Internet Appendix for “Dissecting Green Returns”

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Contents

This Internet Appendix presents additional results and details mentioned in the paper.

1. German twin bonds

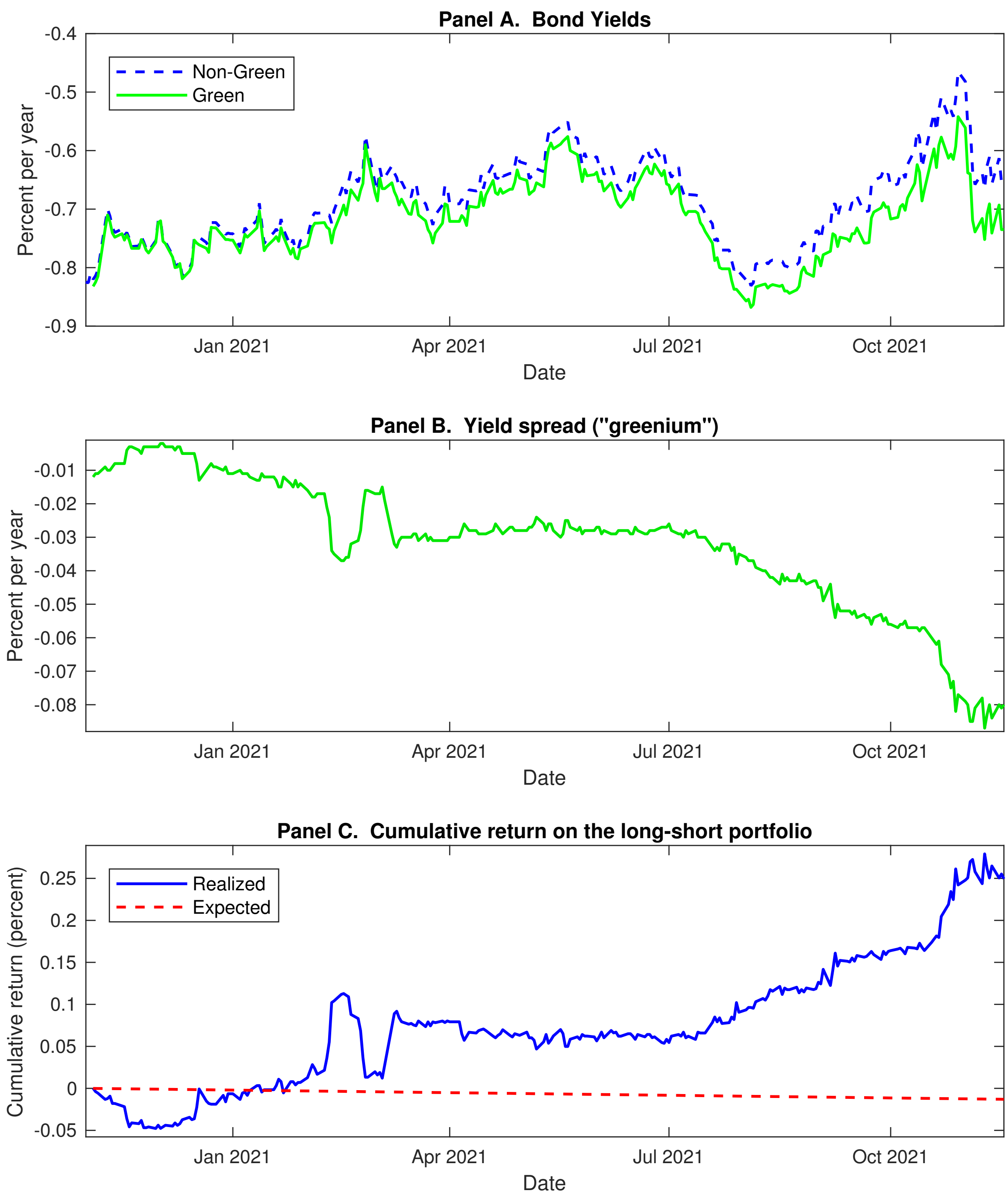

Figure A.1. Five-year German twin bonds. This figure matches Figure 1 in the paper but shows results for five-year rather than ten-year bonds. The five-year bonds were first issued in November 2020.

2. Implied cost of capital (ICC)

2.1. Computing the ICC

This section describes how we compute stocks' ICCs. We follow the approach of Hou, van Dijk, and Zhang (2012), henceforth "HVZ," which builds on the residual-income valuation model of Gebhardt, Lee, and Swaminathan (2001). Instead of using IBES earnings forecasts, the HVZ approach uses earnings forecasts from regressions. We stay as close as possible to the implementation of HVZ by Lee, So, and Wang (2021).

The implied cost of capital, denoted r_e below, is the internal rate of return that equates the present value of future dividends to the current stock price:

$$P_{i,t} = B_{i,t} + \sum_{\tau=1}^{\infty} \frac{E_t[EPS_{i,t+\tau}] - r_e E_t[B_{i,t+\tau}]}{(1+r_e)^{\tau}}, \tag{1}$$

where $P_{i,t}$ is the current stock price, $EPS_{i,t+\tau}$ is the forecast of earnings per share in year $t+\tau$, and $B_{i,t+\tau}$ is the book value per share. The ICC (r_e) is specific to firm i and time t, but we omit those subscripts for notational ease. We also drop the i subscripts going forward. Using a twelve-year forecast horizon with a terminal perpetuity, and recognizing that earnings equal ROE times book equity, the equation becomes

$$P_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[(ROE_{t+\tau} - r_e)B_{t+\tau-1}]}{(1+r_e)^{\tau}} + \frac{E_t[(ROE_{t+12} - r_e)B_{t+11}]}{r_e(1+r_e)^{11}}. \tag{2}$$

For the first three years ahead, earnings are forecasted using the HVZ methodology. Each month, and for each horizon $\tau = 1$, 2, and 3 years, we estimate a pooled cross-sectional regression of firms' τ-years-ahead realized dollar earnings (net income before extraordinary items) on lagged dollar assets, earnings, dividend payment, dividend-payment dummy, negative-earnings dummy, and accruals. The regressions are estimated using the previous ten years of data as of the forecasting date. Following HVZ, variables are measured in dollars without scaling, and we winsorize the cross section of dollar-denominated variables at the 1% and 99% levels each year. We use the estimated cross-sectional regressions to forecast future dollar earnings. Note this approach allows forecasted earnings to be negative.

For forecast horizons $\tau = 4, ..., 12$ years, we forecast each firm's ROE using a linear interpolation from the three-year-ahead ROE forecast to the industry median ROE. The assumption is that ROE is expected to revert to the historical industry median value by year $t+12$. Following Lee et al. (2021), we compute industry median ROEs each year using available data over the preceding ten years. We classify firms into industries based on the 48 Fama-French industry categories. Following HVZ, we exclude loss-making firms when calculating the median industry ROEs.

Book-equity forecasts are derived from clean-surplus accounting and depend on forecasted net income (E) and dividends (D):

$$B_{t+\tau} = B_{t+\tau-1} + E_{t+\tau} - D_{t+\tau}. \tag{3}$$

HVZ assume that the dividend-payout ratio remains constant over the entire forecasting horizon and equal to the realized payout ratio in year t. For firms with positive earnings in year t, dividends are calculated from the current dividend payout ratio, d_t:

$$D_{t+\tau} = d_t E_{t+\tau} = \frac{D_t}{E_t} E_{t+\tau}. \tag{4}$$

For firms with negative earnings in year t, dividends are calculated from the current dividends and a fraction of total assets:

$$D_{t+\tau} = \frac{D_t}{0.06 A_t} E_{t+\tau}. \tag{5}$$

Since a dividend-payout ratio above one is unrealistic over the long run, we set $d_t = 1$ if the data imply $d_t > 1$. We further adjust these "raw" dividend forecasts, $D_{t+\tau}$, if the forecasted $B_{t+\tau} < 0$ but $B_{t+\tau-1} > 0$ for some τ, with $1 \leq \tau \leq 11$. In these cases, we set dividends τ periods ahead equal to net earnings in the same period, i.e., $D_{t+\tau} = E_{t+\tau}$. After this adjustment, dividends may be negative, which can be interpreted as equity issuance by the firm. We make this adjustment because ROE is undefined—producing a missing ICC value—if book equity is negative, and the adjustment produces fewer negative book-equity forecasts.

We compute r_e from equation (2) for each firm and month. We discard less than 0.2% of ICC values that are implausibly large (above 100%) or small (below -50%). We discard roughly 0.07% of observations where the bisection and Newton-Raphson algorithms deliver different solutions for r_e in equation (2). We winsorize the remaining ICC values at the 1st and 99th percentiles.

Table A.1
Panel regressions of ICC on greenness

The dependent variable is the firm's ICC estimate at the beginning of the month, in units of percent per year. Regressor g is the firm's greenness, also measured at the beginning of the month. Time Trend equals the number of months since November 2012, the beginning of our sample. Both regressions include month fixed effects and cluster by firm.

	(1)	(2)
g	-0.483	-0.262
	(-11.90)	(-5.62)
$g\times$ Time Trend		-0.00544
		(-5.52)
Observations	193,216	193,216
R^2	0.056	0.058

3. Comparing $\bar{r}$ and $\hat{a}$

This section contains derivations of the probabilities in Figure 5 of the paper. We compare $\bar{r}$ and $\hat{a}$ as estimators of μ_r, deriving the distributions of the usual t-statistics for both estimators when $\mu_r \neq 0$.

Let $\hat{\theta}$ denote the OLS estimator of $\theta = [a\ b]'$, and note that the two estimators of μ_r that we compare, $\bar{r}$ and $\hat{a}$, are of the form

$$\hat{\mu}_r = h'\hat{\theta}, \tag{6}$$

with $h = [1\ \bar{x}]'$ for $\hat{\mu}_r = \bar{r}$ and $h = [1\ 0]'$ for $\hat{\mu}_r = \hat{a}$. Define the $T \times 1$ vectors $r = [r_1\ r_2\ \cdots r_T]'$, $x = [x_1\ x_2\ \cdots x_T]'$, $\iota = [1\ 1\ \cdots 1]'$ and the $T \times 2$ matrix $X = [\iota\ x]$. The t-statistic for $\bar{r}$ is

$$t_{\bar{r}} = \frac{\bar{r}}{\widehat{se}(\bar{r})}, \tag{7}$$

where $\widehat{se}(\bar{r}) = \hat{\sigma}_r/\sqrt{T}$ and $\hat{\sigma}_r^2 = (r - \iota\bar{r})'(r - \iota\bar{r})/(T-1)$. The t-statistic for $\hat{a}$ is

$$t_{\hat{a}} = \frac{\hat{a}}{\widehat{se}(\hat{a})}, \tag{8}$$

where

$$\widehat{se}(\hat{a}) = \sqrt{\frac{s^2}{T}\left(1 + \frac{\bar{x}^2}{\hat{\sigma}_x^2}\right)}, \tag{9}$$

which is the square root of the (1,1) element of

$$\hat{\Omega} = s^2(X'X)^{-1} = \frac{s^2}{T\hat{\sigma}_x^2}\begin{bmatrix} \hat{\sigma}_x^2 + \bar{x}^2 & -\bar{x} \\ -\bar{x} & 1 \end{bmatrix}, \tag{10}$$

with $s^2 = (r - X\hat{\theta})'(r - X\hat{\theta})/(T-2)$ and $\hat{\sigma}_x^2 = (x - \iota\bar{x})'(x - \iota\bar{x})/T$. We derive here the sampling distributions, conditional on x, of the above t-statistics when $\mu_r \neq 0$.

Let σ_ϵ^2 denote the variance of ϵ_t in equation (4). Define Ω as the same matrix as in equation (10) but with σ_ϵ^2 replacing s^2. From standard regression theory, $\hat{\theta} \sim N(\theta, \Omega)$, and thus

$$z = \frac{h'(\hat{\theta} - \theta)}{\sqrt{h'\Omega h}} \sim N(0,1), \tag{11}$$

while, distributed independently,

$$q = (T-2)s^2/\sigma_\epsilon^2 \sim \chi^2_{T-2} \tag{12}$$

("$\sim$" denotes "is distributed as"). Also, by a standard result for the noncentral t distribution, for a given constant δ,

$$\frac{z + \delta}{\sqrt{q/(T-2)}} \sim t(\delta, T-2), \tag{13}$$

where $t(\delta, \nu)$ denotes a noncentral-t variate with noncentrality parameter δ and ν degrees of freedom. We set $\delta = h'\theta/\sqrt{h'\Omega h}$, giving

$$\frac{h'\hat{\theta}}{\sqrt{h'\Omega h}}\sqrt{\sigma_\epsilon^2/s^2} \sim t\left(\frac{h'\theta}{\sqrt{h'\Omega h}}, T-2\right). \tag{14}$$

To derive the distribution of $t_{\bar{r}}$, first note that when $h = [1\ \bar{x}]'$, it is easily verified that

$$h'\Omega h = \sigma_\epsilon^2/T \tag{15}$$

$$h'\hat{\theta} = \bar{r} \tag{16}$$

$$h'\theta = \mu_r + b\bar{x}, \tag{17}$$

which when combined with (14) give

$$\frac{\bar{r}}{\sqrt{s^2/T}} \sim t\left(\frac{\mu_r + b\bar{x}}{\sqrt{\sigma_\epsilon^2/T}}, T-2\right). \tag{18}$$

Also, the regression's true R-squared is

$$R^2 = \rho_{rx}^2 = 1 - \sigma_\epsilon^2/\sigma_r^2, \tag{19}$$

where ρ_{rx} is the correlation between r_t and x_t. Next observe that the t-statistic for $\bar{x}$ is

$$t_{\bar{x}} = \frac{\bar{x}}{\widehat{se}(\bar{x})} = \frac{\bar{x}}{\sqrt{\frac{T}{T-1}}\hat{\sigma}_x/\sqrt{T}} = \frac{\bar{x}}{\hat{\sigma}_x/\sqrt{T-1}}, \tag{20}$$

recalling that $\hat{\sigma}_x^2$ is defined with a divisor of T instead of $T-1$. Using (19) and (20),

$$b\bar{x} = \left(\frac{\sigma_r}{\sigma_x}\rho_{rx}\right)\bar{x} = \sigma_r\sqrt{R^2}\left(\frac{\bar{x}}{\sigma_x}\right) = \sigma_r\sqrt{R^2/(T-1)}\left(\frac{\hat{\sigma}_x}{\sigma_x}\right)t_{\bar{x}}, \tag{21}$$

where σ_x^2 is the variance of x_t, and the square root of R^2, applying (19), is positive since $b \geq 0$. The sample's adjusted R-squared is given by

$$\bar{R}^2 = 1 - s^2/\hat{\sigma}_r^2, \tag{22}$$

so, using (7),

$$\frac{\bar{r}}{\sqrt{s^2/T}} = \frac{\bar{r}}{\sqrt{(1-\bar{R}^2)\hat{\sigma}_r^2/T}} = \frac{t_{\bar{r}}}{\sqrt{1-\bar{R}^2}}. \tag{23}$$

Combining (19), (21), and (23) allows (18) to be rewritten as

$$t_{\bar{r}} \sim \sqrt{1-\bar{R}^2} \times t\left(\frac{\mu_r + \sigma_r\sqrt{R^2/(T-1)}\left(\frac{\hat{\sigma}_x}{\sigma_x}\right)t_{\bar{x}}}{\sqrt{(1-R^2)\sigma_r^2/T}}, T-2\right). \tag{24}$$

To derive the distribution of $t_{\hat{a}}$, first note that when $h = [1\ 0]'$, it is easily verified that

$$h'\Omega h = \frac{\sigma_\epsilon^2}{T}\left(1 + \frac{\bar{x}^2}{\hat{\sigma}_x^2}\right) \tag{25}$$

$$h'\hat{\theta} = \hat{a} \tag{26}$$

$$h'\theta = \mu_r, \tag{27}$$

which when combined with (14) give

$$\frac{\hat{a}}{\sqrt{\frac{s^2}{T}\left(1 + \frac{\bar{x}^2}{\hat{\sigma}_x^2}\right)}} \sim t\left(\frac{\mu_r}{\sqrt{\left(1 + \bar{x}^2/\hat{\sigma}_x^2\right)\sigma_\epsilon^2/T}}, T-2\right). \tag{28}$$

Using (8), (9), (19), and (20) allows (28) to be rewritten as

$$t_{\hat{a}} \sim t\left(\frac{\sqrt{T}\mu_r}{\sqrt{\left(1 + \frac{t_{\bar{x}}^2}{T-1}\right)(1-R^2)\sigma_r^2}}, T-2\right). \tag{29}$$

Recall that we assume $\mu_r < 0$ in constructing Figure 5 in the paper.

For $\bar{r}$, Panel B of Figure 5 in the paper plots the probability that $t_{\bar{r}} > t^{crit}_{0.975,T-1}$, where $t^{crit}_{0.975,T-1}$ is the 97.5 percentile of Student's t distribution with $T-1$ degrees of freedom, i.e., the positive critical value for the usual two-tailed 5% test of significance for the sample mean. We compute this probability using the distribution in (24), making the simplifying assumptions that $\bar{R}^2 = R^2$ and $\hat{\sigma}_x^2 = \sigma_x^2$. For $\hat{a}$, Panel B plots the probability that $t_{\hat{a}} > t^{crit}_{0.975,T-2}$, where $t^{crit}_{0.975,T-2}$ is the 97.5 percentile of Student's t distribution with $T-2$ degrees of freedom, i.e., the positive critical value for the usual 5% test of significance for the intercept in a simple regression. This probability is computed using the distribution in (29). Panel A of Figure 5 in the paper plots the probabilities that $\bar{r} > 0$ and $\hat{a} > 0$. These probabilities can be computed as above by setting the t^{crit} values to zero, or they can be computed using the normal distribution in (11), with

$$\frac{h'\hat{\theta}}{\sqrt{h'\Omega h}} \sim N\left(\frac{h'\theta}{\sqrt{h'\Omega h}}, 1\right), \tag{30}$$

and using (15) through (17) for $\bar{r}$ and using (25) through (27) for $\hat{a}$.

4. Explaining GMB's performance

Table A.2
How much stock return variance is explained by measures of earnings news?

This table shows results from panel regressions of quarterly percent stock returns on contemporaneous earnings-news measures and quarter fixed effects. Earnings announcement ret. is the stock's sum of the three-trading-day excess returns (stock minus market, in percent) around earnings announcements and management earnings forecasts (if available) during the quarter. Delta earnings forecast is the change in analysts' mean long-term earnings growth rate forecast for the stock during the quarter. The bottom row shows the R-squared from a regression of stock returns on quarter fixed effects only. The gap between that R-squared and the R-squared in the penultimate row measures the fraction of return variance explained by the earnings-news variable. Robust t-statistics clustered by quarter are in parentheses.

	(1)	(2)
Earnings announcement ret.	1.02	
	(22.57)	
Delta earnings forecast		29.04
		(8.84)
Observations	60057	64134
R^2	0.371	0.225
R^2 (FEs only)	0.201	0.222

Table A.3
Version of paper's Table 4 comparing early and late subperiods

This is the same as the paper's Table 4 but estimates the regressions in two subsamples, early (November 2011 to August 2015) and late (September 2015 to June 2018).

	Dependent variable			
Independent variable	GMB return		GMB alpha	
Panel A: Early subperiod				
Δ Climate concerns (same month)	0.86	3.90	0.73	3.64
	(0.38)	(2.01)	(0.33)	(1.77)
Δ Climate concerns (prev. month)	1.54	3.63	1.53	3.49
	(0.66)	(1.67)	(0.79)	(1.85)
Earnings announcement returns		1.33		1.19
		(2.13)		(1.90)
Δ Earnings forecasts		68.20		69.02
		(1.94)		(2.66)
Constant	0.67	-0.37	0.47	-0.51
	(1.63)	(-0.75)	(1.37)	(-0.99)
Observations	34	34	34	34
R^2	0.012	0.211	0.015	0.251
Panel B: Late subperiod				
Δ Climate concerns (same month)	6.28	7.08	6.34	6.58
	(2.83)	(3.80)	(3.19)	(3.33)
Δ Climate concerns (prev. month)	2.59	3.44	1.90	2.35
	(1.21)	(1.69)	(1.14)	(1.52)
Earnings announcement returns		1.13		0.91
		(2.97)		(2.25)
Δ Earnings forecasts		-31.36		-18.10
		(-1.81)		(-0.83)
Constant	-0.27	-0.45	-0.39	-0.49
	(-0.81)	(-1.41)	(-1.17)	(-1.49)
Observations	34	34	34	34
R^2	0.330	0.476	0.319	0.433

4.1. Computing ESG assets

We provide details on computing "ESG assets," which first appears in the paper in Table 5. From Morningstar's *2021 Sustainable Funds U.S. Landscape Report*, we obtain annual sustainable fund AUM. We convert Morningstar's annual series to a quarterly series by using data on ESG flows and market returns, to approximate capital gains and losses. We estimate ESG funds' AUM at the end of quarter t, denoted $\widehat{AUM}_t$ as

$$\widehat{AUM}_t = \begin{cases} \text{True, known } AUM_t \text{ if } t \text{ is the year's last quarter} \\ \widehat{AUM}_{t-1}(1 + R_t^{mkt}) + ESGFlow_t(1 + \frac{1}{2}R_t^{mkt}) \text{ otherwise,} \end{cases} \tag{31}$$

where R_t^{mkt} is the market return in quarter t. The fraction 1/2 reflects that flows arrive throughout a quarter.

Table A.4
Version of paper's Table 5 using Fama-French alphas

This table is the same as Table 5 in the paper but replaces returns on GMB and the green and brown legs with their respective Fama-French three-factor alphas as the dependent variables. GMB alphas are computed as in the paper's Table 4. Green and brown alphas are computed the same way, except we replace the GMB spread with the leg's return in excess of the risk-free rate.

	Dependent variable					
Independent variable	GMB alpha		Green leg		Brown leg	
Δ Climate concerns (same month)	3.69		2.12		-1.56	
	(2.67)		(3.06)		(-1.90)	
Δ Climate concerns (prev. month)	2.74		0.48		-2.26	
	(2.15)		(0.76)		(-2.89)	
Earnings announcement returns	0.70	0.72	0.29	0.32	-0.40	-0.40
	(2.64)	(2.31)	(2.48)	(2.08)	(-2.22)	(-2.08)
Δ Earnings forecasts	16.95	9.40	3.33	1.50	-13.62	-7.90
	(1.29)	(0.80)	(0.62)	(0.30)	(-1.50)	(-0.99)
ESG flows	30.45	6.39	13.77	1.13	-16.68	-5.26
	(1.42)	(0.98)	(1.65)	(0.35)	(-1.07)	(-1.19)
ESG assets	-0.52	-0.78	-0.20	-0.24	0.33	0.54
	(-0.81)	(-1.13)	(-0.65)	(-0.79)	(0.77)	(1.19)
Constant	-0.42	1.98	-0.34	0.65	0.09	-1.34
	(-0.36)	(1.45)	(-0.55)	(1.13)	(0.12)	(-1.46)
Observations	68	95	68	95	68	95

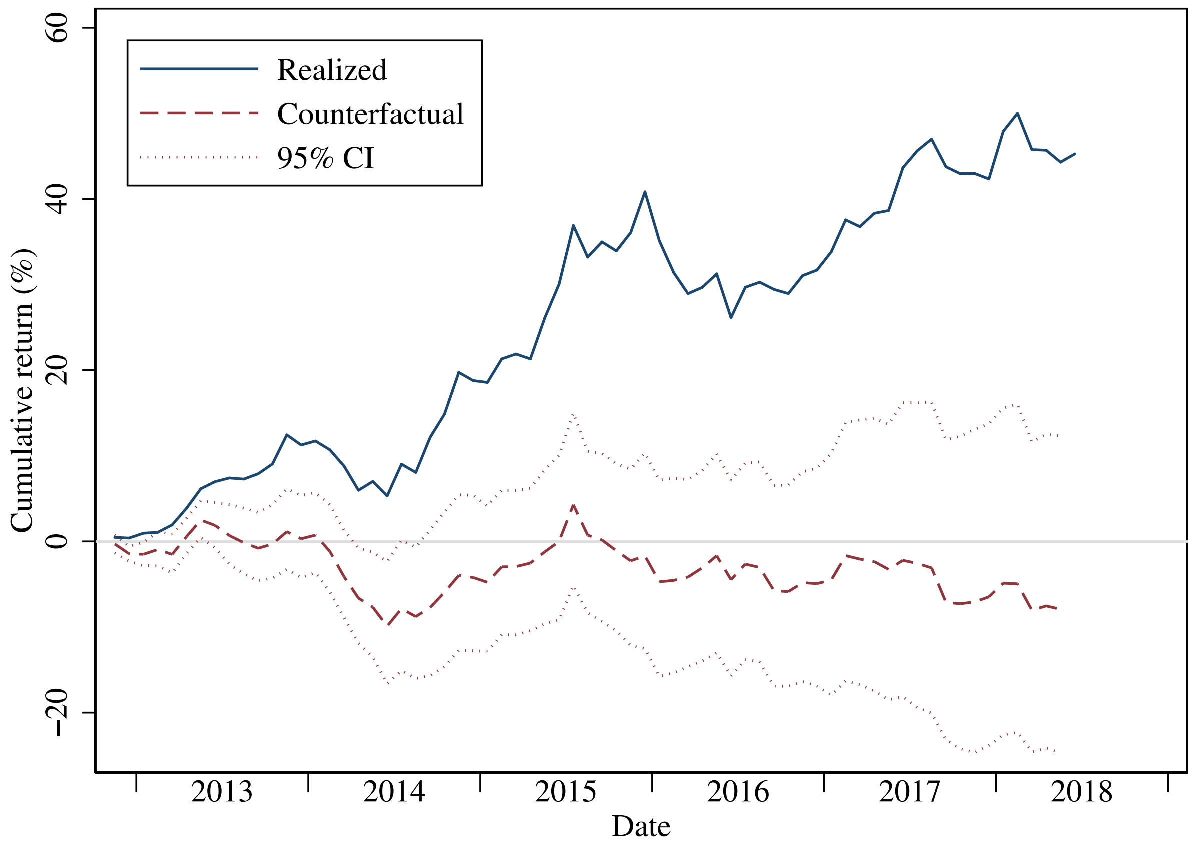

Figure A.2. Version of paper's Figure 7 including the climate news measure of Engle et al. (2020). Engle et al. create two climate indexes, one using data from the Wall St. Journal and one using data from Crimson Hexagon. We use the latter since it has a longer time series. We download AR(1) innovations in the Crimson Hexagon index from the authors' website and add its same- and previous-month values to the regressors used in column 2 of Table 4 in the paper. We use that expanded regression to compute counterfactual GMB returns. When computing counterfactual returns, we set all shocks, including those based on the Engle et al. measure, to zero. Remaining details are the same as in Figure 7 Panel A in the paper.

Table A.5
Components of the climate concern index

Each row contains results from a time-series regression with dependent variable equal to the monthly percent GMB return. Each regression is the same as in Table 4 column 1 in the paper, except Δ Climate concerns is computed using one of the eight themes provided by Ardia et al. (2021). We start with the 40 sub-topics' scores provided by Ardia et al. (2021). For each theme, we sum the daily scores across the theme's constituent topics. We then average this sum across days in a month to compute a monthly theme-level MCCC measure. For each theme, we create an analogue of our main ΔC variable by computing the prediction error from rolling AR(1) models applied to the theme-level MCCC measure. Each time-series regression has 68 monthly observations. Remaining details are the same as in Table 4 in the paper.

	Coefficient on Δ Climate concerns		
Theme	Same month	Prev. month	R^2
Agreement and Summit	0.017	0.025	0.15
	(1.85)	(2.61)	
Societal Impact	0.029	0.016	0.12
	(2.48)	(1.17)	
Financial and Regulation	0.014	0.018	0.11
	(1.86)	(2.07)	
Environmental Impact	0.063	0.015	0.10
	(2.54)	(0.57)	
Research	0.062	0.019	0.08
	(2.01)	(0.65)	
Agricultural Impact	0.047	0.006	0.05
	(1.63)	(0.20)	
Disaster	0.014	0.009	0.02
	(0.91)	(0.55)	
Other	0.103	0.020	0.03
	(1.35)	(0.23)	

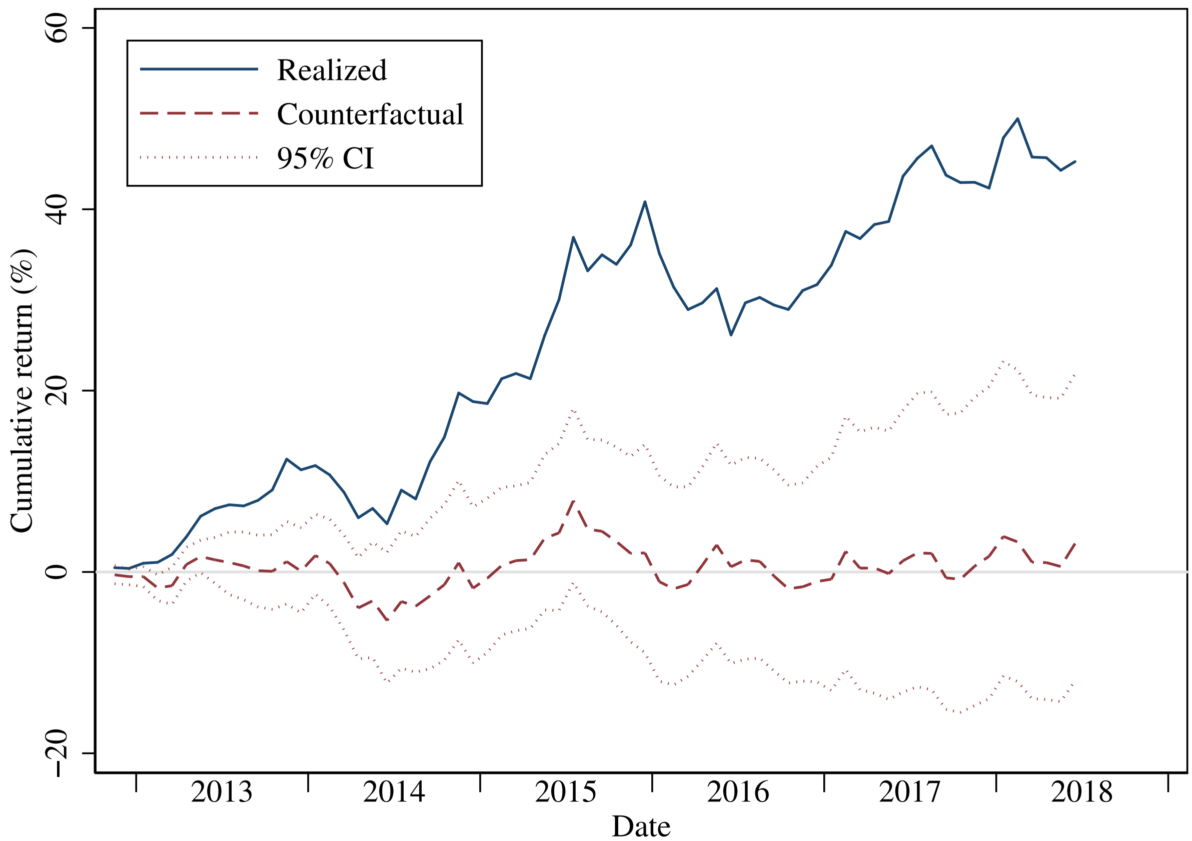

Figure A.3. Version of paper's Figure 7 including oil price shocks and long-term bond returns. Details are the same as in Figure 7 Panel A in the paper, except we also control for oil price shocks and monthly returns on 30-year U.S. Treasury bond in the regression model used to compute counterfactual returns. We set oil price shocks and bond returns to zero when computing counterfactual returns. The oil price shock is derived from data on Cushing, Oklahoma crude oil future contracts. The shock equals the fraction change in expected "front month" value of oil during the month. Bond returns are from CRSP.

Table A.6
Performance of industry-adjusted GMB

This table is the same as the paper's Table 3, except this table uses the industry-adjusted GMB return rather than the original GMB return as the dependent variable. Industry-adjusted GMB is constructed the same as GMB except we replace g with $gWithin = g - gAcross$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.16	0.30	0.12	0.12	0.12	0.12	0.09	0.09
	(0.99)	(1.59)	(0.82)	(0.78)	(0.79)	(0.79)	(0.59)	(0.56)
Mkt-RF		-0.11	-0.01	-0.01	-0.01	-0.01	0.03	0.03
		(-1.99)	(-0.36)	(-0.18)	(-0.26)	(-0.24)	(0.80)	(0.72)
SMB			-0.35	-0.35	-0.33	-0.31		
			(-5.57)	(-5.37)	(-4.89)	(-4.50)		
HML			-0.14	-0.12	-0.13	-0.19		
			(-2.40)	(-1.91)	(-2.44)	(-3.48)		
UMD				0.03				
				(0.65)				
LIQ					-0.03			
					(-0.69)			
RMW						0.09		
						(1.00)		
CMA						0.17		
						(1.68)		
ME							-0.32	-0.32
							(-4.94)	(-4.83)
I/A							0.05	0.05
							(0.57)	(0.55)
Roe							0.19	0.19
							(3.45)	(2.48)
Eg								-0.00
								(-0.02)
Observations	98	98	98	98	98	98	98	98
R^2	0.00	0.08	0.44	0.44	0.44	0.47	0.45	0.45

Table A.7
FAANG returns, GMB, and climate concerns

The dependent variable is the monthly percent return on the value-weighted FAANG portfolio. The sample begins in November 2012. The sample ends in December 2020 in column 1 and June 2018 in column 2.

	(1)	(2)
GMB	0.18	
	(0.54)	
Δ Climate concerns (same month)		0.39
		(0.09)
Δ Climate concerns (prev. month)		5.18
		(1.22)
Constant	2.07	1.61
	(3.48)	(2.23)
Observations	98	68
R^2	0.00	0.03

Table A.8
Explaining the industry-neutral HML factor with the green factor

The dependent variable is the monthly HML industry-neutral return, obtained from Peter Hecht of AQR. Remaining details are the same as in Table 9 in the paper.

	(1)	(2)
Constant	-0.66	-0.23
	(-2.69)	(-1.37)
Mkt-RF	0.26	0.21
	(3.02)	(3.03)
Green Factor		-0.62
		(-5.60)
Observations	98	98
R^2	0.23	0.53

Table A.9

Version of paper's Table 9 replacing green factor with GMB

	Value		Momentum	
Constant	-0.71	-0.32	0.66	0.21
	(-1.93)	(-1.07)	(1.92)	(0.63)
Mkt-RF	0.14	0.11	-0.37	-0.34
	(1.18)	(1.23)	(-3.75)	(-3.71)
GMB		-0.55		0.64
		(-3.22)		(3.61)
Observations	98	98	98	98
R^2	0.04	0.19	0.17	0.29

Table A.10
Green-factor performance

This is the same as Table 3 in the paper but replaces the monthly GMB return with the monthly green factor as the dependent variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.58	0.69	0.38	0.34	0.38	0.39	0.41	0.30
	(2.91)	(3.38)	(2.48)	(2.46)	(2.42)	(2.60)	(2.28)	(1.61)
Mkt-RF		-0.09	0.01	0.07	0.02	0.01	0.00	0.03
		(-1.28)	(0.17)	(1.19)	(0.29)	(0.17)	(0.00)	(0.43)
SMB			-0.23	-0.18	-0.20	-0.32		
			(-3.77)	(-3.54)	(-2.24)	(-4.02)		
HML			-0.37	-0.22	-0.37	-0.28		
			(-6.42)	(-3.78)	(-5.70)	(-4.49)		
UMD				0.24				
				(4.57)				
LIQ					-0.04			
					(-0.38)			
RMW						-0.24		
						(-1.62)		
CMA						-0.26		
						(-2.36)		
ME							-0.27	-0.23
							(-3.57)	(-2.99)
I/A							-0.49	-0.40
							(-4.89)	(-3.61)
Roe							0.16	0.04
							(1.37)	(0.28)
Eg								0.24
								(2.41)
Observations	98	98	98	98	98	98	98	98
R^2	0.00	0.03	0.41	0.52	0.41	0.46	0.38	0.40

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