ESG as Protection Against Downside Risk or ESG Regulatory Uncertainty and Option-Based Risk Measures

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5th JRC Summer School on Sustainable Finance

Increasing ESG-related regulatory developments around the world

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1st Question - ESG regulatory uncertainty

- Is uncertainty related to environmental, social, and governance (ESG) regulation developments reflected in asset prices?
- Yes.
- High ESG regulatory uncertainty in the economy is associated with a high cost of protection against downside risk.
- We find that the sensitivity of firms to ESG regulations as proxied by their ESG rating is negatively related to the cost of protection against downside risk.

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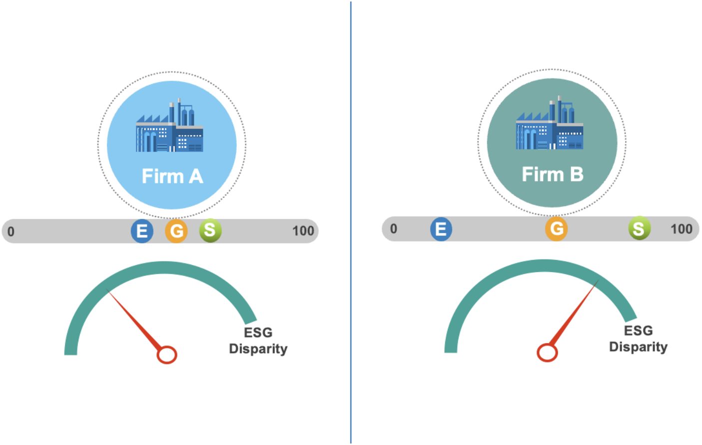
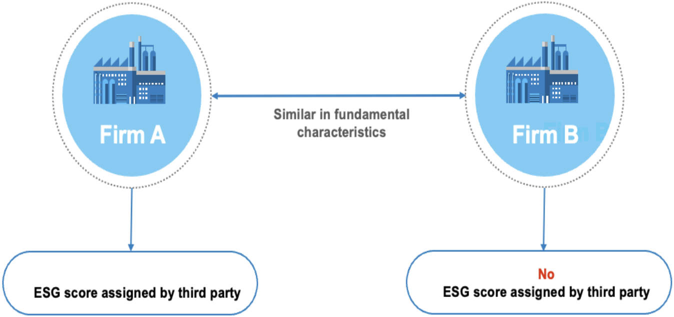
Signal: Firms' ability to manage ESG regulatory development



- Are firms with high (low) ESG disparity associated with high (low) cost of protection against downside risk?
- Yes

2nd Question - ESG Treatment



- What is the impact of ESG treatment (labeling) on the cost of protection against downside risk?
- It lowers the cost of protection against downside risk.

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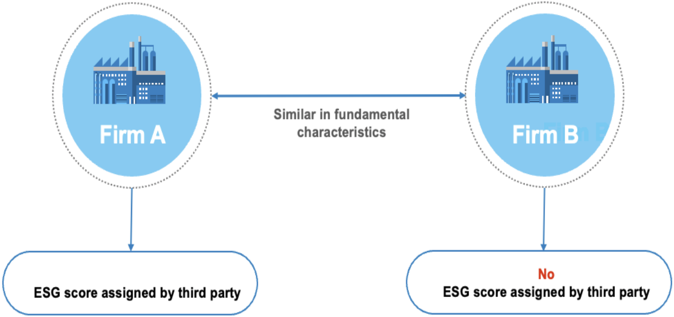

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3rd Question - Hedge against downside risk

- Can ESG-based investment serves as a hedge against downside risk?
- No

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Related literature

- Closely related to our study:
  - Ilhan et al. (2021) - find that climate policy uncertainty is priced in the options market.
  - Cao et al. (2022) - relates ESG scores to the expensiveness of their options.
- ESG-related performance and risk in other markets - Glossner (2017); He et al. (2021); Hoepner et al. (2018).
- ESG ratings disagreement - Christensen et al. (2022); Berg et. al. (2020); Gibson et al. (2021b); Eccles et al. (2019).
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Data Description - US data

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Estimating the Cost of protection against downside risks

- We extract daily options data (over 2 billion data points) from Optionmetrics covering the period from 2001 to 2021.
- We refer to the Implied Volatility Slope (IVS) as the cost of protection against downside risks.
- Following Kelly et al. (2016), We estimate IVS by relating the left-tail implied volatility to the moneyness measured by the option's Black Scholes delta.
- We also compute alternative risk measures.

Risk Measures Descriptive

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Risk Measures Descriptive

ESG regulatory uncertainty: At the aggregate level

In the framework of Pastor and Veronesi (2012 - JF, 2013 - JFE)

- Pastor and Veronesi (2012 - JF, 2013 - JFE) look at the implication of government policy or political uncertainty on stock prices/risk premia.
- Their framework is directly applicable to our research on the implication of ESG regulatory uncertainty on asset prices.
- Think of ESG regulatory uncertainty as one case of government policy uncertainty.
- Is ESG regulatory uncertainty priced in the options market?

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Specification 1

- $ACOP_t = \alpha + \beta ESGRU_t + \epsilon_t$
  - $ACOP_t$ is the aggregate cost of protection against downside risk (value-weighted by total assets).
  - $ESGU_t$ is the ESG regulatory uncertainty.

	Dependent variable:					
	slopedn	smfiv	smfivd	mfiv_bkm	mfiv_bjn	rix
	(1)	(2)	(3)	(4)	(5)	(6)
EP_index100	0.042***	0.074***	0.034***	0.086***	0.079***	0.011***
	(0.014)	(0.020)	(0.010)	(0.024)	(0.022)	(0.003)
Constant	0.232***	0.056**	0.029**	0.051	0.054*	−0.003
	(0.019)	(0.027)	(0.013)	(0.033)	(0.030)	(0.005)
Observations	219	219	219	219	219	219
R^2	0.040	0.060	0.053	0.055	0.056	0.049
Adjusted R^2	0.036	0.056	0.048	0.051	0.052	0.044
Residual Std. Error (df = 217)	0.090	0.129	0.064	0.158	0.143	0.022
F Statistic (df = 1; 217)	9.075***	13.964***	12.111***	12.615***	12.986***	11.079***
Note:				*p<0.1; **p<0.05; ***p<0.01		

EPU - Renewables Index | CPU Index

Specification 2

- $ACOP_t = \alpha + \beta ESGRU_t + \gamma Econ_t + \epsilon_t$
  - $Econ_t$ is the economic condition.

	Dependent variable:				
	slopedn				
	-NBER rec	CAPE	CFNAI	IPG	Real GDP
EP_index100	0.030**	0.031**	0.013	0.025*	0.012
	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)
ECON	−0.084***	−0.006***	−0.083***	−0.008***	−0.021***
	(0.018)	(0.001)	(0.011)	(0.001)	(0.004)
Constant	0.237***	0.393***	0.256***	0.258***	0.313***
	(0.018)	(0.044)	(0.017)	(0.018)	(0.023)
Observations	219	219	219	219	219
R^2	0.124	0.106	0.247	0.177	0.153
Adjusted R^2	0.116	0.098	0.240	0.169	0.145
Residual Std. Error (df = 216)	0.086	0.087	0.080	0.084	0.085
F Statistic (df = 2; 216)	15.327***	12.789***	35.353***	23.233***	19.558***

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

▸ EPU - Renewables Index ▸ CPU Index

ESG regulatory uncertainty: At the firm level

ESG Level and Firm's Downside Risk

The baseline regression equation is as follows:

$$IVS_{i,m,t+1} = \alpha_0 + \beta_1 Sustain_{i,t} + \boldsymbol{\delta X_{i,t}} + \epsilon_{i,m,t+1} \tag{1}$$

- $IVS_{i,m,t+1}$ denotes the implied volatility slope of firm i at month m in year $t+1$.
- $Sustain_{i,t}$ is the $ESG_{i,t}$, $E_{i,t}$, $S_{i,t}$, $G_{i,t}$ of firm i sustainability score in year t.
- $X_{i,t}$ is a vector of controls for firm i at time t.

Baseline regression result

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
ESG	−0.00117*** (0.0001)			
Environmental		−0.00103*** (0.0001)		
Social			−0.00141*** (0.0001)	
Governance				0.0002*** (0.0001)
Controls and Constants	Yes	Yes	Yes	Yes
Fixed year effect	Yes	Yes	Yes	Yes
Observations	103,051	103,051	103,051	103,051
R^2	0.258	0.259	0.259	0.256
Adjusted R^2	0.257	0.258	0.259	0.256
Residual Std. Error (df = 103023)	0.369	0.369	0.368	0.369
F Statistic (df = 27; 103023)	1,323.920***	1,331.071***	1,335.745***	1,312.477***
Note:				*p<0.1; **p<0.05; ***p<0.01

▸ Controls and constant ▸ Quantile Reg. - Governance

Second level of disaggregation

Dimension	Environmental	Social	Governance
	Dependent variable : *Cost of protection against downside risk*		
Panel A: Environmental			
Resource use	-0.001^{***} (0.00004)		
Emissions reduction	-0.001^{***} (0.00004)		
Innovation	-0.0001^{***} (0.00004)		
Panel B: Social			
Workforce		-0.001^{***} (0.0001)	
Human rights		-0.001^{***} (0.00004)	
Community		-0.001^{***} (0.0001)	
Product responsibility		-0.0004^{***} (0.00004)	
Panel C: Governance			
Management			0.0004^{***} (0.00004)
Shareholder			-0.0001^{***} (0.00004)
CSR strategy			-0.001^{***} (0.00004)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Based on Thomson ESG weighting methodology, the governance components = Management (19%) + Shareholders (7%) + CSR Strategy (4.50%) = 30.50%.

ESG disparity as a continuous variable: Aggregate ESG

Augumented regression:

$$IVS_{i,m,t+1} = \alpha_0 + \beta_1 Sustain_{i,t} + \lambda_1 ESGdisparity_{i,t} + \boldsymbol{\delta X_{i,t}} + \epsilon_{i,m,t+1} \quad (2)$$

	Dependent variable : Cost of protection against downside risk	
Coefficients	Sustainability - β_1	ESG disparity - λ_1
Panel A: Aggregate		
ESG	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Panel B: First level:		
Environmental	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Social	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Governance	0.0001	0.001^{***}
	(0.0001)	(0.0001)
Note:		*p<0.1; **p<0.05; ***p<0.01

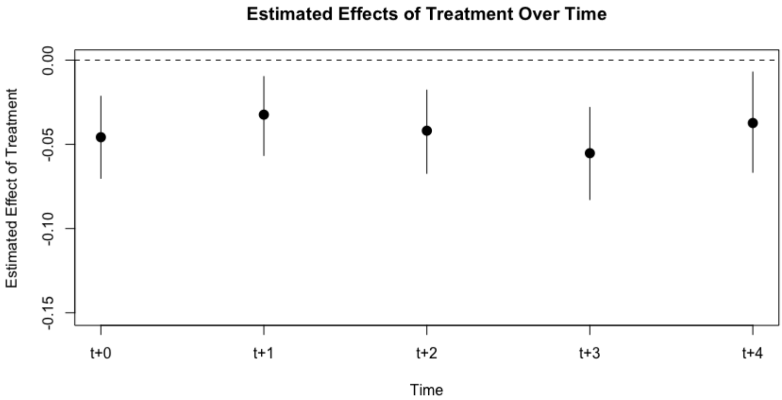
- High ESG disparity is consistently and significantly associated with a higher cost of option protection against left tail risk.

90 and 10th Quantile | Second level | ESG disparity across sectors

ESG treatment and downside risk

What is the impact of ESG treatment on the cost of protection against downside risk?

Average Treatment Effect (ATE)

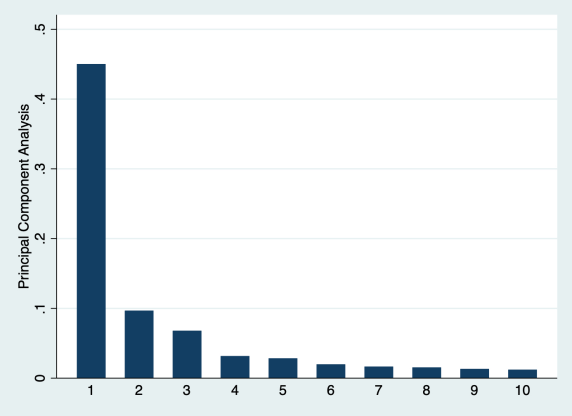


Estimated Average Treatment Effect of ESG status (treatment) on the Cost of Protection Against Downside Risk based on the Weighting Method. The estimates are based on the weighting method that adjusts for treatment and covariates histories during the period of 12 months prior to the treatment. The estimates for the average effects of ESG treatment are shown for the period of four (4) months after the immediate effect, with 95% asymptotic confidence intervals as vertical bars. The bootstrap method is used for the standard error calculation.

▸ Matching technique | ▸ Treatment Variation Plot | ▸ Frequency Distribution | ▸ Covariates

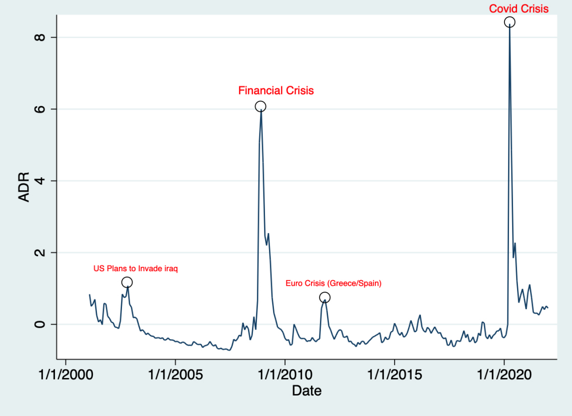
Extension:
Can ESG investment serve as a hedge against downside risk?

Single Factor Structure - PCA



Time-series of the risk-neutral probability of a downside events termed as the "Aggregate Downside risk". The risk - neutral probability of a downside events is the first principal component extracted from the panel of firm downside risk measures, FDR_i , extracted from option prices. The probability is constructed following Siriwardane (2015). A firm must have at least 18 daily observations in a month to be included. Principal component analysis is conducted on the correlation matrix of the monthly FDR_i. This analysis applies to set of firms with at least 192 of its monthly observations and we also fill in the missing value as their mean. The data range is from January 2001 to December 2021 and the frequency is monthly.

FDR and ADR empirical result



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ESG Exposure to Aggregate Downside Risk(ADR)

Sustainability measures	High	Medium	Low
		β_0	
Panel A: ESG performance			
ESG	$-0,026$	$-0,034$	$-0,052$
Environmental	$-0,022$	$-0,041$	$-0,047$
Social	$-0,028$	$-0,041$	$-0,042$
Governance	$-0,034$	$-0,037$	$-0,040$
Panel B: ESG disparity			
ESG disparity	$-0,045$	$-0,033$	$-0,033$

Since the aggregate downside risk is decreasing in downside beta, the most negative downside risk betas connote the highest downside risk.

Pricing of Aggregate Downside Risk based on the full sample

Portfolio	α	λ_{ADR}	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}
ADR	0.010	-0.116					
	(2.980)	(-2.121)					
One Factor + ADR	0.007	-0.087	0.004				
	(2.932)	(-2.059)	(2.059)				
Fama 3 Factor + ADR	0.007	-0.084	0.003	0.002	0.0006		
	(2.891)	(-2.284)	(2.079)	(0.355)	(0.400)		
Fama 5 Factor + ADR	0.008	-0.084	0.003	0.002	0.0007	-0.0005	-0.0006
	(3.091)	(-1.870)	(1.746)	(2.943)	(0.661)	(-0.975)	(-1.135)

Pricing of Aggregate Downside Risk conditioned on the ESG Disparity.

Portfolio	α	λ_{ADR}	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}
Panel B: Low ESG performance							
Low ESG Disparity	0.006	-0.178	0.008	0.004	0.002	0.004	-0.0001
	(1.710)	(-2.297)	(1.956)	(4.041)	(0.986)	(-1.359)	(-0.182)
Medium ESG Disparity	-0.029	0.220	0.023	0.006	0.016	-0.002	-0.002
	(0.785)	(-0.865)	(1.127)	(1.463)	(0.976)	(-2.007)	(-2.748)
High ESG Disparity	0.012	-0.050	-0.001	0.002	0.004	-0.0009	-0.0004
	(3.276)	(-1.208)	(-0.377)	(0.446)	(1.080)	(-1.565)	(-0.538)
Panel C: High ESG performance							
Low ESG Disparity	-0.016	-0.096	0.040	-0.012	-0.041	-0.024	-0.0003
	(-0.836)	(-2.374)	(1.150)	(-0.705)	(-0.929)	(-1.043)	(-0.462)
Medium ESG Disparity	0.005	-0.157	0.008	0.001	0.0003	0.0003	-0.0011
	(1.607)	(-2.353)	(1.736)	(0.770)	(0.103)	(0.380)	(-1.598)
High ESG Disparity	0.009	-0.053	0.005	-0.005	-0.005	0.0002	-0.0009
	(2.570)	(-0.053)	(2.186)	(-0.414)	(-0.620)	(0.297)	(-1.224)

Robustness Check

- First concern is the positive relationship between governance performance and the cost of protection against downside risk
  - Perform quantile regression ▸ Quantile
- Run a number of sub-sample regressions.
  - Restrict our sample to only observations from 2010 onward.
  - Exclude firms with zero environmental scores. ▸ Sub-sample
- Second concern with the use of ESG data is the low correlation of ESG data among ESG data providers
  - Use MSCI ESG data as an alternative source for data ▸ MSCI result
- Compute different risk measures other than the main risk measure ▸ Alternative downside risk
- We also use bond-based measure - Credit default swap (CDS). ▸ CDS

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  - The ESG uncertainty emanating from the development of ESG regulations,
  - The firm's ability to manage the regulatory development or the firm's disparity
  - The pricing of ESG exposure to aggregate downside risk.
- Uncertainty relating to environmental, social, and governance (ESG) regulation developments is reflected in asset prices.
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Thank You. Any Question or Comment?

Panel A: Risk Measures

Statistic	N	Mean	St. Dev.	Min	Max
IVS	119,406	0.444	0.436	−2.112	4.308
smfiv	119,406	0.201	0.286	0.012	8.059
mfiv_bkm	119,406	0.213	0.296	0.012	7.535
mfiv_bjn	119,406	0.204	0.273	0.012	6.779
smfivd	119,406	0.091	0.105	0.006	2.110
mfivd_bkm	119,406	0.137	0.211	0.007	5.651
mfivd_bjn	119,406	0.119	0.165	0.006	4.042
mfis	119,406	−0.617	0.498	−3.786	4.200
mfik	119,406	5.281	2.024	1.832	29.022
cvix_sigma2	119,406	0.206	0.294	0.011	7.543
cvix_sigma5	119,406	0.213	0.296	0.012	7.542
cvix_mnes20	119,406	0.163	0.158	0.012	2.574
cvix_mnes25	119,406	0.178	0.185	0.012	3.149
rix	119,406	0.018	0.047	0.0002	1.609
rixnorm	119,406	0.081	0.037	0.021	0.288

IVS is typically positive which indicates that deeper OTM puts are more expensive.

▸ Computation ◂ Implied measures description

Panel B: Sustainability Measures

Statistic	N	Mean	St. Dev.	Min	Max
ESG	119,406	41.979	17.873	0.869	92.516
E	119,406	32.755	28.620	0.000	98.546
S	119,406	45.804	21.726	0.741	97.963
G	119,406	53.417	21.722	0.292	98.599
Resource use	119,070	35.010	34.747	0.000	99.884
Emissions reduction	119,070	33.763	33.591	0.000	99.807
Innovation	119,070	21.267	30.017	0.000	99.367
Workforce	119,070	49.165	26.737	0.162	99.835
Human rights	119,070	21.701	30.953	0.000	99.206
Community	119,070	68.124	23.363	0.362	99.900
Product responsibility	119,070	40.423	30.413	0.000	99.780
Management	119,070	57.773	27.436	0.052	99.983
Shareholders	119,070	55.924	27.484	0.051	99.969
CSR strategy	119,070	28.278	34.151	0.000	99.804

ESG data description

Panel C: Controls

Statistic	N	Mean	St. Dev.	Min	Max
return	119,111	1.225	10.767	−84.353	305.691
volatility	119,028	8.903	5.720	1.310	96.651
beta	117,147	1.199	1.010	−9.380	12.198
logassets	119,394	22.941	1.582	17.766	28.620
divnetinc	118,206	0.792	43.731	−162.716	4,300.375
ebitassets	106,927	0.100	0.090	−0.843	0.917
capexassets	115,722	0.044	0.052	0.000	0.865
booktomar	119,096	1.025	48.868	−5.945	4,868.352
debtassets	119,370	0.264	0.211	0.000	3.892

◂ ESG data description

Controls

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
beta	0.008***	0.007***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
volatility	−0.011***	−0.011***	−0.011***	−0.011***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
return	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
logassets	−0.077***	−0.071***	−0.072***	−0.084***
	(0.001)	(0.001)	(0.001)	(0.001)
divnetinc	0.0001**	0.0001***	0.0001**	0.0001**
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
ebitassets	−0.374***	−0.365***	−0.355***	−0.399***
	(0.014)	(0.014)	(0.014)	(0.013)
capexassets	−0.091***	−0.081***	−0.109***	−0.075***
	(0.023)	(0.023)	(0.023)	(0.023)
debtassets	0.078***	0.073***	0.076***	0.084***
	(0.006)	(0.006)	(0.006)	(0.006)
booktomar	0.00001	0.00001	0.00001	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Constant	2.146***	1.980***	2.035***	2.258***
	(0.024)	(0.027)	(0.025)	(0.023)
Fixed year effect	Yes	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

Baseline result

Specification 1

	Dependent variable:					
	slopedn	smfiv	smfivd	mfiv_bkm	mfiv_bjn	rix
	(1)	(2)	(3)	(4)	(5)	(6)
EP_index100_RI	0.023***	0.028***	0.014***	0.034***	0.031***	0.005***
	(0.005)	(0.008)	(0.004)	(0.010)	(0.009)	(0.001)
Constant	0.242***	0.098***	0.046***	0.096***	0.097***	0.003
	(0.012)	(0.017)	(0.009)	(0.021)	(0.019)	(0.003)
Observations	219	219	219	219	219	219
R^2	0.077	0.056	0.058	0.056	0.056	0.057
Adjusted R^2	0.073	0.052	0.053	0.052	0.051	0.052
Residual Std. Error (df = 217)	0.088	0.129	0.064	0.158	0.143	0.022
F Statistic (df = 1; 217)	18.183***	12.853***	13.279***	12.844***	12.796***	12.996***
Note:						*p<0.1; **p<0.05; ***p<0.01

EPU Index

Specification 1

	Dependent variable:					
	slopedn	smfiv	smfivd	mfiv_bkm	mfiv_bjn	rix
	(1)	(2)	(3)	(4)	(5)	(6)
CPU_index100	0.078***	0.044***	0.015***	0.044***	0.042***	0.006***
	(0.010)	(0.010)	(0.005)	(0.012)	(0.011)	(0.002)
Constant	0.241***	0.118***	0.060***	0.126***	0.123***	0.007***
	(0.013)	(0.014)	(0.007)	(0.017)	(0.015)	(0.002)
Observations	252	252	252	252	252	252
R^2	0.200	0.067	0.037	0.050	0.053	0.052
Adjusted R^2	0.197	0.063	0.034	0.046	0.049	0.048
Residual Std. Error (df = 250)	0.131	0.139	0.065	0.164	0.149	0.023
F Statistic (df = 1; 250)	62.570***	17.830***	9.725***	13.157***	14.031***	13.605***

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

◂ EPU Index

Specification 2

	Dependent variable:				
	slopedn				
	(1)	(2)	(3)	(4)	(5)
EP_index100_RI	0.021***	0.016***	0.014***	0.018***	0.013**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
NBER_rec_minus	−0.085***				
	(0.018)				
CAPE		−0.005***			
		(0.002)			
CFNAI			−0.079***		
			(0.010)		
Industrial_Production_Growth_percen				−0.008***	
				(0.001)	
Real_GDP_Growth_percent					−0.019***
					(0.004)
Constant	0.235***	0.376***	0.246***	0.257***	0.299***
	(0.011)	(0.045)	(0.011)	(0.011)	(0.016)
Observations	219	219	219	219	219
R^2	0.167	0.116	0.271	0.208	0.172
Adjusted R^2	0.160	0.108	0.265	0.201	0.165
Residual Std. Error (df = 216)	0.084	0.087	0.079	0.082	0.084
F Statistic (df = 2; 216)	21.726***	14.168***	40.249***	28.396***	22.489***
Note:					*p<0.1; **p<0.05; ***p<0.01

EPU Index

Specification 2

	Dependent variable:				
	slopedn				
	(1)	(2)	(3)	(4)	(5)
CPU_index100	0.076***	0.070***	0.075***	0.071***	0.078***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
NBER_rec_minus	−0.068***				
	(0.026)				
CAPE		0.005***			
		(0.002)			
CFNAI			−0.009		
			(0.006)		
Industrial_Production_Growth_percen				−0.005**	
				(0.002)	
Real_GDP_Growth_percent					0.001
					(0.004)
Constant	0.236***	0.115**	0.242***	0.250***	0.239***
	(0.013)	(0.046)	(0.013)	(0.014)	(0.017)
Observations	252	252	252	252	252
R^2	0.221	0.226	0.208	0.219	0.200
Adjusted R^2	0.215	0.219	0.201	0.213	0.194
Residual Std. Error (df = 249)	0.130	0.130	0.131	0.130	0.132
F Statistic (df = 2; 249)	35.398***	36.260***	32.668***	34.933***	31.176***
Note:			*p<0.1; **p<0.05; ***p<0.01		

EPU Index

	Mean Absolute Deviation (MAD)			
	High MAD - 80 Quant		Low MAD - 20 Quant	
ESG	-0,00328	***	-0,00068	***
	(-11,34523)		(-5,66176)	
E	-0,00199	***	-0,00039	***
	(-11,49606)		(-3,46973)	
S	-0,00179	***	-0,00058	***
	(-11,36590)		(-4,74354)	
G	0,00027		-0,00054	***
	(1,51221)		(-4,62737)	

90 and 10th Quantile

ESG disparity as a continuous variable: Second level

	Dependent variable : Cost of protection against downside risk	
Coefficients	Sustainability - β_1	ESG disparity - λ_1
Panel C: Second level:		
Environmental:		
Resource use	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)
Emissions reduction	-0.001^{***}	0.001^{***}
	(0.00005)	(0.0001)
Innovation	-0.00001	0.001^{***}
	(0.00004)	(0.0001)
Social:		
Workforce	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Human rights	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)
Community	-0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)
Product responsibility	-0.0004^{***}	0.001^{***}
	(0.00004)	(0.0001)
Governance:		
Management	0.0003^{***}	0.001^{***}
	(0.00004)	(0.0001)
Shareholder	-0.0002^{***}	0.002^{***}
	(0.00004)	(0.0001)
CSR strategy	-0.001^{***}	0.001^{***}
	(0.00004)	(0.0001)
Note:		*p<0.1; **p<0.05; ***p<0.01

Aggregate ESG

Heterogeneous of ESG disparity across sectors

	Dependent variable :							
	Cost of protection against downside risk							
	ESG		Environmental		Social		Governance	
Coefficients	β_1	λ_1	β_1	λ_1	β_1	λ_1	β_1	λ_1
Industry:								
Energy	-0.001^{***}	0.003^{***}	-0.002^{***}	0.002^{***}	-0.001^{***}	0.003^{***}	-0.00001	0.003^{***}
	(0.0003)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Material	0.001^{***}	0.001	0.001^{***}	0.001^{**}	0.001^{***}	0.001^{*}	0.0003^{*}	0.0003
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Industrials	-0.001^{***}	0.001^{**}	-0.0004^{**}	0.001^{*}	-0.001^{***}	0.001^{**}	0.001^{***}	0.001^{**}
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Consumer Discretionary	-0.001^{***}	0.002^{***}	-0.001^{***}	0.001^{***}	-0.001^{***}	0.002^{***}	-0.0004^{***}	0.002^{***}
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Consumer Staples	-0.0004^{*}	0.002^{***}	-0.0001	0.002^{***}	-0.001^{***}	0.002^{***}	0.0003	0.002^{***}
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Health Care	-0.002^{***}	0.001^{***}	-0.001^{***}	0.0003	-0.002^{***}	0.001^{**}	-0.0001	0.001^{***}
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Financials	-0.0002	0.004^{***}	-0.001^{**}	0.004^{***}	0.001^{**}	0.005^{***}	-0.00002	0.004^{***}
	(0.001)	(0.001)	(0.0003)	(0.001)	(0.0005)	(0.001)	(0.0003)	(0.001)
Information Technology	-0.001^{***}	0.003^{***}	-0.001^{***}	0.002^{***}	-0.001^{***}	0.003^{***}	0.0002	0.003^{***}
	(0.0002)	(0.0003)	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Communication Services	0.004^{***}	-0.001^{**}	-0.001^{***}	-0.001	-0.002^{***}	-0.0003	0.002^{***}	-0.001^{**}
	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.0003)	(0.001)
Utilities	0.0005	0.0001	0.002^{***}	0.001	0.001^{**}	0.0002	0.001^{**}	-0.0003
	(0.0004)	(0.001)	(0.0003)	(0.001)	(0.0004)	(0.001)	(0.0003)	(0.001)
Real Estate	-0.001^{***}	-0.001^{**}	-0.001^{***}	-0.002^{***}	0.00001	-0.001^{**}	-0.0004^{*}	-0.001^{*}
	(0.0003)	(0.0004)	(0.0002)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0005)
No sector identified	0.006^{***}	0.001	0.001^{**}	0.003^{**}	0.005^{***}	0.002^{*}	0.002^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

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

◂ ESG disparity: continuous

Matching Technique

- For each treated observation, we find a set of control observations that have an identical treatment history of 12 months period.
- Adjust the matched set for observed confounding using the covariates balancing propensity score (CBPS) weighting technique as a baseline technique.
- We apply up-to-five matching for the matching technique.
- Then we apply the difference in difference estimator to estimate the causal effect.
- The observed confounding variates are quick ratio, size, financial leverage (FL), hard spending, intangible, growth, cash ratio, profitability, and dividend yield.

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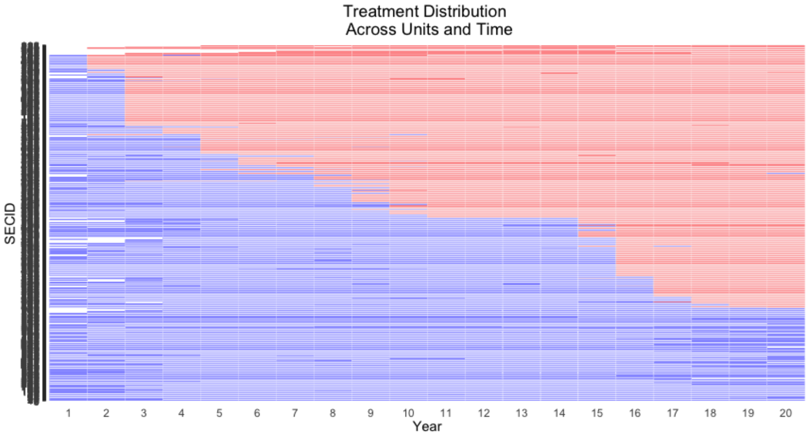
Average Treatment Effect

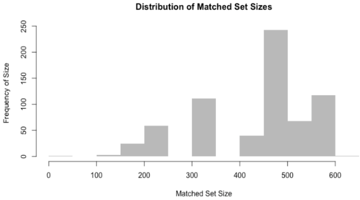
Treatment variation plot



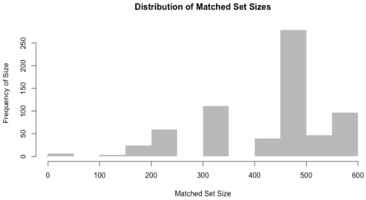
The red(blue) rectangle represents the treatment(control) secid-year observation. The white area represents the year when a firm is not assigned ESG score. The plot starts from year 2001 and ends in year 2020.

Average Treatment Effect

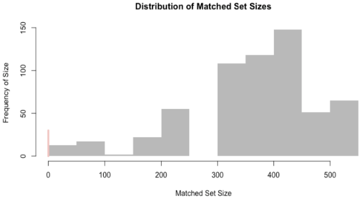
Frequency Distribution of the Number of Matched Control Firms



(a) Up to 6 identical treatment periods



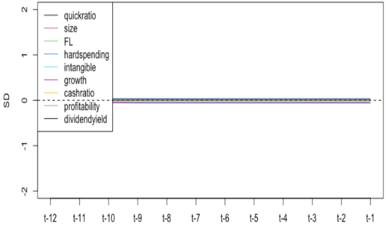
(b) Up to 12 identical treatment periods



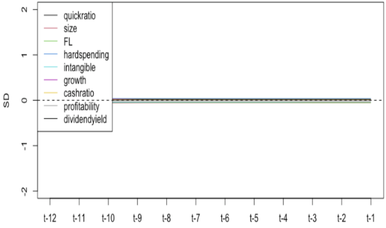
(c) Up to 24 identical treatment periods

The bar represents the number of control matched firms that share the same treatment history as the treated observation prior to the treatment period. Average Treatment Effect

Covariates Balance based on weighting method



(a) CBPS Weighting



(b) PS Weighting

Improved Covariate Balance of matching over 12 months pre-treatment period based on weighting method.

Average Treatment Effect

Quantile Regression

	Dependent variable:			
	Cost of protection against downside risk			
	Quantile			
	(20)	(40)	(60)	(80)
ESG	-0.0003^{***}	-0.001^{***}	-0.001^{***}	-0.002^{***}
	(0.00001)	(0.00002)	(0.00004)	(0.0001)
E	-0.0003^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.00001)	(0.00002)	(0.00003)	(0.0001)
S	-0.0004^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.00002)	(0.00002)	(0.00003)	(0.0001)
G	-0.0001^{***}	-0.00001	0.00004	0.0001^{**}
	(0.00001)	(0.00002)	(0.00003)	(0.0001)
Fixed Year Effect	Yes	Yes	Yes	Yes
Controls and constant	Yes	Yes	Yes	Yes
Observations	103,051	103,051	103,051	103,051
Note:		*p<0.1; **p<0.05; ***p<0.01		

◂ Robustness

Regression on sub-sample

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
Panel A: Sample from 2010 onwards				
ESG	-0.001^{***}			
	(0.0001)			
E		-0.001^{***}		
		(0.0001)		
S			-0.001^{***}	
			(0.0001)	
G				0.0002^{***}
				(0.0001)
ESG disparity	0.002^{***}	0.001^{***}	0.002^{***}	0.002^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed Effects	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Panel B: Exclude firms with zero E score				
ESG	-0.001^{***}			
	(0.0001)			
E		-0.001^{***}		
		(0.0001)		
S			-0.001^{***}	
			(0.0001)	
G				0.00004
				(0.0001)
ESG disparity	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Fixed Effects	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Note:				*p<0.1; **p<0.05; ***p<0.01

◂ Robustness

Regression based on MSCI ESG data.

	Dependent variable:			
	Cost of protection against downside risk			
	(1)	(2)	(3)	(4)
Panel A: MSCI raters				
ESG	-0.021^{***}			
	(0.002)			
E		-0.018^{***}		
		(0.001)		
S			-0.004^{***}	
			(0.001)	
G				0.005^{***}
				(0.001)
ESG disparity	0.006^{***}	0.008^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Fixed Effects	Yes	Yes	Yes	Yes
Constant and Controls	Yes	Yes	Yes	Yes
Observations	79,167	79,167	79,167	79,167
R^2	0.185	0.187	0.184	0.184
Adjusted R^2	0.184	0.186	0.183	0.184
Residual Std. Error (df = 79146)	0.457	0.457	0.458	0.457
F Statistic (df = 20; 79146)	896.532^{***}	907.718^{***}	889.728^{***}	891.151^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Related downside risk

Dimension	ESG	Environmental	Social	Governance
Panel A: Related downside risk				
smfivd	-0.0002^{***}	-0.0002^{***}	-0.0001^{***}	-0.00001
	(0.00002)	(0.00001)	(0.00001)	(0.00001)
mfivd_bkm	-0.0004^{***}	-0.0003^{***}	-0.0001^{***}	0.00003
	(0.00003)	(0.00002)	(0.00003)	(0.00003)
mfivd_bjn	-0.0003^{***}	-0.0002^{***}	-0.0001^{***}	0.00001
	(0.00003)	(0.00002)	(0.00002)	(0.00002)
Panel B: General risk				
smfiv	-0.001^{***}	-0.0003^{***}	-0.0001	0.0001^{**}
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
mfiv_bkm	-0.001^{***}	-0.0004^{***}	-0.0001^{***}	0.00004
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
mfiv_bjn	-0.001^{***}	-0.0004^{***}	-0.0001^{***}	0.00004
	(0.00004)	(0.00003)	(0.00004)	(0.00003)
mfis	0.00004	0.0003^{***}	0.001^{***}	-0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
mfik	-0.001^{***}	-0.003^{***}	-0.005^{***}	0.002^{***}
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
cvix_sigma2	-0.001^{***}	-0.0004^{***}	-0.0001^{***}	0.00004
	(0.00005)	(0.00003)	(0.00004)	(0.00003)
rix	-0.0001^{***}	-0.0001^{***}	-0.00001^{*}	0.00002^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)

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

Robustness

Credit Default Swap

	Dependent variable : Credit Default Swap	
Coefficients	Sustainability - β_1	ESG disparity - λ_1
Panel A: Aggregate		
ESG	-0.276^{***}	0.179^{**}
	(0.055)	(0.088)
Panel B: First level:		
Environmental	-0.145^{***}	0.136
	(0.041)	(0.091)
Social	-0.032	0.217^{**}
	(0.047)	(0.088)
Governance	-0.038	0.230^{***}
	(0.042)	(0.088)
Note:		*p<0.1; **p<0.05; ***p<0.01

Robustness

Panel C: Controls

Statistic	N	Mean	St. Dev.	Min	Max
Panel C: Controls					
Return	119,111	1.225	10.767	−84.353	305.691
Volatility	119,028	8.903	5.720	1.310	96.651
Beta	117,147	1.199	1.010	−9.380	12.198
Logassets	119,394	22.941	1.582	17.766	28.620
Divnetinc	118,206	0.792	43.731	−162.716	4,300.375
Ebitassets	106,927	0.100	0.090	−0.843	0.917
Capexassets	115,722	0.044	0.052	0.000	0.865
Booktomar	119,096	1.025	48.868	−5.945	4,868.352
Debtassets	119,370	0.264	0.211	0.000	3.892

Quantile Regression for Governance

	Dependent variable:						
	slopedn						
	Quantile						
	(10)	(20)	(30)	(40)	(50)	(60)	(70)
G	−0.0001***	−0.0001***	−0.00005	−0.00001	0.00004*	0.00004	0.0001***
	(0.00001)	(0.00001)	(0.0001)	(0.00002)	(0.00002)	(0.00003)	(0.00005)
beta	0.010***	0.008***	0.007***	0.006***	0.006***	0.004***	0.002
	(0.001)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
volatility	−0.006***	−0.005***	−0.005***	−0.006***	−0.007***	−0.008***	−0.009***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
return	0.0004***	0.0002***	0.0002	0.0001**	0.00003	−0.00003	−0.0001
	(0.00004)	(0.00003)	(0.0001)	(0.00004)	(0.0001)	(0.0001)	(0.0001)
logassets	−0.008***	−0.020***	−0.030***	−0.041***	−0.054***	−0.069***	−0.086***
	(0.0002)	(0.0002)	(0.001)	(0.0003)	(0.0005)	(0.001)	(0.001)
divnetinc	0.0001**	0.0001***	0.0001	0.0001***	0.0001	0.0001*	0.0002
	(0.00003)	(0.00000)	(0.0001)	(0.00000)	(0.0001)	(0.0001)	(0.002)
ebitassets	0.036***	−0.060***	−0.125	−0.198***	−0.285***	−0.393***	−0.541***
	(0.004)	(0.003)	(0.076)	(0.005)	(0.007)	(0.008)	(0.012)
capexassets	−0.056***	−0.068***	−0.071	−0.070***	−0.076***	−0.092***	−0.101***
	(0.004)	(0.005)	(0.050)	(0.008)	(0.009)	(0.006)	(0.016)
debtassets	0.008***	0.024***	0.036***	0.050***	0.066***	0.076***	0.079***
	(0.002)	(0.002)	(0.007)	(0.003)	(0.004)	(0.004)	(0.006)
booktomar	0.00001	0.00001***	0.00000	0.00000	0.00001***	0.00001***	0.00001**
	(0.0001)	(0.00000)	(0.035)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Fixed Year Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)
Constant	0.335***	0.618***	0.880***	1.172***	1.517***	1.926***	2.378***
	(0.007)	(0.006)	(0.012)	(0.009)	(0.012)	(0.014)	(0.018)
Observations	103,051	103,051	103,051	103,051	103,051	103,051	103,051
Note:							*p<0.1; **p<0.05; ***p<0.01

Baseline result - Governance

Risk Measures computation

Variable	Definitions
smfiv	simple model-free implied volatility from Ian Martin (2013, 2017)
mfiv_bkm	model-free implied volatility from Bakshi, Kapadia, and Madan (2003).
mfiv_bjn	model-free implied volatility from Britton-Jones and Neuberger (2000). .
smfivd	simple model-free implied volatility for OTM puts (downside) from Ian Martin (2013, 2017)
mfivd_bkm	model-free implied volatility for OTM puts (downside) from Bakshi, Kapadia, and Madan (2003).
mfivd_bjn	model-free implied volatility for OTM puts (downside) from Britton-Jones and Neuberger (2000).
mfis	model-free implied skewness based on Bakshi, Kapadia, and Madan (2003).
mfik	model-free implied kurtosis based on Bakshi, Kapadia, and Madan (2003).
cvix_sigma2	Corridor volatility index from Andersen and Bondarenko (2007), Andersen, Bondarenko, and Gonzalez-Perez (2015) measured on the relative deviation of 2 sigmas from the At-the-Money (ATM) moneyness of 1.
rix	rare disaster concern index (rix) from Gao, Gao and Song, (2018). This is the difference between mfivd_bjn and mfivd_bkm.
tlm_sigma2	Tail loss measure from Vilkov, Xiao (2012) and Hamidieh (2011) measured on the relative deviation of 2 sigmas from the At-the-Money (ATM) moneyness of 1.

◂ Risk Measures

Sustainability Ratings Disparity

Examine whether there is a relationship between ESG disparity and the cost of protection against downside risks

	Mean Absolute Deviation (MAD)			
	High MAD - 90 Quant		Low MAD - 10 Quant	
ESG	-0,00379	***	-0,00044	***
	(-8,93974)		(-2,80907)	
E	-0,00198	***	-0,00009	
	(-6,84420)		(-0,57762)	
S	-0,00162	***	-0,00008	
	(-7,72468)		(-0,47048)	
G	0,00070	***	-0,00006	
	(2,49038)		(-0,40209)	

ESG disparity: continuous

Construction of Aggregate Downside Risk (ADR)

- Construct each firm downside risk (FDR) measure
- Next, We use the principal component analysis (PCA) to extract the aggregate downside risk(ADR) from the firm downside risk (FDR) in line with the Siriwardane (2015)'s procedures:
- $FDR_{it}(\tau) = \Psi_i * ADR_t(\tau)$
- Ψ_i is the firm-specific constant and $ADR_t(\tau)$ is the Aggregate Downside Risk measures at time t which depends on the time to maturity τ.
- Again, the $ADR_t(\tau)$ is the risk neutral probability of downside events from time t to $t + \tau$ and is common to all firms.

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