The Anatomy of Sustainability

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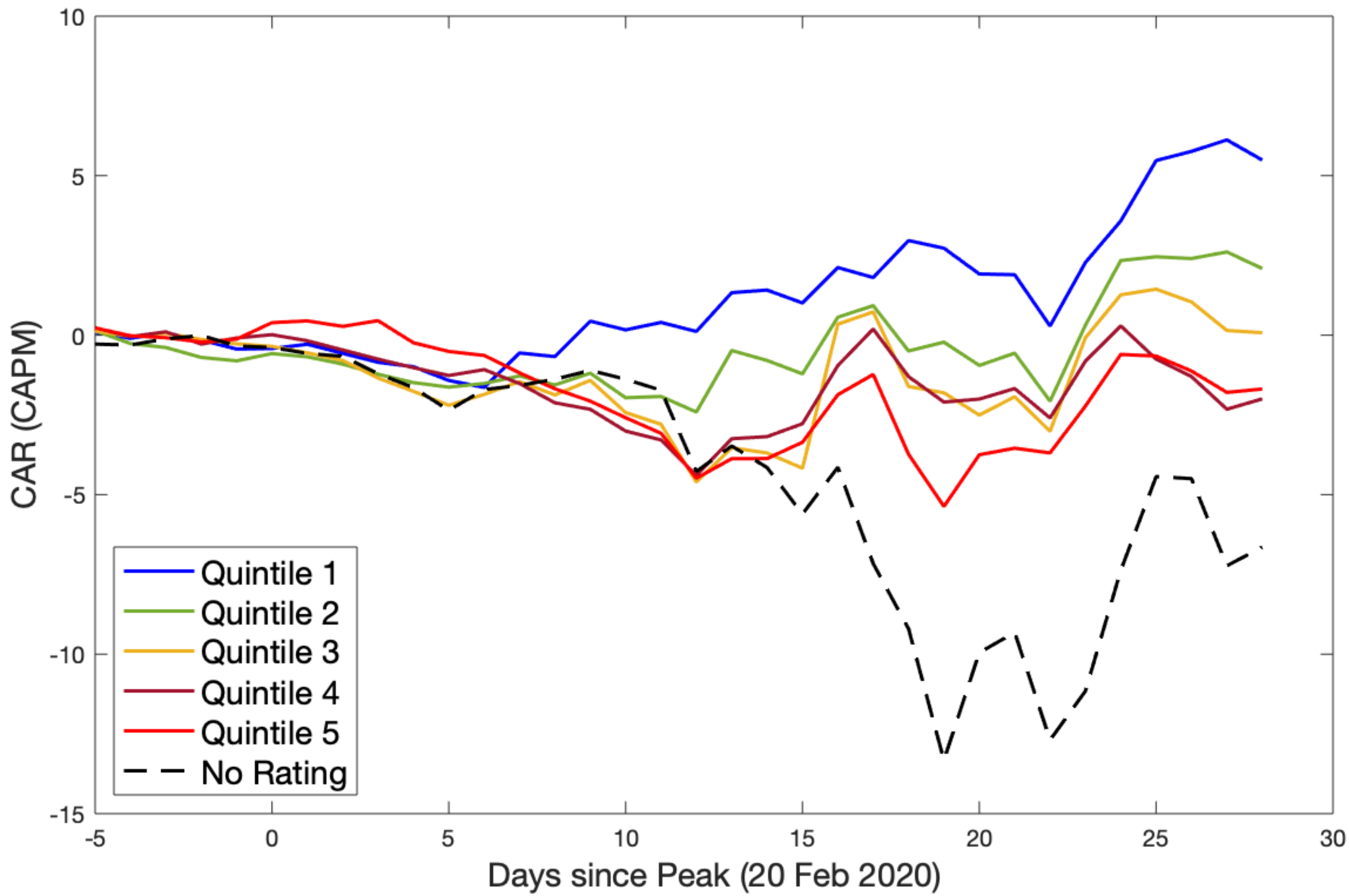
The Corona Crash

Figure: S&P 500 daily price movement

BREAKING NEWS

- “ESG passes the Covid challenge” — Financial Times
- “ESG Stocks Shine in Covid-19 Crisis” — Morningstar
- “Sustainable Funds See Record Inflows in First Quarter” — CNBC
- “Why ESG Stocks Perform Better In The Coronavirus Pandemic” — Forbes
- “Sustainable Funds are Safe Habor in Coronavirus Market Meltdown” — Reuters
- “Coronavirus Pandemic Elevates ESG Factors” — Wall Street Journal

Not just anecdotal evidence



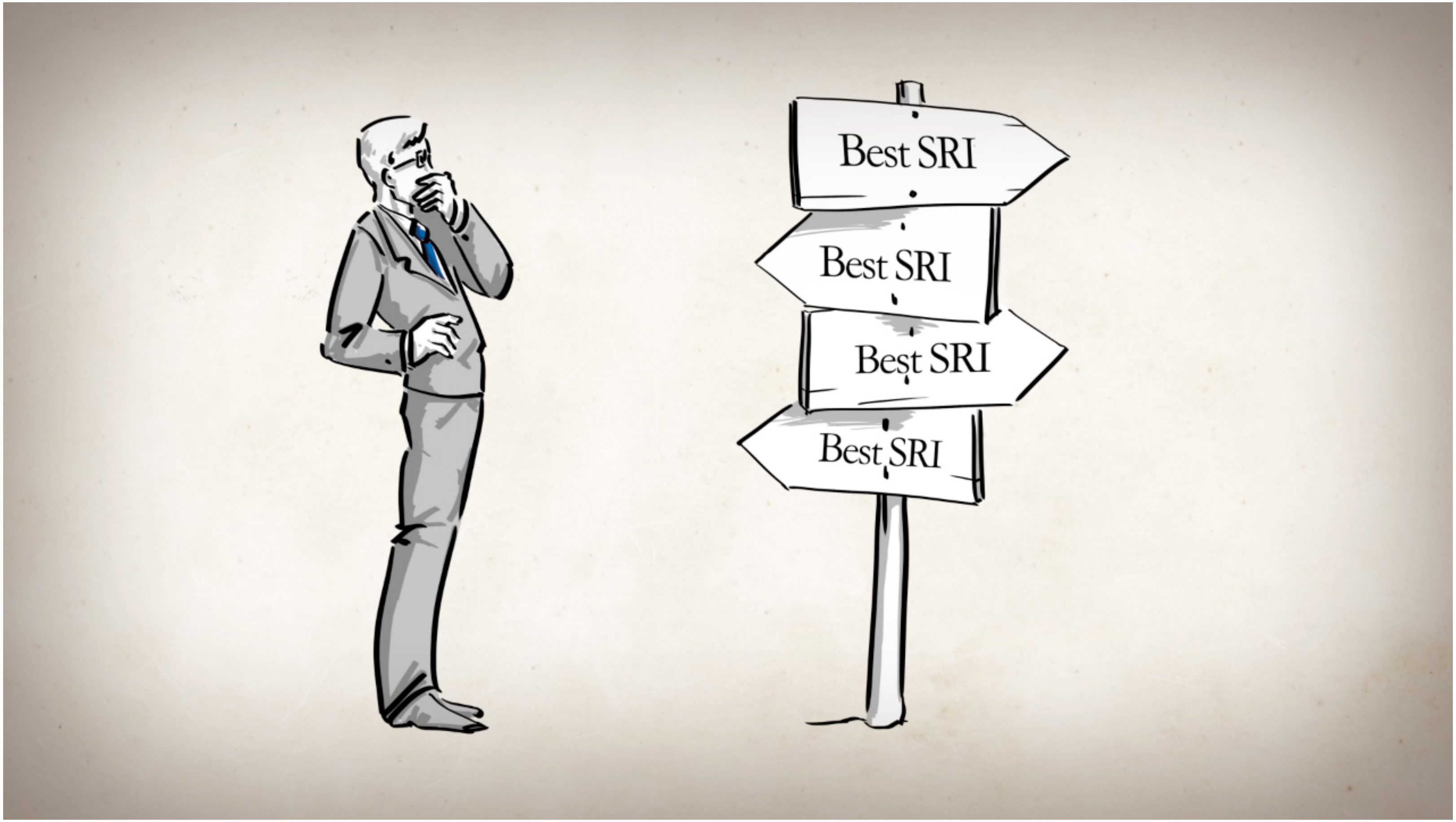
Not just anecdotal evidence

- R. Albuquerque, Y. Koskinen, S. Yang, and C. Zhang, Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *Review of Corporate Finance Studies*, July 2020.
- S. Ramelli and A. Wagner, Feverish Stock Price Reactions to COVID-19. *Review of Corporate Finance Studies*, July 2020.
- W. Ding, R. Levine, C. Lin, and W. Xie, Corporate Immunity to the COVID-19 Pandemic. *Journal of Financial Economics* (forthcoming), 2020.

Suggested mechansims of resiliency:

- Advertising expenditures as a proxy for customer loyalty
- Investor segmentation and loyalty (ESG investors flee the market less)
- Financial conditions, such as cash holdings, lines of credit, total debt, the maturity structure of debt, and profitability

Sustainability ratings



The Anatomy of Sustainability: Executive Summary

Our motivating arguments:

- Any conclusion drawn regarding the performance of sustainable equity necessitates a deeper understanding of what is encoded in the notion of sustainability
- Given the recent (and other) evidence of outperformance during crises, perhaps "sustainability" encompasses relevant market-implied information

Our main contributions:

1. We derive an econometric decomposition of sustainability ratings yielding three components capturing **uncertainty**, **investor sentiment**, and an **idiosyncratic sustainability** factor.
2. We show that the perceived immunity of sustainable stocks during the crash is principally driven through the uncertainty channel, significantly more so than through the idiosyncratic factor.
3. Once controlling for uncertainty and firm fundamentals, the positive relationship between idiosyncratic sustainability and resilience persists, albeit weakly.

Data

- **Equity space:**
  - Constituents of the S&P 1500
  - Variation in market capitalization
  - Covers 90% of U.S. market capitalization
  - Stock prices, bid-ask spread, and trading volume from CRSP
- **Firm fundamentals:**
  - Quarterly accounting information from Compustat Capital IQ:
  - BOOK-MARKET: book value of shareholder's equity divided by market value of equity
  - SIZE: natural logarithm of the market capitalization
  - LEV: total long-term debt divided by total assets
  - CASH: share of cash divided by total assets
  - ROA: return on assets (net income divided by total assets)
  - IDIOVOL: idiosyncratic volatility obtained through a regression on FF5-Factors
- **Implied volatilities:**
  - Option data from the IvyDB US database by OptionMetrics
  - Implied volatility data for both put and call options for each stock on each day as well as their trading volume.
  - $\mathrm{IV}_{i,t}$: the average of the implied volatilities of the available ATM put and call options on each trading day

Data: Sustainability Ratings

OWL Analytics

- OWL aggregates scores from different providers
- 12 categories divided into environmental (E), social (S), and governance (G) indicators
- Overall ESG score averages E, S, and G scores
- Monthly data covering 25000 public companies, coverage startes April 2009

TruValue Labs

- TVL relies on public data, mainly news analytics
- filters through “incidents” using natural language processing (NLP) and artificial intelligence (AI)
- 26 indicators spanning the environmental, social, and governance categories but no separate E, S, and G indicators
- Volume, pulse, **insight**, momentum scores
- Daily data covering over 16000 securities starting from 1 January 2008

$\mathrm{ESG}_{i,t}$ is the average of monthly OWL and TVL scores

Overall Data and ESG Baskets

Monthly ESG data and firm characteristics over the period January 2017 through June 2019 are merged to form our data set. The resulting data set used covers 30 months with an average of 780 stocks per date in 2017, 895 stocks per date in 2018, and 1114 stocks per date in 2019.

We often analyze different sets of stocks ("baskets") based on their ESG score:

- For a given year, we rank stocks based on an exponentially weighted average (with smoothing factor = 0.5) of the monthly ESG scores over the 12 months of that year.
- We divide firms into quintiles/deciles and study average properties of these baskets

Towards decomposing sustainability

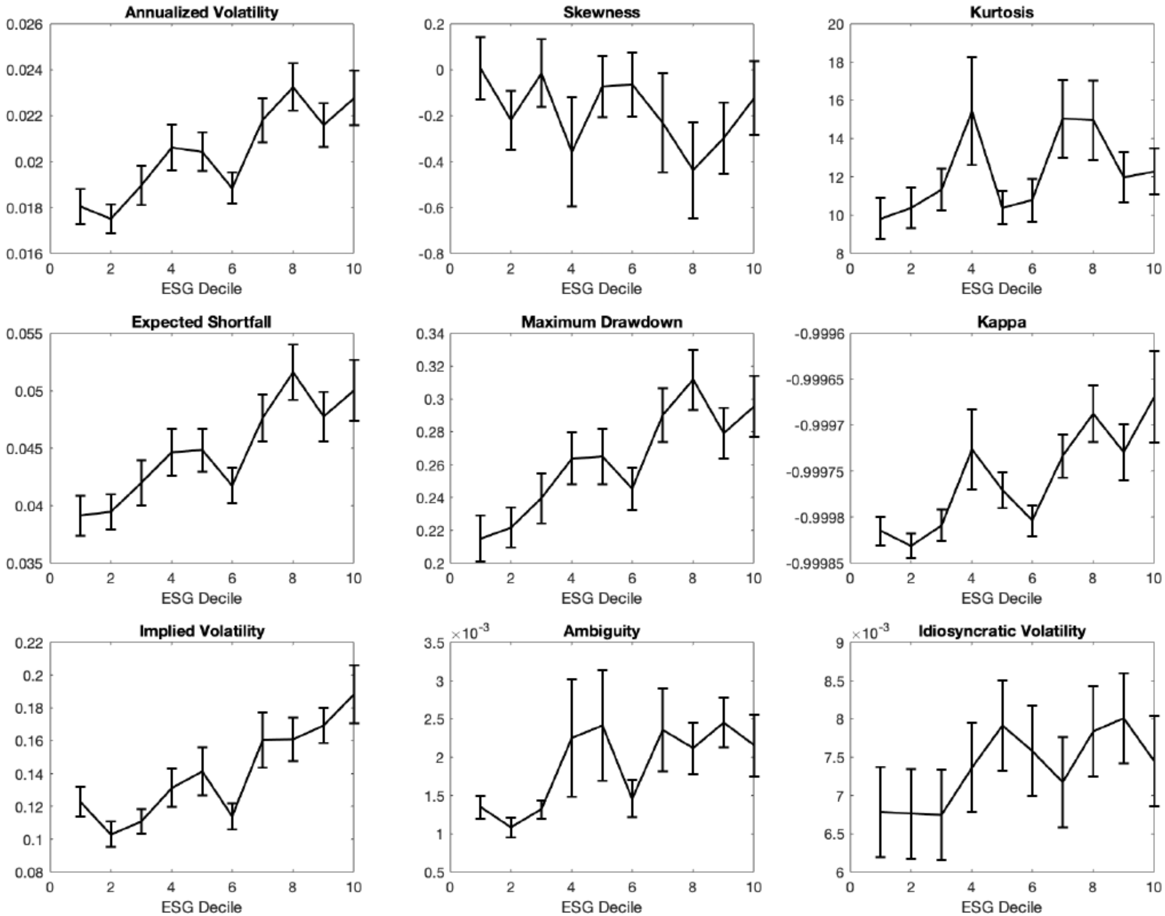
Hypothesis I: sustainability scores can be (linearly) decomposed into time-varying market-driven building blocks plus an idiosyncratic term:

$$\mathrm{ESG} = \sum_j \alpha_j F_j + \varepsilon$$

Hypothesis II: Factors driving sustainability scores are, next to firm fundamentals, **uncertainty** and **sentiment** (and potentially a "temporal" dimension)

Towards decomposing sustainability: risk

FIGURE 3.1. **Descriptive diagnostics of uncertainty measures versus ESG score.** For each of the nine risk measures (volatility, skewness, kurtosis, expected shortfall, maximum drawdown, auto-correlation coefficient kappa, implied volatility, ambiguity, and idiosyncratic volatility) calculated based on daily data over the sample period from January 2017 to June 2019, the plots display the mean of the distribution of the given risk measure calculated for each S&P 1500 listed stock in the given ESG decile, decile 1 containing the highest rated firms. Error bars represent a 95% confidence interval.



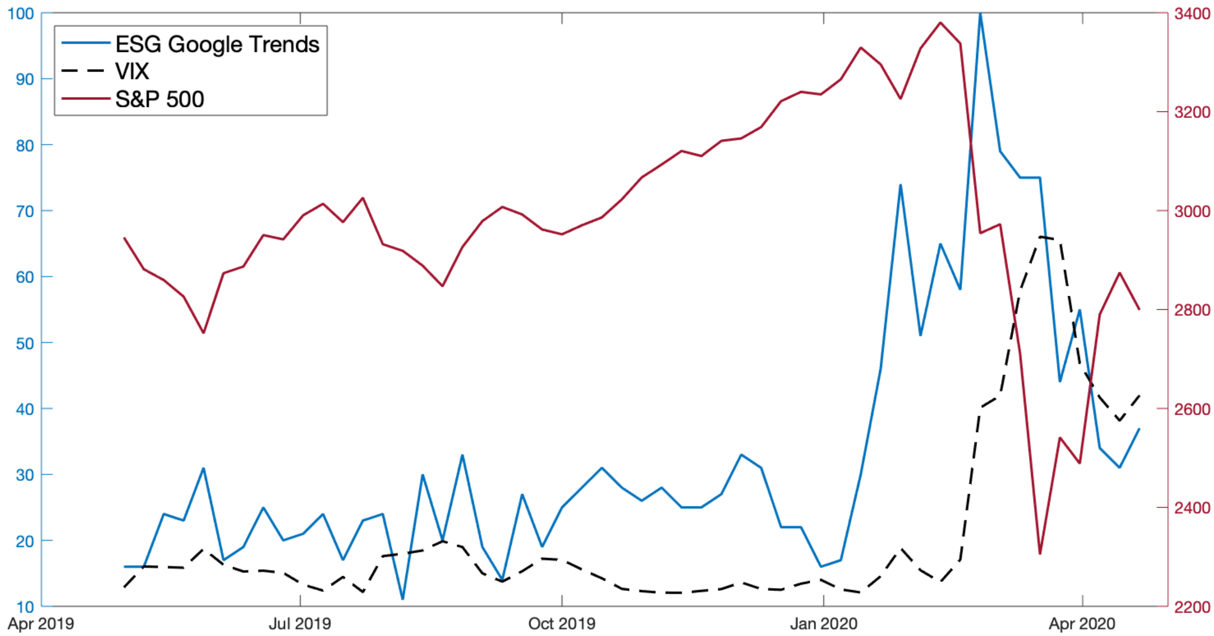
Towards decomposing sustainability: ambiguity

- We introduce an additional dimension of uncertainty which is traditionally not accounted for by risk, namely the uncertainty of probabilities that make up risk, so-called ambiguity or Knightian uncertainty
- Formally, the degree of ambiguity can be measured by the variance of probabilities, just as the degree of risk can be measured by the variance of outcomes
- Our motivation to incorporate ambiguity is threefold:
  1. The intuitive meaning of ambiguity as proposed by Ellsberg (2001): it can be understood as an information-state "in which information [...] is scanty, marked by gaps, obscure and vague, or on the contrary plentiful and precise but highly contradictory."
  2. Experimental evidence on investor preferences
  3. Empirical evidence on ambiuity in asset markets: Brenner and Izhakian (2018) show that ambiguity in the equity market is priced, and introducing it alongside risk provides stronger evidence on the role of risk in explaining expected returns in equity markets
- Our proxy for stock ambiguity is the standard deviation of the variance of daily returns; our proxy for implied ambiguity is the standard deviation of the option implied volatilities

Towards decomposing sustainability: sentiment

1. Investor sentiment for sustainability widely documented (Riedl and Smeets (2017), Hartzmark and Sussman (2018))

2. Investor sentiment for sustainability more pronounced during the Corona crash



UNCERTAINTY and SENTIMENT Factors

UNCERTAINTY

- $RV_{i,t}$ is the realized 1-year volatility of stock i at time t calculated based on daily returns preceding time t.
- $IV_{i,t}$ is the implied volatility of stock i calculated from option prices for date t.
- $Ambiguity_{i,t}$ is the square root of the average of the variances of $RV_{i,t}$ and $IV_{i,t}$.

Take $UNCERTAINTY_{i,t}$ as the first principal component:

$$UNCERTAINTY_{i,t} = 0.61\ RV_{i,t} + 0.54\ IV_{i,t} + 0.57\ Ambiguity_{i,t}\ .$$

SENTIMENT

We approximate investor attention using financial-based market measures (Baker and Wurgler (2006,2007)):

$$SENTIMENT_{i,t} = 0.99\ SPREAD_{i,t} + 0.12\ VOLUME_{i,t} + 0.13\ DY_{i,t} - 0.03\ PE_{i,t} + 0.02\ MOM_{i,t}$$

UNCERTAINTY and SENTIMENT Factors

Econometric approach

We first estimate the following model for each firm i in our sample:

$$\begin{aligned} \mathit{ESG}_{i,t} \;=\; & \gamma_{0,i} + \gamma_{1,i}\ \mathit{SIZE}_{i,t} + \gamma_{2,i}\ \mathit{IDIOVOL}_{i,t} + \gamma_{3,i}\ \mathit{ROA}_{i,t} + \gamma_{4,i}\ \mathit{CASH}_{i,t} + \gamma_{5,i}\ \mathit{LEV}_{i,t} \\ + \; & \gamma_{6,i}\ \mathit{BOOK/MARKET}_{i,t} + \gamma_{7,i}\ \mathit{SECTOR}_{i} + \gamma_{8,i}\ \mathit{FIRM}_{i} + \gamma_{9,i}\ \mathit{MONTH}_{i,t} + \epsilon_{i,t} \end{aligned}$$

We then estimate the effect of uncertainty and sentiment on ESG ratings:

$$\hat{\epsilon}_{i,t} = \beta_{0,i} + \beta_{1,i}\mathit{UNCERTAINTY}_{i,t} + \beta_{2,i}\mathit{SENTIMENT}_{i,t} + \upsilon_{i,t}\ .$$

Regression 1

Table: **Regression of ESG and firm fundamentals.** The table reports regression results of our regression model defined in (3.1), with dependent variable the monthly (aggregate OWL-TVL) ESG score, and independent variables size (*SIZE*), idiosyncratic volatility (*IDIOVOL*), return on assets (*ROA*), cash ratio (*CASH*), leverage (*LEV*), book-to-market ratio (*BOOK/MARKET*), including sector, firm, and month fixed effects. The analysis covers the period January 2017 through June 2019, with an average of 780 stocks per date in 2017, 895 stocks per date in 2018, and 1114 stocks per date in 2019.

	coefficient	Std. Error	t-statistic	p-value	Variance contr. (%)
γ_0	-0.1472	0.167	-0.883	0.39	
SIZE	0.141	0.007	20.004	0.000	**77.52**
IDIOVOL	0.040	0.007	5.757	0.000	**5.77**
ROA	-0.011	0.008	-1.314	0.189	**0.37**
CASH	-0.029	0.007	-3.997	0.000	**3.22**
LEV	-0.005	0.006	-0.772	0.391	**0.10**
BOOK/MARKET	-0.050	0.008	-6.110	0.00	**7.28**
SECTOR	0.005	0.003	1.549	0.004	**0.45**
FIRM	-0.000	0.00	-5.403	0.000	**5.09**
MONTH	-0.002	0.002	-1.001	0.074	**0.12**
Observations N	*28440*				
Adj. R^2	*0.071*				
F-statistic	*103*				

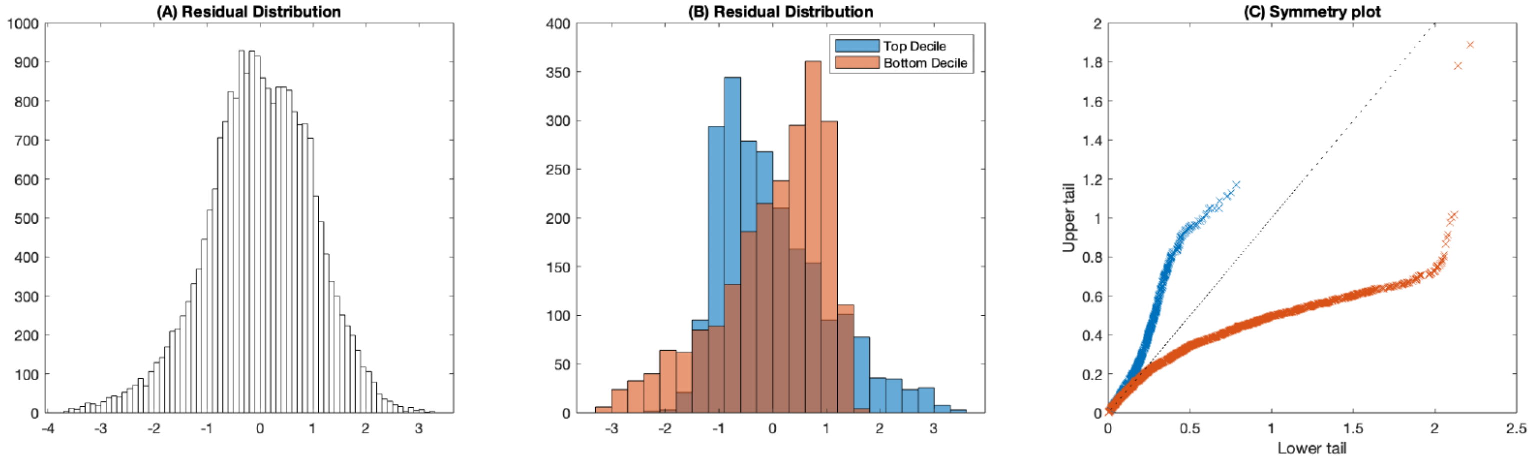
Regression 2

Table: **Regression of ESG and uncertainty and sentiment indicators.** The table reports regression results of our regression model defined by $\hat{\epsilon}_{i,t} = \beta_{0,i} + \beta_{1,i} UNCERTAINTY_{i,t} + \beta_{2,i} SENTIMENT_{i,t} + \upsilon_{i,t}$, where $\hat{\epsilon}_{i,t}$ are the residuals estimated from Regression (4.1), *UNCERTAINTY* is defined as the first principal component of realized volatility, implied volatility, and our proxy for ambiguity, while *SENTIMENT* is defined as the first principal component of levels in five measures of sentiment: bid-ask spread, trading volume, dividend yield, price-earnings ratio, and price momentum. All variables have been standardized to have mean zero and standard deviation 1 using z-score normalization. Significance at the 10% confidence level indicated by *, at 5% confidence level indicated by **, and at 1% confidence level indicated by ***.

	(1) **Full sample**	**(2)** **Top Decile**	**(3)** **Top Quintile**	**(4)** **Bottom Decile**	**(5)** **Bottom Quintile**
β_0	0.007 (1.118)	1.644*** (221.07)	1.434*** (209.44	-1.838*** (-149.93)	-1.454*** (-153.34)
UNCERTAINTY	-0.170*** (-12.642) **50.32**	-0.316*** (-19.824) **73.30**	-0.253*** (-18.917) **66.21**	-0.173*** (-17.880) **94.66**	-0.165*** (-9.287) **95.55**
SENTIMENT	0.188*** (6.990) **49.68**	0.173*** (10.603) **26.70**	0.147*** (12.53) **33.79**	0.004 (1.385) **5.34**	0.027 (1.144) **4.45**
Observations N	22440	2244	4488	2244	4488
Adj. R-squared	0.071	0.341	0.173	0.108	0.049
F-statistic	43.1	99.6	117.0	33.8	28.6

RESIDUALS

Figure 3.4. **ESG Residual distribution.** The Figure displays distributions of the standardized estimated residuals $\hat{\upsilon}_{i,t}$ defined by the regression $\hat{\epsilon}_{i,t} = \beta_{0,i} + \beta_{1,i} UNCERTAINTY_{i,t} + \beta_{2,i} SENTIMENT_{i,t} + \upsilon_{i,t}$, where $\hat{\epsilon}_{i,t}$ are the estimated residuals obtained from Regression (4.1) with dependent variable the aggregate ESG score and independent variables a set of fundamental firm-specific controls. Both regressions are based on monthly data over the time period January 2017 to June 2019 covering an average of 930 stocks per date. Figure (A) shows the distribution of all $N = 22440$ standardized residuals across all firms and dates; Figure (B) shows the standardized residual distributions of firms whose raw ESG scores are in the top and bottom deciles on each date; Figure (C) shows the symmetry plot of residuals of firms in the top and bottom ESG deciles around their median (residuals in upper tail - median vs. median – residuals in lower tail).



Miscellaneous

Environmental, social, and governance effects

- OLS regression of uncertainty, sentiment, and ESG residual components against the 12 ESG indicators of OWL Analytics
- E and S indicators are most significant in the uncertainty and sentiment components, respectively
- G appears most strongly in the residuals, especially business ethics

Volatility regimes

- We partition our data set into different volatility regimes using a VIX threshold
- We observe an increase in the significance and variance contribution of UNCERTAINTY to the model, which goes up from 50.32% to 77.98%
- Better model fit (R-squared) in the high-vol regime

The Nature of the Perceived Resilience: Econometric Approach

Event window: 33-trading-day period starting 5 days before our event day, 12 February 2020, and ending 31 March 2020.

Estimation window: 250 trading days (from 22 February 2019 through 12 February 2020) ends five trading days before the start of the crash, which we define as 20 February 2020.

For each company i and each day t in the event window, we calculate the daily abnormal return $AR_{i,t}$ as the difference of the actual return of the company $R_{i,t}$ and its expected return that we estimate in market regressions with the Fama-French 5-factor model:

$$AR_{i,t} = R_{i,t} - \alpha_i - \sum_{n=1}^{5} \beta_{n,i} \mathsf{Factor}_{n,t} \; . \tag{0.1}$$

We cumulate abnormal returns $CAR_i[\theta_0, \theta_1]$ for a given period $[\theta_0, \theta_1]$ as the sum of the company-specific abnormal returns estimated above, that is

$$CAR_i[\theta_0, \theta_1] = \sum_{t=\theta_0}^{\theta_1} AR_{i,t} \; . \tag{0.2}$$

Confirming ESG Resilience

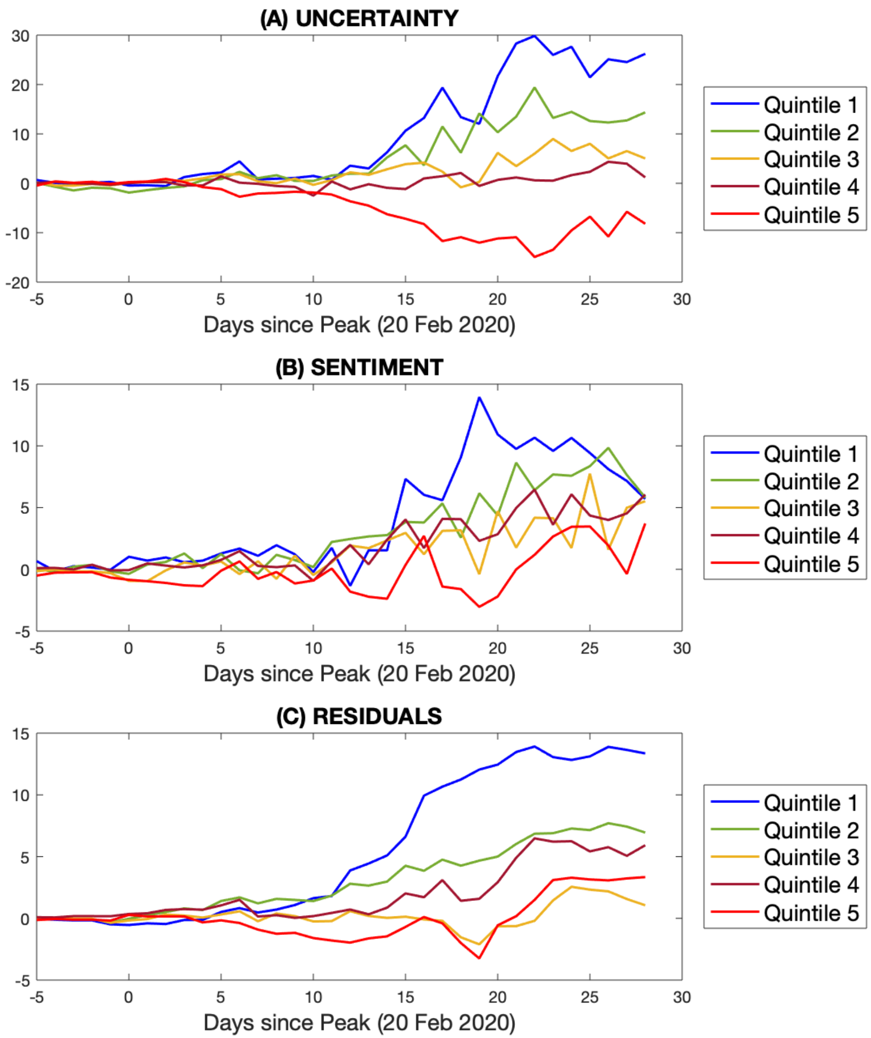
Table: **Regression of CAR and ESG.** This table presents regression estimates of returns on one period lagged ESG scores and one period lagged control variables in the crash period. Crisis-period returns are displayed as abnormal Fama-French 5 Factor adjusted returns (FF) over the overall period between 20 February 2020 and 31 March 2020 and in the sub-period of downturn only until 18 March 2020 , indicated by a $(-)$, as well as the rebound period between 18 March 2020 and 31 March 2020, indicated by a $(+)$.

	CAR	CAR$(-)$	CAR$(+)$	MDD	Drawup
ESG	0.197*	0.242**	-0.051	-0.116**	-0.262**
	(1.846)	(2.080)	(-0.874)	(-2.061)	(-2.504)
SIZE	-1.128*	-0.170	-0.963***	-2.621***	-3.904***
	(-1.918)	(-0.253)	(-3.137)	(-8.496)	(-7.426)
CASH	0.501***	0.500***	-0.002	-0.256***	-0.210***
	(6.523)	(5.619)	(-0.046)	(-5.779)	(-2.800)
B/M	-0.450	-0.080	-0.382	0.038	-0.117
	(-1.045)	(-0.135)	(-1.573)	(0.158)	(-0.370)
LEV	-0.127***	-0.159***	0.033*	0.113***	0.211***
	(-2.978)	(-3.157)	(1.676)	(4.349)	(4.764)
ROA	-0.692*	-0.705*	0.009	-0.521***	-0.622***
	(-1.875)	(-1.740)	(0.129)	(-7.508)	(-5.314)
IDIOVOL	-2.869***	-2.342***	-0.524*	-0.374	-1.366***
	(-5.902)	(-3.789)	(-1.675)	(-1.616)	(-3.168)
Constant	-1.728	-10.812	9.443**	71.642***	80.557***
	(-0.243)	(-1.321)	(2.420)	(18.562)	(11.850)
Sector FE	Yes	Yes	Yes	Yes	Yes
N	1169	1169	1148	1169	1162
R-squared	0.107	0.075	0.015	0.207	0.123
F-statistic	22.387	14.177	2.404	42.183	18.442

t statistics in parentheses

Drivers of Resilience

Figure: Cumulative abnormal returns based on ESG components.



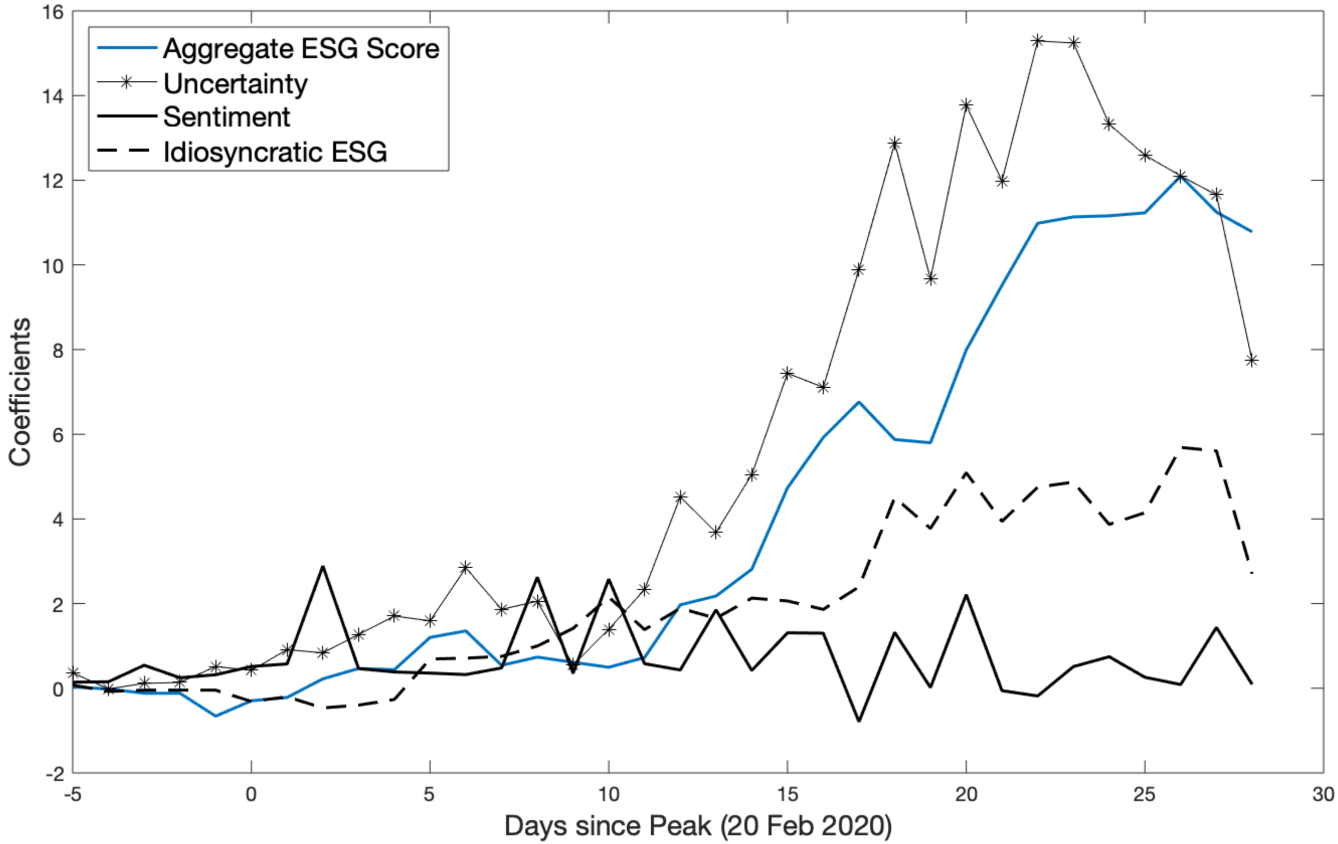
Drivers of Resilience

Table: **Event study with ESG indicators.** The table reports regression estimates of Fama-French-estimated cumulative abnormal returns, maximum drawdown (MDD) and drawup on each of the three components of ESG, namely *UNCERTAINTY*, *SENTIMENT*, and *RESIDUALS*. Abnormal returns are displayed over the entire event period (CAR) as well as for the crisis (CAR(-)) and rebound (CAR(+)) periods, separately.

	CAR	**CAR**$(-)$	**CAR**$(+)$	**MDD**	**Drawup**
Constant	0.657* (1.677)	3.957*** (2.813)	3.751*** (6.445)	48.373*** (84.417)	49.970*** (45.186)
UNCERTAINTY	-1.301** (-2.316)	-9.568*** (-4.496)	-0.810 (-1.462)	4.663*** (9.166)	-7.510*** (-7.728)
SENTIMENT	0.205 (0.853)	-0.137 (-0.348)	-0.185 (-0.588)	1.008* (1.917)	1.379 (1.603)
IDIOSYNCRATIC ESG	0.919*** (2.837)	4.071*** (3.522)	-0.966* (-1.909)	-0.271 (-0.529)	-1.259 (-1.330)
Observations N	804	804	792	804	802
Adj. R-squared	0.040	0.116	0.008	0.125	0.097
F-statistic	6.114	8.695	2.294	29.292	21.898

Drivers of Resilience

Figure: **Contribution of ESG components to resilience during the crash.** The Figure shows for each day in the crash period the coefficients of both the aggregate ESG score and its components *UNCERTAINTY*, *SENTIMENT* and *RESIDUALS*, based on the regression of the cumulative abnormal returns in the event window, with abnormal returns estimated using the Fama-French 5-Factor model.



Recap and Conclusion

Our COVID-motivated questions:

- Is there a common denominator to the empirical notion of sustainability?
- What information – if any – is in this common denominator?
- Can this perhaps explain the "immunity"?

The uncertainty **association**:

- the quality of environmental and social related disclosure and the respective sustainability score
- investors perceive sustainability as less uncertain (less of an "unknown unknown")
- low uncertainty is predictive of lower future uncertainty

Future developments:

- Extend data (equity space, time horizon, sustainability ratings)
- Towards new factors: sentiment, temporal, and sustainability

Thank You!