Does it pay to invest in environmental stocks?

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Online Appendix: Does it pay to invest in environmental stocks?

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Abstract

The appendices contain the PVAR methodology and some additional tables of the study. Initially, Appendix: PVAR describes the pvar methodology. Then, Appendix: Sub-sample results reports new results for the period (i) 2005-2009, including financial crisis and (ii) 2010-2018, excluding financial crisis. Next, Appendix: Complete table of FEVD includes more detailed results for the Forecast-error variance decomposition. Finally, Appendix: lnGHG reports the first stage results for lnGHG.

Keywords: Environmental stocks; greenhouse gas emissions; returns; risk.

JEL Classification: G12; G32; M14

Appendix: PVAR

Our panel-data vector autoregression treats all variables in the system as endogenous, while allows for unobserved individual heterogeneity. We, thus, specify a first order panel VAR model as follows:

$$w_{i,t} = \mu_i + \Phi w_{i,t-1} + e_{i,t}, \quad i = 1, \ldots, N, \; t = 1, \ldots, T, \tag{1}$$

where $w_{i,t}$ is a vector of (for simplicity of the exposition we consider a $2x2$ panel VAR) two random variables, Φ is a $2x2$ matrix of coefficients, μ_i is a vector of μ individual firm fixed effects and $e_{i,t}$ is a multivariate white-noise vector of residuals. As with standard panel VAR models, all variables depend on the past of all variables in the system, the main difference being the presence of the individual firm specific terms μ_i.

The system of equations (1) allows to proceed with dynamic simulations so as to estimate impulse response functions (IRF) and variance decompositions (VDC)[1]. In detail, we model *Stock Return, EP, Total Risk, Idiosyncratic Risk, Sharpe Ratio, Alpha and Systematic Risk*. For brevity we represent a system of equations between *Stock Return* (*Ret* thereafter) and *EP* as follows:

$$\begin{aligned} Ret_{i,t} &= \mu_{1i0} + \mu_{10t} + \alpha_{11} \sum_{j=1}^{J} Ret_{i,t-j} + a_{12} \sum_{j=1}^{J} EP_{i,t-j} + e_{1i,t}, \\ EP_{i,t} &= \mu_{2i0} + \mu_{20t} + \alpha_{21} \sum_{j=1}^{J} Ret_{i,t-j} + a_{22} \sum_{j=1}^{J} EP_{i,t-j} + e_{2i,t} \end{aligned} \tag{2}$$

$Ret_{i,t}$ and $EP_{i,t}$, and μ_{i0} and μ_{0t} are the firm and time fixed effects respectively.[2]

[1] As the system of equations (1) is reduced form a prior identification using the Choleski decomposition would be applied. Such identification requires that the ordering of variables that enter the VAR is selected so as that an exogenous variable would impact first on an endogenous variable. This implies a recursive orthogonal structure in the shocks $e_{i,t}$. The reverse causation would be also tested. It is worth noting that the ordering of variables is not of importance if the estimated covariances between the errors across equations are low, as it is the case herein.

[2] Sims (1980) in his original VAR analysis shows that the individual parameter estimates of the system of equations (2) are not of importance. Sims (1980) argues that the importance lies with the error terms of (2) as one could employ them to estimate IRF and VDC. To this end, we solve herein the estimated system of equations (2) to get its underlying moving average (MA) representation. Note, that this approach depends crucially on the assumption that the

Following Sims's argument of the importance of the errors terms in the system of equations (2), we employ a moving average (MA) representation where all variables in the panel VAR will be treated as endogenous variables that depend on the lagged residuals from the reduced form in (2). Hence, the MA representation refers to a system of equations for $Ret_{i,t}$ and $EP_{i,t}$ respectively on present and past residuals e_1 and e_2 as:

$$\begin{aligned} Ret_{i,t} &= a_{10} + b_{11}\sum_{j=1}^{\infty} e_{1i,t-j} + b_{12}\sum_{j=1}^{J} e_{1i,t-j}, \\ EP_{i,t} &= a_{20} + b_{21}\sum_{j=1}^{\infty} e_{2i,t-j} + b_{22}\sum_{j=1}^{J} e_{2i,t-j} \end{aligned} \tag{3}$$

The orthogonalized[3] MA representation is:

$$\begin{aligned} Ret_{i,t} &= a_{10} + \beta_{11}\sum_{j=1}^{\infty} \epsilon_{1i,t-j} + \beta_{12}\sum_{j=1}^{J} \epsilon_{1i,t-j}, \\ EP_{i,t} &= a_{20} + \beta_{21}\sum_{j=1}^{\infty} \epsilon_{2i,t-j} + \beta_{22}\sum_{j=1}^{J} \epsilon_{2i,t-j} \end{aligned} \tag{4}$$

and

$$\begin{pmatrix} \beta_{11j} & \beta_{12j} \\ \beta_{21j} & \beta_{22j} \end{pmatrix} = \begin{pmatrix} b_{11j} & b_{11j} \\ b_{11j} & b_{11j} \end{pmatrix} = P \begin{pmatrix} \epsilon_{1i,t} \\ \epsilon_{2i,t} \end{pmatrix} = P^{-1}\epsilon_{2i,t} \begin{pmatrix} e_{1i,t} \\ e_{2i,t} \end{pmatrix} \tag{5}$$

where P is the Cholesky decomposition of the covariance matrix of the residuals and:

underlying data generating process of our variables is stationary. Preliminary results show that our variables are stationary. This is true given that the time series dimension of our series is rather limited. Nevertheless, unit roots tests were carried out for all data, providing evidence of strong stationarity (results are available under request).

[3]Note that here we employ the Choleski decomposition as the identification strategy. As the residuals in 3 are correlated because of possible endogeneity the coefficients of the MA representation cannot be interpreted. We opt, therefore, to orthogonalize the residuals by multiplying the MA representation with the Cholesky decomposition of the covariance matrix of the residuals.

$$\begin{pmatrix} Cov(e_{1it}, e_{1it}) & Cov(e_{1it}, e_{2it}) \\ Cov(e_{2it}, e_{1it}) & Cov(e_{2it}, e_{2it}) \end{pmatrix} = PP^{-1} \tag{6}$$

The orthogonal residuals in (4) are shocks: ϵ_{1it} is a shock in Ret added and ϵ_{2it} is a shock in EP. To this end, the coefficients in the equations (4), β_j, are the impact multipliers of the underlying shocks and provide the current response of the endogenous variable in the left-hand side variable to shocks that would take place j periods ago.

Such MA representation where residuals are orthogonal we call it impulse response function (IRF). Thus, the IRF would provide the response of each endogenous variable in the system of equations (4) to shocks from each of the variables for j periods ahead. In our case the first IRF would provide estimates for the impact of a shock in EP on Ret for a chosen set of periods ahead and *vice versa*. We are primarily interested in the impact multiplier $\epsilon_{2i,t-j}$, which reflects the response of Ret to a shock in EP for different time horizons j. But since there are no theoretically motivated priors, it could be also the case that EP responds to shocks in Ret. The advantage of this reduced form panel-VAR specification is that we can assess the dynamic interdependencies between Ret and EP (as well as $Risk$) with the minimum of restrictions imposed.

References

Sims, C. A. (1980). Comparison of interwar and postwar business cycles: Monetarism reconsidered. *The American Economic Review*, 70(2):250–257.

Appendix: Sub-sample results

Table A.1: Reproducing Table 4 (of the main document) using the sub-period 2005-2009

	(1) Stock return	(2) Total risk	(3) Idios	(4) Sharpe	(5) Alpha	(6) Systematic
EP	0.1119***	-0.1381***	-0.1347***	0.0284***	0.0064	0.0097
	(0.0308)	(0.0515)	(0.0495)	(0.0091)	(0.0069)	(0.0260)
Lev	0.0003**	-0.0047	0.0004	0.0001	-0.0000	0.0004
	(0.0001)	(0.0030)	(0.0011)	(0.0002)	(0.0001)	(0.0005)
Spread	-0.0420	-5.0809***	-1.1644***	0.0647	-0.0311	0.5718
	(0.1493)	(0.9769)	(0.4031)	(0.0737)	(0.0837)	(0.3767)
lnVol	-0.2370***	0.3612***	0.5313***	-0.0975***	0.0066	0.0661**
	(0.0304)	(0.0673)	(0.0606)	(0.0111)	(0.0067)	(0.0279)
Liq	0.0014	0.3393***	0.0384	0.0035	0.0012	-0.0394
	(0.0291)	(0.1009)	(0.0700)	(0.0128)	(0.0125)	(0.0445)
BMV	-0.0376**	0.2353***	0.0418***	-0.0050**	-0.0051***	-0.0085
	(0.0184)	(0.0254)	(0.0134)	(0.0025)	(0.0019)	(0.0073)
Sales growth	0.0683	0.0724	0.0663	0.0068	0.0110	0.0903
	(0.0989)	(0.3174)	(0.1271)	(0.0232)	(0.0238)	(0.1176)
Constant	2.0924***	-2.2822**	-5.0186***	1.0481***	-0.1632	-0.3602
	(0.4954)	(1.0536)	(1.0442)	(0.1908)	(0.1120)	(0.4936)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.1038	0.3100	0.1094	0.0405	0.0360	0.0759
N	450	450	450	450	450	450

Notes: As a robustness, we excluded the latest period of our sample (2010-2018) and we re-estimate Table 4. Results are qualitative very similar. This table reports random and fixed effects regressions between EP and financial performance measures with other covariates. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses.

Table A.2: Reproducing Table 4 (of the main document) using the sub-period 2010-2018

	(1) Stock return	(2) Total risk	(3) Idios	(4) Sharpe	(5) Alpha	(6) Systematic
EP	0.0010	-0.0332**	-0.0909***	0.0048*	-0.0020	0.0066
	(0.0095)	(0.0145)	(0.0153)	(0.0028)	(0.0032)	(0.0170)
Lev	0.0007	0.0018**	-0.0005	0.0002*	-0.0004	-0.0006
	(0.0004)	(0.0007)	(0.0006)	(0.0001)	(0.0003)	(0.0009)
Spread	0.0195	-1.8714**	-0.2992	-0.0414	0.0004	-0.9525
	(0.2425)	(0.7437)	(0.5629)	(0.0990)	(0.2060)	(0.7693)
lnVol	0.0174	0.2502***	0.3167***	-0.0085*	-0.0022	0.0652***
	(0.0107)	(0.0211)	(0.0243)	(0.0045)	(0.0027)	(0.0200)
Liq	0.0060	0.0149	-0.0186	0.0043**	-0.0025	0.0130
	(0.0039)	(0.0134)	(0.0115)	(0.0022)	(0.0038)	(0.0162)
BMV	-0.0622***	0.1737***	0.0026	-0.0191***	0.0002	0.0001
	(0.0145)	(0.0119)	(0.0100)	(0.0019)	(0.0026)	(0.0132)
Sales growth	0.0140	-0.0740	0.0239	0.0077	0.0020	0.0134
	(0.0145)	(0.0475)	(0.0353)	(0.0067)	(0.0151)	(0.0677)
Constant	-0.1392	-1.3227***	-2.5831***	0.1323*	0.0000	-0.3482
	(0.1973)	(0.3513)	(0.3915)	(0.0723)	(.)	(0.3666)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2844	0.4222	0.0765	0.2898	0.0112	0.0378
N	1781	1781	1781	1781	1781	1781

Notes: As a robustness, we excluded the initially period of our sample (2005-2009) and we re-estimate Table 4. Results are qualitative very similar. This table reports random and fixed effects regressions between EP and financial performance measures with other covariates. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses.

Appendix: Complete table of FEVD

Table A.3: Forecast-error variance decomposition

Response	Impulse:	Stock return	EP	Total Risk	Idios.	Sharpe	Alpha	Systematic
Stock return								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	2	0.930	0.000	0.039	0.003	0.027	0.001	0.000
	3	0.929	0.000	0.039	0.003	0.027	0.001	0.000
	4	0.929	0.001	0.039	0.003	0.027	0.001	0.000
	5	0.928	0.003	0.039	0.003	0.027	0.001	0.000
	6	0.924	0.006	0.038	0.003	0.027	0.001	0.000
	7	0.918	0.013	0.038	0.003	0.027	0.001	0.000
	8	0.903	0.030	0.037	0.003	0.026	0.001	0.000
	9	0.872	0.063	0.036	0.003	0.025	0.001	0.000
	10	0.812	0.129	0.033	0.002	0.023	0.001	0.001
EP								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.212	0.788	0.000	0.000	0.000	0.000	0.000
	2	0.255	0.739	0.002	0.000	0.001	0.000	0.002
	3	0.257	0.733	0.005	0.000	0.002	0.000	0.002
	4	0.258	0.732	0.005	0.000	0.002	0.000	0.003
	5	0.258	0.731	0.006	0.000	0.002	0.000	0.003
	6	0.258	0.731	0.006	0.000	0.002	0.000	0.003
	7	0.258	0.731	0.006	0.000	0.002	0.000	0.003
	8	0.258	0.731	0.006	0.000	0.003	0.000	0.003
	9	0.258	0.731	0.006	0.000	0.003	0.000	0.003
	10	0.258	0.731	0.006	0.000	0.003	0.000	0.003
Total Risk								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.346	0.154	0.500	0.000	0.000	0.000	0.000
	2	0.407	0.301	0.286	0.002	0.000	0.000	0.005
	3	0.356	0.467	0.169	0.001	0.002	0.000	0.005
	4	0.312	0.590	0.091	0.001	0.002	0.000	0.004
	5	0.284	0.662	0.047	0.000	0.002	0.000	0.003
	6	0.270	0.699	0.025	0.000	0.002	0.000	0.003
	7	0.263	0.716	0.015	0.000	0.002	0.000	0.003

	8	0.260	0.724	0.010	0.000	0.003	0.000	0.003
	9	0.259	0.728	0.008	0.000	0.003	0.000	0.003
	10	0.258	0.730	0.007	0.000	0.003	0.000	0.003
Idiosyncratic								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.190	0.120	0.238	0.452	0.000	0.000	0.000
	2	0.309	0.245	0.162	0.278	0.000	0.000	0.006
	3	0.313	0.405	0.101	0.174	0.001	0.000	0.006
	4	0.293	0.544	0.059	0.097	0.002	0.000	0.005
	5	0.277	0.636	0.032	0.049	0.002	0.000	0.004
	6	0.267	0.686	0.018	0.023	0.002	0.000	0.003
	7	0.262	0.710	0.012	0.011	0.002	0.000	0.003
	8	0.260	0.721	0.009	0.005	0.002	0.000	0.003
	9	0.259	0.727	0.007	0.002	0.003	0.000	0.003
	10	0.258	0.729	0.006	0.001	0.003	0.000	0.003
Sharpe								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.767	0.001	0.013	0.002	0.217	0.000	0.000
	2	0.751	0.001	0.018	0.004	0.222	0.003	0.000
	3	0.750	0.002	0.018	0.004	0.222	0.003	0.000
	4	0.749	0.003	0.018	0.004	0.221	0.003	0.000
	5	0.747	0.006	0.018	0.004	0.220	0.003	0.000
	6	0.743	0.013	0.018	0.004	0.218	0.003	0.000
	7	0.733	0.027	0.018	0.004	0.214	0.003	0.000
	8	0.713	0.058	0.017	0.004	0.205	0.003	0.000
	9	0.672	0.118	0.016	0.004	0.187	0.003	0.001
	10	0.603	0.220	0.015	0.003	0.156	0.002	0.001
Alpha								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.001	0.000	0.000	0.000	0.001	0.997	0.000
	2	0.002	0.002	0.000	0.002	0.001	0.992	0.001
	3	0.003	0.005	0.000	0.003	0.001	0.987	0.001
	4	0.006	0.012	0.000	0.002	0.001	0.976	0.001
	5	0.012	0.029	0.000	0.002	0.001	0.953	0.001
	6	0.025	0.064	0.001	0.002	0.001	0.906	0.002
	7	0.048	0.130	0.001	0.002	0.001	0.816	0.002
	8	0.086	0.240	0.002	0.002	0.001	0.666	0.002
	9	0.136	0.384	0.003	0.001	0.002	0.472	0.002
	10	0.185	0.521	0.004	0.001	0.002	0.285	0.002

Systematic								
	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	1	0.000	0.001	0.001	0.000	0.000	0.021	0.977
	2	0.000	0.003	0.001	0.001	0.002	0.022	0.971
	3	0.002	0.007	0.001	0.001	0.002	0.021	0.964
	4	0.006	0.017	0.001	0.001	0.002	0.021	0.951
	5	0.014	0.037	0.001	0.001	0.002	0.021	0.924
	6	0.029	0.080	0.002	0.001	0.002	0.019	0.867
	7	0.056	0.158	0.002	0.001	0.002	0.017	0.763
	8	0.099	0.281	0.003	0.001	0.002	0.013	0.601
	9	0.151	0.427	0.004	0.001	0.002	0.009	0.406
	10	0.196	0.555	0.005	0.000	0.002	0.005	0.236

Appendix: lnGHG

Table A.4: Predicting lnGHG

lnGHG	Coef.	Std. Err.	P-value
CT	0.0558	0.0304	0.067
lnTang	-0.0417	0.0274	0.128
lnInta	-0.0667	0.0185	0
lnEmp	0.3245	0.0361	0
ESG disclosure	0.0026	0.0014	0.058
lnTA	0.5757	0.0535	0
Liq	-0.0364	0.0175	0.037
Tobin's Q	-0.0114	0.0176	0.518
Lev	-0.0008	0.0012	0.497
Year:			
2006	-0.0095	0.0554	0.863
2007	-0.0378	0.0541	0.484
2008	-0.0662	0.0562	0.238
2009	-0.1154	0.0543	0.034
2010	-0.1025	0.0543	0.059
2011	-0.1629	0.0551	0.003
2012	-0.1868	0.0553	0.001
2013	-0.2246	0.0562	0
2014	-0.2635	0.0570	0
2015	-0.3538	0.0583	0
2016	-0.3899	0.0599	0
2017	-0.4172	0.0618	0
2018	-0.4466	0.0684	0
Industry:			
Consumer Discretionary	-2.2955	0.2846	0
Consumer Staples	-1.6514	0.3002	0
Energy	-0.0202	0.3410	0.953
Financials	-3.6112	0.5098	0
Health Care	-2.8588	0.3018	0
Industrials	-1.9214	0.2831	0
Real estate	-1.2940	0.7542	0.086
Technology	-3.0859	0.2921	0
Telecommunications	-2.6426	0.3848	0
Utilities	1.5665	0.3203	0
Constant	4.2301	0.6041	0
N	2,260		
R^2	0.7471		

Notes: Random effect regression for estimating lnGHG as shown in equation 10 of the main document. These coefficients have been used to generate lnGHG values.