthly measures of systemic and specific risk. Daily specific risk is obtained as:

$$SysRisk_{d,i} = \beta_{i,t}^{N,G} r_{G,d} + \beta_{i,t}^{N,C} r_{C,d} + \beta_{i,t}^{N,S} r_{S,d} \tag{2}$$

While specific risk is the residual of the regression:

$$SpecRisk_{d,i} = r_{d,i} - \beta_{i,t}^{N,G} r_{G,d} + \beta_{i,t}^{N,C} r_{G,d} + \beta_{i,t}^{N,S} r_{S,d} \tag{3}$$

Where G, C, and S represent each of the three indices, d indexes days, i indexes firms and t indexes months.

The two measures are then only considered if negative, squared, averaged monthly and finally their squared root is obtained.

Methodology I

We find a matching firm for every targeted firm using genetic matching, as proposed by Diamond and Sekhon (2013). This method is a generalization of Mahalanobis Distance and Propensity Score Matching (PSM) that iteratively assigns weights to the matching variables to minimize a balance measure, in our case, the p-value of a t-test on the mean.

The more popular PSM method provided a decent match in terms of all variables but market cap, while genetic matching was able to find matches to firms with a closer size.

We opt for one-to-one matching to avoid any bias originating from portfolio diversification.

Methodology II

We further control for distributional differences of the control variables in the two groups by re-weighting observations using Entropy Balancing (Hainmueller, 2012) to match the first moment of both groups.

Finally, we also introduce a Heckman (1979) model to account for potential selection bias, where we include firm-level variables and a country-level variable (Anti-Director Rights Index (Spamann, 2010)) that might influence the decision of targeting a firm.

Methodology III

Once the match is obtained a diff-in-diff model is estimated:

$$RiskMeasure_{i,m} = \beta_1 Target_i * Post_{i,m} + \beta_2 Target_i + \beta_3 Post_{i,m} + \beta_4^{'} Controls_{i,m} + \epsilon_{i,m} \quad (4)$$

The estimation window is of two years pre and post the first engagement if that first engagement topic is climate change.

We estimate the regression with country, sector and year fixed-effects. The standard errors are clustered at the firm level. In robustness tests we iterate the different FEs variables to include country-sector, country-year and sector-year FEs. We also cluster the errors at the firm-month level.

Results I

Globally, neither systemic risk...

Table: Climate Engagement on Global Sample. Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.074*	−0.113	−0.068	−0.073
	(0.044)	(0.093)	(0.049)	(0.070)
Post	0.060	0.163**	0.049	0.081
	(0.038)	(0.079)	(0.046)	(0.059)
Target	4.391***	6.470***	4.401***	4.256***
	(1.041)	(1.468)	(1.186)	(1.430)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	10,705	1,700	9,005	4,112
R^2	0.239	0.293	0.242	0.299
Note:				*p<0.1; **p<0.05; ***p<0.01

Results II

... nor specific risk are found to decrease.

Table: Climate Engagement on Global Sample. Specific Risk

	Dependent variable:			
	SpecRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.020	−0.092	−0.008	−0.064
	(0.037)	(0.068)	(0.041)	(0.053)
Post	−0.007	0.026	−0.021	0.023
	(0.037)	(0.058)	(0.043)	(0.057)
Target	2.718***	3.434***	2.796***	2.810**
	(0.834)	(1.075)	(0.937)	(1.156)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	10,705	1,700	9,005	4,112
R^2	0.337	0.407	0.335	0.392
Note:				*p<0.1; **p<0.05; ***p<0.01

Results III

However, a geographical analysis shows both types of risk going down for US headquartered firms.

Table: Climate Engagement on US Sample. Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	-0.136^{*}	-0.201	-0.145^{*}	-0.155^{*}
	(0.069)	(0.135)	(0.075)	(0.091)
Post	0.018	0.061	0.029	0.046
	(0.054)	(0.067)	(0.061)	(0.074)
Target	3.263^{**}	2.417	3.872^{***}	3.566^{**}
	(1.462)	(2.251)	(1.490)	(1.418)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.302	0.241	0.316	0.361
Adjusted R^2	0.294	0.199	0.307	0.352
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Results IV

Table: Climate Engagement on US Sample. Specific Risk

	Dependent variable:			
	SpecRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.106**	−0.131	−0.105*	−0.144**
	(0.052)	(0.115)	(0.057)	(0.062)
Post	−0.042	0.036	−0.057	−0.037
	(0.050)	(0.089)	(0.060)	(0.067)
Target	1.433	−0.548	1.780	1.532
	(1.035)	(2.800)	(1.133)	(1.221)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.400	0.480	0.411	0.454
Adjusted R^2	0.393	0.451	0.403	0.446
Note:			*p<0.1; **p<0.05; ***p<0.01	

Results V

We can break down Systemic risk on Global, Country and Sector specific. The general effect observed on US firms is not explained by a disconnection from global markets...

Table: Climate Engagement on US Sample. Global Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	-0.067^{*}	-0.160	-0.075^{*}	-0.068
	(0.040)	(0.100)	(0.044)	(0.052)
Post	-0.016	0.037	-0.013	0.007
	(0.032)	(0.043)	(0.036)	(0.039)
Target	1.721^{**}	2.840^{*}	2.021^{***}	1.718^{**}
	(0.756)	(1.658)	(0.773)	(0.710)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.270	0.300	0.277	0.314
Adjusted R^2	0.262	0.261	0.268	0.304
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results VI

...but rather from a reduction on risk with respect to the own country...

Table: Climate Engagement on US Sample. Country Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	-0.038^{**}	-0.070	-0.039^{*}	-0.057^{**}
	(0.019)	(0.049)	(0.021)	(0.027)
Post	0.004	0.036	0.005	0.011
	(0.015)	(0.031)	(0.018)	(0.020)
Target	0.768^{***}	0.997	0.910^{***}	0.772^{***}
	(0.293)	(0.752)	(0.308)	(0.286)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.262	0.295	0.262	0.285
Adjusted R^2	0.254	0.256	0.253	0.275
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results VII

... and, to a lesser extent, the own industry.

Table: Climate Engagement on US Sample. Sector Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.083**	−0.049	−0.084*	−0.096*
	(0.041)	(0.048)	(0.044)	(0.052)
Post	0.031	0.022	0.037	0.034
	(0.031)	(0.030)	(0.034)	(0.045)
Target	1.948**	−0.539	2.279**	2.239**
	(0.891)	(0.942)	(0.912)	(0.886)
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.315	0.134	0.338	0.394
Adjusted R^2	0.308	0.086	0.329	0.384

Note: *p<0.1; **p<0.05; ***p<0.01

Conclusion and Next Steps I

Climate Change investor engagement reduces both systemic and, specially, specific risk of US firms, with the effect being higher with more successful engagements. However, a global effect is not found. In unreported tests, we split countries to common or civil law (excluding the US), given that law systems influence the degree of power that shareholders may have in a firm. However, models showed no effect in any of the groups.

As further tests, we will use LaPorta, Florencio-De-Silanes and Shleifer (2008) legal origin country classification to further explore geographical results.

Conclusion and Next Steps II

Other steps include:

- Exploring channels that might explain the risk reduction. Is there any variable capturing changes within the firm? e.g. do firms increase their capital expenditures after a successful engagement?
- Looking at unsuccessful engagements, do these firms adapt in any way to knowing that investors are worried about a particular aspect of its operations?
- Add all engagements for a given firm, as we are only looking at the first one. However, it is econometrically challenging to isolate effects of all the individual engagements.

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Appendix: Robustness Tests I

Adding combined FEs show stronger results in the US sample.

Table: Climate Engagement on US Sample with Iterated FEs. Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.142**	−0.230	−0.148**	−0.167**
	(0.059)	(0.144)	(0.068)	(0.076)
Post	−0.069	0.097	−0.032	−0.098
	(0.064)	(0.069)	(0.075)	(0.101)
Target	4.334***	2.570	4.497***	4.237***
	(1.302)	(2.456)	(1.402)	(1.431)
Country-Year FE	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.331	0.262	0.341	0.389
Adjusted R^2	0.303	0.185	0.312	0.359
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table: Climate Engagement on US Sample with Iterated FEs. Specific Risk

	Dependent variable:			
	SpecRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.111**	−0.154	−0.108**	−0.143**
	(0.043)	(0.122)	(0.049)	(0.060)
Post	−0.113**	0.121	−0.098*	−0.113*
	(0.051)	(0.098)	(0.059)	(0.064)
Target	2.157**	−1.151	2.305**	2.143*
	(0.995)	(3.028)	(1.065)	(1.196)
Country-Year FE	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.437	0.494	0.443	0.487
Adjusted R^2	0.414	0.441	0.418	0.462
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

The next tables drop the entropy balancing weighting and the Heckman model, while it also adds time to the standard error clustering.

Table: Climate Engagement on US Sample with Iterated FEs, firm-month errors. Systemic Risk

	Dependent variable:			
	SystemicRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.083***	−0.198	−0.086**	−0.106***
	(0.032)	(0.123)	(0.038)	(0.038)
Post	−0.090	0.119	−0.074	−0.144
	(0.067)	(0.098)	(0.080)	(0.123)
Target	−0.001	−0.133*	0.002	0.023
	(0.043)	(0.078)	(0.054)	(0.063)
Heckman Model	No	No	No	No
Entropy Balancing Weighting	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.294	0.266	0.300	0.340
Adjusted R^2	0.264	0.191	0.270	0.308
Note:				*p<0.1; **p<0.05; ***p<0.01

Table: Climate Engagement on US Sample with Iterated FEs, firm-month errors. Specific Risk

	Dependent variable:			
	SpecRisk			
	ALL	Below Mil 2	Mil 2 and above	Mil 3 and above
	(1)	(2)	(3)	(4)
Target x Post	−0.082**	−0.170	−0.077**	−0.116***
	(0.036)	(0.107)	(0.039)	(0.043)
Post	−0.127**	0.127	−0.121*	−0.133*
	(0.060)	(0.116)	(0.069)	(0.078)
Target	0.088*	−0.124***	0.089	0.107
	(0.050)	(0.040)	(0.059)	(0.066)
Heckman Model	No	No	No	No
Entropy Balancing Weighting	No	No	No	No
Country-Year FE	Yes	Yes	Yes	Yes
Country-Sector FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	3,262	476	2,786	1,945
R^2	0.425	0.495	0.428	0.470
Adjusted R^2	0.401	0.443	0.403	0.444

Note: *p<0.1; **p<0.05; ***p<0.01