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Does it pay to invest in environmental stocks?

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Abstract

This paper examines market based returns and risks of environmental vis-à-vis non environmental stocks from a portfolio selection point of view. The selection of environmental stocks is a function of greenhouse gas emissions of firms in S&P 500 for the period from 2005 to 2018. Our findings show that stocks with superior environmental performance have lower idiosyncratic risk, but higher systematic risk. Results reveal that it pays to invest on environmental stocks while we also control for endogeneity. Robustness analysis, such as counterfactual regressions and panel VAR, confirm main findings and demonstrate some of underlying complexities.

Keywords: Environmental stocks; portfolio selection; returns; risk.
JEL Classification: G12; G32; M14

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1 Introduction

Although a plethora of studies show a positive association between environmental investment and performance as measured by accounting ratios (Konar and Cohen, 2001; Aggarwal and Dow, 2012; Matsumura et al., 2014), the focus on portfolio selection based on market returns and risk of environmental stocks has been rather neglected (Galema et al., 2008). The purpose of this paper is to shed light on whether investing on environmental stocks is justified from a portfolio selection point of view. Accordingly, we provide an identification that encompasses market-based and risk-adjusted stock performance measures such as Sharpe ratio (Sharpe, 1964) and by utilising Fama-French Five Factor (FF5) modelling (Fama and French, 2015).

Following from the seminal research of Markowitz (1952) and Sharpe (1964) investors preferences have been analysed based on the notion that there should be a trade off between risk and return. Various modelling approaches have ever since been proposed with reference to the the mean and variance of underlying portfolio assets. In this paper we propose to model market-based performance for investors who forms their preferences in terms of environmental considerations of the underlying portfolio assets. To this end, we propose to investigate whether there are environmental cautious investors and whether their preferences towards environmental investments pay out.

Theoretically, we link the socially responsible investing (SRI) with the market-based financial performance. Out study is further motivated by the fact that in the US, the SRI assets market is steadily growing, reaching \$12 trillion in 2018. We attempt to provide evidence on whether this growth is driven by asset managers and institutional investors, who lean towards environmental, social and governance (ESG) criteria in their portfolios allocations (US SIF, 2018), given the underlying risk and return. More specifically, we focus on a component of socially responsible investing which can be closely linked to sustainable investment in response to the challenges that climate change brings. These challenges have been escalated in recent years (IPCC, 2014). Due to this fact, investment sentiment might lean towards environmental friendly assets (Fama and French, 2007; Lagoarde-Segot and Paranque, 2018) as well as to high returns.

In recent years, a growing literature such as Griffin et al. (2017); Baker et al. (2018); Benz et al. (2019); Krueger et al. (2019) and Engle et al. (2020) focus on environmental performance (EP thereafter) of firms and report that firms with high EP are also associated with high profitability. Commonly, profitability is measured by accounting ratios (e.g., ROA, ROE) but also by Tobin's Q. Environmental investing is known to benefit firms in terms of long-term operational costs (Hart and Ahuja, 1996), and in terms of compliance with regulation and social norms, which complement SRI (Reinhardt and Stavins, 2010). Therefore, we focus on identifying on whether a component of SRI; namely EP, is justified in terms of higher market-based returns whilst we also control for market risk.

We differentiate from prior studies by focusing on market-based returns and financial risk. Previous studies mainly refer to the observation that SRI stocks can be associated with higher returns due to the effects of asymmetric information (Merton, 1987; Galema et al., 2008). SRI firms disclose more transparent and higher quality of financial information that would lead to higher evaluations of these stocks (Fama and French, 2007; Grougiou et al., 2014). According to Galema et al. (2008), differences in demand due to SRI can explain why responsible firms might experience higher demand for their shares that would increase market returns vs. non-responsible firms. However, empirical results report that SRI stocks have no effect on pricing in capital markets (Widyawati, 2019). Instead, we investigate the close association between market return, financial risk and EP. The association between EP and risk-adjusted returns would shed light on whether the EP is valid for portfolio management. Against this background, the objective of this study is to bring into the forefront all possible associations between environmental performance and financial performance simultaneously; EP-return, EP-risk as well as EP-risk-adjusted return.

In terms of measurement, environmental firms are considered firms that have lower greenhouse gas (GHG) emissions than their competitors. In the literature, EP, environmental performance (or sometimes carbon performance), is also defined as inverted ratio of firm's GHG emissions relative to its size (Aggarwal and Dow, 2012; Misani and Pogutz, 2015).[1] It appears that there is strong link between environmental and financial performance and indicates, to a certain extent, that it is profitable for a firm to invest in clean-technologies (Hart and Ahuja, 1996; Albertini, 2013; Cumming et al., 2016). Likewise, there is a strong link between EP and firm risk. Their connection is justified since the long term operational cost and the cost of capital are lower for environmental firms (Sharfman and Fernando, 2008). Therefore, it seems that environmental firms are able to offset the so-called carbon risk(Jung et al., 2018).[2]

Our contribution is five-fold: First, we contribute to the literature that investigates how different types of assets (in our case environmental stocks) would improve the performance of an investment portfolio (e.g Brzeszczyński and McIntosh, 2014; Ang et al., 2009; Fama and French, 2015). Given the close association between market return and financial risk, we include in our analysis a compre-

[1] Literature has provided many ways to measure environmental performance (see for example, Dyck et al., 2019; Boiral et al., 2020), however, our approach aims to emphasise on the role of carbon emissions - frequently referred in the literature as carbon performance (Luo and Tang, 2014) -.

[2] Carbon risk is defined as the financial risk, which is associated with the transition of firms to low-emissions economy.

hensive list of different financial variables. Second, to the best of our knowledge, we examine, for the first time, the association between EP and risk-adjusted returns. Understanding the effects of EP on the risk-adjusted performance not only gives a more complete picture about the investment decisions towards an environmental stock portfolio, but also offers a potential avenue to reconcile ambiguous research findings (Albertini, 2013; Endrikat et al., 2014; Busch and Lewandowski, 2017). Reasonably, high returns might be associated with high risk - this has been neglected in the previous studies - thus, the risk-adjusted performance might be instrumental towards unravelling this relationship. Third, we shed light on which CSR-economic theory is more relevant in a financial context. According to *neoclassic theory*, EP has a negative impact on firms' performance, while the opposite is true for *stakeholder theory*. Fourth, the financial performance and EP relationship is more likely to be endogenous. Studies have attempted to deal with this issue by adopting different econometric techniques (see, inter alia Al-Tuwaijri et al., 2004; Bansal, 2005; Farag et al., 2015). Our dynamic approaches not only control for endogeneity but also report the market-based variables that influence the EP. Lastly, in our study we offer new evidence from the S&P 500 index for the period 2005–2018, in light also that public debate in US over climate change has gained much prominence.

The results show that environmental stocks would offer higher returns, would have lower idiosyncratic and total risk. Interestingly, their systematic risk appears either positive or insignificant. The overall risk-adjusted performance, measured my means of Sharpe ratio, of environmental stocks clearly outperforms non-environmental stocks, but it is insignificant when FF5 Alpha is considered. We, further, form a portfolio based on industries and results demonstrate that all portfolios have benefits from superior environmental performance, with largest gainers being Consumer Discretionary, Energy, Financial and Health Care portfolios. The main findings of the paper are robust under different specifications. Particularly, by instrumenting greenhouse gases at a firm level with other firm-specific and governance characteristics, the results appear even stronger. Controlling for endogeneity with dynamic panel and panel auto-regressive models, results remain unaltered. Noteworthy, we document that there is a bi-directional relationship between total risk and EP.

The remainder of the paper is organised as follows. Section 2 describes the literature review and develops the hypotheses of the study. Section 3 presents the research design; data, risk and return measures as well as the econometric methods. Section 4 reports the results. In Section 5, we present some robustness checks. Lastly, the paper concludes with Section 6.

2 Literature review and hypotheses

2.1 Background of the CSR literature

The investigation between CSR and firm's financial performance has provided a variety of studies and theories. CSR plays an essential role in promoting stakeholders' interests and influencing the profitability and risk of firms. The connection between CSR and risk-return is based on a rather complex theoretical framework. The objective of various CSR theories is to respond whether CSR improves risk-return of firms or not.

It is possible that CSR would decrease returns and increase risk, which is supported by the trade-off view, implying that CSR investments merely reduce firms' cash-flows. This negative output of CSR can be attributed to the higher cost that firms have to bear. In fact, *neoclassical theory* shows that some firms experience high compliance costs and therefore would face a competitive disadvantage (Wagner et al., 2002). In a similar vein, the *agency theory* argues that CSR is in conflict with the main objective of the firm (e.g. maximise shareholder value) and hence CSR would only decrease shareholders' satisfaction (Jensen and Meckling, 1976).

On the contrary, a different theoretical framework suggests that CSR increases the value of the firm. This positive link between CSR and risk-return is proposed by the *instrumental stakeholder theory*, which assumes that CSR projects establish a consistent strategy that increase the intangible assets, reduce future uncertainty about legal issues and develop dynamic capabilities that attract shareholders. The theory is a combination of the *legitimacy theory*, which suggests that firms will adhere to social demands, and the *agency theory*. It states that trust and cooperation among company's stakeholders can create a competitive advantage (Jones, 1995). For example, by satisfying investors' demands concerning climate change, firms may improve investors' loyalty and might be better equipped to respond more effectively to external demands (Endrikat et al., 2014; Tzouvanas et al., 2020b).

In terms of the empirical studies, evidence shows that firms with strong CSR would also generate strong profits (Orlitzky and Benjamin, 2001). Some of this literature includes studies such as Bansal (2005); Ferreira and Laux (2007); Humphrey et al. (2012) Bouslah et al. (2013); Mishra and Modi (2013); Dimson et al. (2015); Becchetti et al. (2015); Ng and Rezaee (2015); Cheung (2016); Ferrell et al. (2016); Benlemlih et al. (2016); Liang and Renneboog (2017); Sun and Gunia (2018); Griffin et al. (2018); Jung et al. (2018); Dyck et al. (2019); Albuquerque et al. (2019) and Chen et al. (2020). The above literature investigates how CSR strengths and weaknesses can impact the profitability of firms, or firm risk (total, systematic and idiosyncratic risk). The main result is that CSR activities would reduce risk and the cost of capital, at the same time they diminish agency problems, create a product differentiation and thus improve management practices. In terms of profitability, in fact, CSR attracts various stakeholders that in turn they increase the firm's stock price.

Even though, the majority of the studies find that CSR increases firm's value and decreases risk, the definition of CSR has attracted some criticism. In particular, Ding et al. (2016) claim that conventional aggregation of CSR scores are subject to aggregation bias. Therefore, empirical findings should be interpreted with caution, unless the CSR components are to be examined.

2.2 Environmental stocks and portfolio selection

There is a large literature with long roots that focuses on the relationship between environmental performance and firm performance. Environmental performance is normally approximated by the greenhouse gas (GHG) emissions, whilst firm performance is mainly measured with accounting ratios (e.g. ROA, ROE). Among others, Hart and Ahuja (1996); Konar and Cohen (2001); Aggarwal and Dow (2012); Matsumura et al. (2014); Endrikat et al. (2014); Clarkson et al. (2015); Misani and Pogutz (2015); Busch and Lewandowski (2017); Griffin et al. (2017); Baker et al. (2018); Benz et al. (2019); Krueger et al. (2019) and Engle et al. (2020) show that lower GHG would increase the firm's financial performance, increases the equity valuation, decrease the costs of forecasts and generally makes firms more attractive to various stakeholders (see also Oikonomou et al., 2012). Heightened environmental performance implies that firms develop new clean technologies, which decrease the long-term operational costs attracts various stakeholders and thus improving the future prospects of the firm (Hart and Ahuja, 1996). However, only few studies find that environmental performance has either negative or no effect on profitability (Wagner et al., 2002; Farag et al., 2015).

While there are abundant empirical studies that investigate the effects of EP on either returns or risk (e.g. Misani and Pogutz, 2015; Benlemlih et al., 2016), there is a lack of empirical evidence regarding the risk-adjusted returns. Also, few studies have considered the risk-adjusted performance of CSR stocks (Galema et al., 2008; Chan and Walter, 2014; Blankenberg and Gottschalk, 2018), but neglected testing for environmental stocks. We expand on this literature based on the seminal research of Markowitz (1952) and Sharpe (1964) to investigate whether investing on environmental stocks is justified from a portfolio selection point of view. We model so as to identify whether an investor that forms their preferences in terms of environmental considerations when selecting underlying portfolio assets is payed out. To this end, we provide a identification that encompasses market based risk-adjusted performance such as Sharpe ratio whereas we also consider Fama-French Five Factor modelling. Informed by previous empirical studies on EP and the *stakeholder theory* our first hypothesis is as follows:

Hypothesis 1: Portfolio selection of environmental stocks is justified in terms of higher risk weighted stock returns vis-à-vis non-environmental stocks.

Besides the relationship between environmental performance and return, we also consider the association between the former and risk (Mishra and Modi, 2013; Baker et al., 2018; Benz et al., 2019; Engle et al., 2020; Krueger et al., 2019; Tzouvanas et al., 2020b). To be more explicit, the risk of financial investment (or otherwise total risk) can be decomposed into the systematic and idiosyncratic components. Several studies have argued that environmental performance affects systematic risk because based on the portfolio theory only systematic risk is priced in financial markets (Albuquerque et al., 2019), while others imply that environmental performance is associated with idiosyncratic risk because EP is firm specific (Bouslah et al., 2013). Our expectation is that superior environmental performance should decrease the financial risk as it acts as an insurance policy for the investors (Lins et al., 2017). We will proceed to analyze all these three risk types as they have also been rather neglected in previous studies (Orlitzky and Benjamin, 2001).

Hypothesis 2: Environmental stocks have lower total risk, systematic risk and idiosyncratic risk compared to non-environmental stocks.

Lastly, endogeneity could be a concern as environmental performance, risk and stock return might be all endogenous variables (Busch and Lewandowski, 2017; Misani and Pogutz, 2015). It is possible to assume that firms with available capital are able to invest more in environmental projects, leading to a situation where financial performance impacts EP (Orlitzky and Benjamin, 2001; Tzouvanas et al., 2020a). If this reverse causality is true, our estimations may suffer from endogeneity. To examine for such endogeneity we would also imply a different identification strategy, i.e. we shall opt for a type of 2SLS analysis, dynamic panel analysis and a panel Vector Autoregessive system of equations whereby all variables are treated as endogenous.

Hypothesis 3: There is a bi-directional causal relationship between risk-adjusted returns and environmental stocks.

3 Research design

3.1 Measuring environmental performance, risk and return

Literature has provided various ways to measure the environmental performance of firms. For example, Dyck et al. (2019) derived a score from the environmental strengths and weaknesses, Boiral et al. (2020) conducted some interviews in order to understand in depth what practitioners really think about sustainability risk measures. However, our approach is slightly different. We focus on a component of the environmental performance, which is inevitably related to climate change; namely GHG emissions. Following King and Lenox (2001); Wagner (2005); Aggarwal and Dow (2012); Cormier and Magnan (2015); Misani and Pogutz (2015); Tzouvanas et al. (2020a), we define EP as the reverse logarithmic ratio of GHG emissions reported by the firm (scope 1 and scope 2) to market value standardised by the average industry GHG emissions.

$$EP_{i,t} = \Big[\frac{ln(GHG_{i,t}) - ln(Industry\ GHG_{j,t})}{ln(Market\ Value_{i,t})}\Big]^{-1}, \tag{1}$$

where i is the firm, t is the year and j is the industry where firm i is classified. Higher values correspond to better environmental performance, this measure avoids high skewness while controlling for the market size of the firms, as well as capturing industry-relative EP performance.

3.2 Risk-return measures

Regarding risk and return measures, we opt to employ a variety of measures to enhance the robustness of our empirical analysis. First we measure stock return as:

$$Stock\ Return_{i,t} = ln\frac{Price_{i,t}}{Price_{i,t-1}} \times 100\%, \tag{2}$$

where i is the firm and t is the year.

To consider returns adjusted for risk we opt for Sharpe ratio that measures the annual financial performance (returns) of EP portfolios adjusted for risk.

$$Sharpe\ Ratio_{i,t} = \frac{Stock\ Return_{i,t} - R_{f,t}}{Total\ Risk_{i,t}}, \tag{3}$$

where $R_{f,t}$ is the risk free rate of year t.

In terms of risk, we employ several measures: First, firm's total risk also matters as indicated by Bouslah et al. (2013) and Benlemlih et al. (2016). *Total Risk* includes both the systematic and idiosyncratic risk components and can be measured as the annualized standard deviation of the daily stock returns.

$$Total\ Risk_{i,t} = \sigma(StockReturn_{i,d}) \times \sqrt{K} \times 100\%, \tag{4}$$

where i is the firm and d is the day and k corresponds to trading days of any year given with $k \approx 251$

Following from the capital asset pricing models, such as the three-factor (Fama and French, 1993) and four-factor (Carhart, 1997) models have been extensively used in the empiral literature (Ang et al., 2006, 2009; Mishra and Modi, 2013; Bouslah et al., 2013; Cai et al., 2016). Similar to Qadan (2019), we build our approach on the comprehensive five-factor capital asset pricing model following Fama and French (2015):

$$R_{i,d}-R_{f,d} = \alpha_i+\beta_{i,1}(R_{m,d}-R_{f,d})+\beta_{i,2}SMB_d+\beta_{i,3}HML_d+\beta_{i,4}RMW_d+\beta_{i,5}CMA_d+u_{i,d}, \tag{5}$$

the left part of the equation corresponds to the excess stock return, FF5 Alpha (α_i) shows the performance of a stock relative to the market portfolio, $(R_{m,d} - R_{f,d})$ is the excess return on the market portfolio, the second factor (SMB_d) measures the return of small over large stocks, (HML_d) the return of value over growth stocks, RMW is the difference of stock returns between robust and weak profitability firms, CMA is the return of low over high investment firms and $u_{i,d}$ is the residuals. $R_{m,d}, R_{f,d}, SMB_d, HML_d, RMW_d$ and CMA_d values for the US market are retrieved from *Kenneth R. French website*. Data on stock prices is obtained from Datastream. All the aforementioned values are on a daily frequency (d) for all 500 firms for the 14 year period. We next run time series regressions to Equation (5) by assuming that the residuals are normally distributed with zero mean and constant variance. We repeat this procedure for every firm and each year of the sample in order to obtain 14 different variances per firm. Then, we retain the constant (a_i) as measure of the relative performance of the firms and $\beta_{i,1}$, which denotes the systematic risk.

Following Fu (2009) we also measure idiosyncratic risk by estimating the daily return process, using the mean equation of the Fama-French five-factor model (equation 5), while the variance equation is specified in equation 6. The conditional (on the information set at time d-1) distribution of residual is assumed to be normal with the mean of zero and the variance of σ^2. The objective is to estimate the conditional variance σ^2, that is a function of the lagged residuals. For this reason, EGARCH (1, 1)[3] is employed. The model is employed independently for each

[3] Fu (2009) considers different lag orders (e.g. EGARCH(p,q)) and shows that EGARCH(1,1) was the appropriate model in 7.4% of the cases.

individual stock for every different year. We also require firms to have at least 30 daily returns to be eligible for estimation otherwise, the models do not converge.

$$ln\sigma^2_{i,d} = \alpha_i + \sum_{l=1}^{p} b_{i,l} ln\sigma^2_{i,d-1} + \sum_{k=1}^{q} c_{i,k} \left\{ \theta\left(\frac{\epsilon_{i,d-k}}{\sigma_{i,d-k}}\right) + \gamma\left[\left|\frac{\epsilon_{i,d-k}}{\sigma_{i,d-k}}\right| - (2/\pi)^{1/2}\right]\right\}, \quad (6)$$

where $ln\sigma^2_{i,d}$ is the conditional idiosyncratic volatility (*Idiosyncratic Risk*).

3.3 Data and summary statistics

The sample consists of 500 firms from the S&P500 index, covering a 14 year period from 2005 to 2018. The sample starts from 2005 because the unavailability of environmental data creates constrains for exploiting larger time series. We acknowledge that previous studies have already examined the US market (e.g. Delmas et al., 2015; Nollet et al., 2016), however, investigating the US market during this period (2005-2018) is of paramount importance for main two reasons. First, the S&P 500 is regarded as the best single gauge of large US firms. There is over $ 11.2 trillion indexed or benchmarked to this index, with its total market capitalisation being more than $24 trillion in 2020.[4] Second, we examine a period, when the US ratified the *Paris Agreement* in 2016, and one year after withdrew from it.[5] Thus, it is interesting to examine how investors perceive this alteration in the US climate change policy. The firm-year financial data have been jointly downloaded from Datastream and COMPUSTAT, while environmental data (i,e GHG, ESG, TC) from Datastream. Our daily stock return data have been retrieved from Datastream and the five factors, needed to construct the capital asset pricing model for the US market, are obtained from *Kenneth R. French website*.

[INSERT Table 1 HERE]

Table 1 reports the descriptive statistics of the variables of the study. In has to be noted that $lnGHG$ is the variable with the most missing values, 2975, while the financial variables enumerate more than 6000 valid firm-year observations. The average GHG emissions for the S&P500 index is around 932 (mean $lnGHG$ = 13.745) thousand metric tons for the examined period, with minimum 169 metric tones and maximum 166 million metric tones. The market value of the examined firms varies from 15.24 million dollars to 867.39 billion dollars with an average size of 14.17 (mean $lnMV$ = 16.467) billion dollars.

[4] See more about S&P500 index on: https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview

[5] See more about *Paris Agreement* on: https://treaties.un.org/Pages/ViewDetails.aspx?src=TREATY&mtdsg_no=XXVII-7-d&chapter=27&clang=_en

[INSERT FIGURE 1 HERE]

Figure 1 displays the return and risk of environmental against non-environmental stocks over the sample period. Apparently, environmental stocks seems to exceed non-environmental stocks both in return and risk.

[INSERT FIGURE 2 HERE]

Figure 2 illustrates the relationship between environmental performance and different financial performance measures. It seems that environmental performance increases the *Stock Return*, deceases both the *Total* and the *Idiosyncratic Risk*, and the overall stock performance, measured by *Alpha* and *Sharpe Ratio*, is improving. Surprisingly, environmental performance increases *Systematic Risk* and this warrants further investigation.

Next, in Table 2, we show how different portfolios sorted by environmental performance perform. It is evident that an environmental stock portfolio (High 6) outperforms in all aspects an non-environmental portfolio (Low 1), apart from the systematic risk. As previously noted, environmental stocks contain a high degree of systematic risk.

[INSERT Table 2 HERE]

3.4 Econometric methods

3.4.1 Panel data model

We now proceed with the identification. Following previous studies (e.g., Delmas et al., 2015; Nollet et al., 2016) we employ panel regression analysis as:

$$Y_{i,t} = a_0 + a_1 EP_{i,t} + \mathbf{X}'_{i,t}\phi + \sum_{t=2}^{T} \delta_t Year_t + \sum_{m=2}^{M} \delta_m Industry_m + e_{i,t}, \tag{7}$$

where the subscripts i and t correspond to firm and year respectively, $i = 1, 2, ..., n$ and $t = 1, 2, ..., T$ and $e_{i,t}$ the error term. Y denotes the dependent variable and could be the stock returns, financial risk or adjusted risk performance and $\mathbf{X}'$ is a vector that contains control variables (Lev, $Spread$ (Bid-Ask), $lnVol$, Liq, BMV and $Sales\ growth$). We also control for year and industry fixed effects, so a_0 intercept is refereed to the base year (2005) and industry (Basic materials) where $m = 1, 2, ..., M$. Particular attention should be placed on the variable of interest, which is the EP, and the coefficient we should observe is a_1.

The results are presented under the fixed effects and random effects models. For all different specifications, we use robust standard errors. Fixed effects model is appropriate when we focus on a specific firm characteristics (c_i) and therefore $e_{i,t}= v_{i,t} + c_i$ with $v_{i,t}$ being a time-varying error component. Note that in case of fixed effects model industry and country dummies are dropped from the model to avoid multicollinearity. Random effect model represents random draws from the population so that c_i allows for individual effects. Finally, we report the Hausman test in order to identify if the individual effects c_i are unobserved and are correlated with explanatory variables (Baltagi, 2008; Oikonomou et al., 2012).

3.4.2 Dynamic panel data model

The problem of endogeneity which has been reported continuously should be carefully considered (Tamazian and Bhaskara Rao, 2010; Coban and Topcu, 2013; Albertini, 2013; Endrikat et al., 2014; Busch and Lewandowski, 2017). Endogeneity arises due to simultaneity or omitted variable bias. Riskier and more profitable firms normally undertake more environmental projects and thus risk-return and EP might be endogenous (Orlitzky and Benjamin, 2001). This is because it involves a commitment to financially support environmental actions. Therefore, financial performance might influence the environmental performance of firms. Endogeneity in panel data is commonly controlled with generalized method of moments model (GMM) or with two-stage least squares (2SLS). The main advantage of GMM is that it can treat all control variables as endogenous as well as there is no need to identify exogenous instruments. Identifying exogenous variables to instrument the endogenous variable may be challenging task and eventually may never be exogenous precisely (Broadstock et al., 2018). For this reason, GMM relies on internal instruments (lagged values or internal transformation). For example, it may not be the current environmental performance that affects stock returns, but rather the previous year's performance could be playing a significant role.

A system of generalized method of moments (Sys-GMM), which is proposed by Blundell and Bond (1998), can control for endogeneity in our estimations. Hence, equation 7 is now tested with dynamic panel model:

$$Y_{i,t} = a_0 + a_1 EP_{i,t} + \beta_1 Y_{i,t-1} + \mathbf{X}'_{i,t}\phi + \sum_{t=3}^{T} \delta_t Year_t + \sum_{m=2}^{M} \delta_m Industry_m + e_{i,t}, \quad (8)$$

the equation 8 is instrumented with lagged values of the explanatory variables. However, lagged values are usually weak instruments and thus Sys-GMM combines the first-difference estimator with the estimator in levels in order to efficiently deal with endogeneity. The description of the variables is as above and again $e_{i,t} = v_{i,t} + c_i$ is referred to the typical fixed effects components of the error term, with the assumption that $E(v_{i,t}) = E(c_i) = E(v_{i,t}c_i) = 0$, for $i = 1, .., n$ and $t = 2, .., T$.

In order to satisfy the orthogonality condition, we collapse instruments after two lags as proposed by Roodman (2009) because large number of instruments would lead to finite sample bias and therefore we assume that $E(Y_{i,t-1}\Delta v_{i,t}) = E(\Delta Y_{i,t}v_{i,t-1})= 0$. Also, Hansen's (1982) J-test measures the validity of instruments. We also use two-step Sys-GMM which is based on corrected standard errors (Windmeijer, 2005).

3.4.3 Panel VAR approach

We additionally argue that risk, return and environmental performance are all endogenously related. In detail, 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:

$$w_{i,t} = \mu_i + \Phi w_{i,t-1} + e_{i,t}, \quad i = 1, \ldots, N, \; t = 1, \ldots, T, \tag{9}$$

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 (See more about the PVAR approach on the Online Appendix).

4 Results

4.1 The impact of environmental performance on return, risk

Table 3 reports results based on equation 7 without considering any control variable. Columns (1) to (6) display results having as dependent variable *Stock Return*, *Total Risk*, *Idiosyncratic Risk*, *Sharpe Ratio*, *Alpha* and *Systematic Risk*, respectively. According to Hausman specification test, in columns (1), (3) and (4) fixed effects model is used, otherwise random effects. Our regressions enumerate 2953 valid observations. Environmental performance (EP) can explain a large proportion of the variability of the dependent variables, except from the *Alpha* and *Systematic Risk*, where their R^2 is around 1% and 3%, respectively. Importantly, the results reveal that EP increases *Stock Return* (coef.=0.0306, $p<0.01$), decreases both total (coef.=-0.1145, $p<0.01$) and idiosyncratic risk (coef.=-0.0863, $p<0.01$) and the overall return-risk-adjusted performance (*Sharpe Ratio*) is improved (coef.=0.0159, $p<0.01$). However, *Alpha* is unaffected by EP, while EP increases the *Systematic Risk* (coef.=0.0246, $p<0.05$).

[INSERT Table 3 HERE]

4.2 Environmental performance, risk and return with control variables

Next, we consider a set of control variables as a part of our robustness checks. Therefore, we run the same estimations by considering the following control variables. Note that we also control for the time and industry fixed effects (Mishra and Modi, 2013). For example, during financial crisis firms might experience low returns and high risk. In addition, firms in different industries have substantially different levels of risk and return.

Table 4 reports results based on equation 7 by considering several control variables. The estimations reveal that *EP* decreases *Total Risk* (coef.=-0.0580, $p<0.05$) and *Idiosyncratic Risk* (coef.=-0.0556, $p<0.01$) and *Sharpe Ratio* (coef.=0.0087, $p<0.01$) is increasing. The effect of *EP* on *Stock Return*, *Alpha* and *Systematic Risk* is confirmed once again to be unimportant.[6]

[INSERT Table 4 HERE]

In terms of control variables, we expect that leverage increases the expected equity returns and holds asset volatility and expected returns at equilibrium. Therefore, leverage should have an effect on firm's risk as well as the stock returns (Psillaki et al., 2010). Leverage (*Lev*) is calculated as the total debt to total (shareholder) equity ratio. However, significance is an issue in results reported in Table 4. As liquidity measure we opt for the bid-ask spread which measures the average annual bid-ask spread over the previous year bid-ask spread for each stock (Ang et al., 2006, 2009). Results show that an increase in *Spread* would increase the risk and reduces the stock returns. Studies find that firms with high trading volume ($lnVol$) have higher returns (Ang et al., 2006, 2009). Also, trading volume might provide more liquidity to the investors and thus lower risk. Our results show variability. Another liquidity proxy (*Liq*), measured as the ratio between current assets and current liabilities, is argued to be an important factor to explain the cross section of stock returns (Bansal, 2005; Tzouvanas et al., 2020b). We report a positive and significant association between *Liq* and *Sharpe Ratio*. Some studies show high book-to-market (BMV) firms have high returns (Ang et al., 2006, 2009). We report deviations from previous findings, though BMV reduces risks. *Sales growth* is a proxy for the financial performance of the firms. High growth firms should have high stock returns because they heavily invest in new projects (Benlemlih et al., 2016). Also, larger firms are normally less risky. We report some variability in the results.

[6] As a robustness we reproduced Table 4 by considering two different sub-samples. The first sub-sample is related to the period before and during (2005-2009), while the second sub-sample for the period after the financial crisis (2010-2018). The results are qualitative similar and are available in Tables A.1 and A.2 in the Online Appendix.

Next, Table 5 presents results based on equation 8 by considering control variables. System GMM controls for endogeneity in our estimations. It is important to satisfy the GMM conditions and thus there is first order auto-correlation (AR(1) p-value), not second order auto-correlation (AR(2) p-value) and our over-identifying restrictions are valid for 4 models (see Hansen p-value). The auto-regressive term ($Y_{i,t-1}$) is positive when having as dependent variables the *Idiosyncratic Risk* and *Sharpe Ratio* and insignificant for the rest of the models. Controlling for endogeneity, we can observe some variation on the results. The more robust evidence is that *EP* always decreases *Idiosyncratic Risk* (coef.=-0.0264, $p<0.01$), at the same time GMM estimations reveal that EP increases Stock Return (coef.=0.0345, $p<0.05$), while the rest of the factors are unaffected by the EP.

[INSERT Table 5 HERE]

4.3 Panel VAR analysis

We move to examine the Granger causation among *EP*, *Stock Return*, risk-adjusted returns and different types of financial risk. In Table 6, we report the chi-square Wald statistics for the null hypothesis that one variable does not Granger cause the other variable and *vice versa*. The final row of every panel reports the joint probability of all lagged variables in the equation, in which we test the null hypothesis that all lags of all variables can be excluded from each equation in the VAR system. The main result is that *EP* is affected by lagged values of *Total Risk*, *Sharpe Ratio* and *Systematic Risk*, also all variables (*Stock Return*, *Total Risk*, *Idiosyncratic Risk*, *Sharpe ratio*, *Alpha* and *Systematic Risk*) in the system can have an impact on *EP*. Importantly, lagged *EP* values affect the *Total Risk* and *Idiosyncratic Risk*. Therefore, we can argue that the causality runs both ways only between *EP* and *Total Risk*.

[INSERT Table 6 HERE]

Table 7 reports the forecast-error variance decomposition (FEVD) of the PVAR model from 1 to 10 periods (The full FEVD table can be found in Table A.2 on the Online Appendix). The variance decomposition provides a clearer picture of the percentage of the variability of the dependent variables (response variable) that is due to their own shocks or shocks to the other variables (impulse variables) in the model. At period 10, we observe that an *EP* shock explains approximately 13% of the total variance in *Stock Return*. *Total Risk* and *Idiosyncratic Risk* variance can both be explained 73% of an *EP* shock. EP can also explain the total variance of *Sharpe*, *Alpha* and *Systematic Risk* by 22%, 52% and 55%, respectively. In terms of other shocks on *EP*, only *Stock Return* and lagged values of *EP* can explain future EP variations.

[INSERT Table 7 HERE]

FEVD provides information as to the proportion of variation in future values of a system variable that is explained by other variables in the system (Zhang and Broadstock, 2018). In the same vein, the impulse response function (IRF) illustrates how a shock to one variable is met by responses from other components of the system. Figure 3 shows the IRF among the seven examined variables. Column 6 shows how EP is influenced by different shocks for a time horizon of 10 years. It is evident that an increase in one standard deviation (SD) of $Systematic\ Risk$, $Sharpe\ Ratio$, $Idiosyncratic\ Risk$, $Total\ Risk$ and $Stock\ Return$ increase EP, while only $Alpha$ shock decreases EP. Going back to the main hypothesis (the impact of EP on financial variables), we now observe in row 6 of Figure 3 that an increase in one SD of EP can decrease the $Systematic$, $Idiosyncratic$ and $Total\ Risk$, while $Alpha$, $Sharpe\ Ratio$ and $Stock\ Return$ remain flat over time.

[INSERT FIGURE 3 HERE]

Overall, the PVAR analysis reveals a few important findings. First, both the graphical illustration (IRF) and the Granger causation indicate that EP decreases the $Total$ and $Idiosyncratic\ Risk$. Note that, from the Granger causation analysis, there is also a bidirectional relationship between $Total\ Risk$ and EP. This causality is attributed to the fact that, on one hand EP affects $Idiosyncratic\ Risk$, while on the other, $Systematic\ Risk$ affects EP. A plausible explanation is that EP is considered as a firm-specific characteristic, which can reduce the idiosyncratic risk (Tzouvanas et al., 2020b), whereas EP is mainly affected by macroeconomic, regulatory and social factors, which essential constitute the systematic risk (Albuquerque et al., 2019). Second, stock returns appear to be uncorrelated with EP, but risk-adjusted returns as measured by Sharpe, have an impact on EP. Lastly, the FEVD analysis denotes that EP shocks can predict large proportion of future variation of all variables in the system.

4.4 Controlling for industry heterogeneity

Environmental performance is a factor that should have more important effect on manufacturing industries (Balvers et al., 2017). In order to test the sensitivity of the previous results, we construct industry clusters. Eleven clusters are constructed as shown in Table 8. Then, we run fixed effects regressions separately for every cluster. Table 8 presents these results. First (column 1), EP increases the returns on Consumer Discretionary, Energy, Financials, Health Care, Industrials and Technology clusters and it has no effect on other industry clusters. Second (column 2), EP reduces the $Total\ Risk$ on Consumer Discretionary, Energy, Health Care and Telecommunications, while increases the risk only on Utilities. Third (Column 3), *Idiosyncratic Risk* is going down to all industry clusters with significant results being in Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care and Real Estate portfolios. Similarly in column (4), all portfolios improve their performance by adding more environmental stocks, the most positive ones are industries such as: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Real Estate, Technology and Utilities portfolios. Lastly, columns 5 and 6 report the effect of EP on $Alpha$ and $Systematic\ Risk$, respectively. Arguably, with a very few exceptions, EP is unrelated with these two factors.

[INSERT Table 8 HERE]

5 Robustness

5.1 Additional results for idiosyncratic and systematic risk

Previous studies (e.g., Ferreira and Laux, 2007; Fu, 2009) define idiosyncratic risk as the standard deviation of the residuals of the pricing models. Thus, we re-estimate the idiosyncratic risk as the annualized standard deviation of the residuals from Equation 5, $[Idio(OLS) = \sigma(u_{i,d}) \times \sqrt{K} \times 100\%]$ (Boehme et al., 2009), where k corresponds to trading days of any year given with $k \approx 251$).

[INSERT Table 9 HERE]

Once again, in Table 9 we can confirm the strong negative impact of EP on $Idio(OLS)$ (coef.=-0.1137, p<0.01). In addition, the rest four factors from the five factor model seem no be unrelated by the EP. Using control variables in Table 10, we can verify the above afresh that EP decreases idiosyncratic risk but is uncorrelated with systematic risk factors.

[INSERT Table 10 HERE]

5.2 A simple exercise of predicting EP

We proceed with a counterfactual analysis, where we estimate predictions for EP. This task is very similar with the 2SLS procedure with the only difference that we can also estimate some missing values from the original data-set. For this, we follow Griffin et al. (2017) to estimate the GHG emissions:

$$\widehat{lnGHG}_{i,t} = a_0 + a_1 CT_{it} + a_2 lnTang_{it} + a_3 lnInta_{it} + a_4 lnEmp_{it} + a_5 ESG_{it} + \\ a_6 lnTa_{it} + a_7 Liq_{it} + a_8 TQ_{it} + a_9 Lev_{it} + + \sum_{t=2}^{T} \delta_t Year_t + \sum_{m=2}^{M} \delta_m Industry_m \tag{10}$$

where CT is a dummy if firms participate in Carbon trading, $lnTang$ is the tangible assets, $lnInta$ the intangible assets, $lnEmp$ the number of employees, ESG the environmental social governance disclosure, $lnTa$ the Total assets, Liq the liquidity (or current ratio), TQ is the Tobin's Q and Lev the leverage. The model is motivated by previous literature, which represents GHG emissions as a function of firm's size ($lnTang$, $lnEmp$, $lnTa$), research and development (captured by $lnInta$), ESG characteristics (CT, ESG *disclosure*), slack resources (Liq), economic profitability (TQ), risk (Lev) and depending upon the time and industry, where firms operate (Konar and Cohen, 2001; Al-Tuwaijri et al., 2004; Bansal, 2005; Matsumura et al., 2014; Clarkson et al., 2015; Griffin et al., 2017; Liesen et al., 2017; Broadstock et al., 2018; Sun and Gunia, 2018; Tzouvanas et al., 2020a). Our expectations are that the size coefficients should be positive because larger firms pollute more, R&D ($lnInta$) should decrease the GHG (Griffin et al., 2017), high profitability firms (TQ) should decrease their emissions because firms have funds to invest in new technologies (Tzouvanas et al., 2020a). Firms with slack resources (Liq) are able to minimise their emissions (Bansal, 2005) and lastly firms with high risk should have lower emissions due to the fact that riskier firms undertake more environmental projects (Orlitzky et al., 2003). In terms of the environmental characteristics, CT and ESG *disclosure*, their coefficients are ambiguous. Firms that participate in carbon trading they might already have a large amount of emissions and target to buy more carbon allowances in order to legitimise their actions, or they might sell allowances because they have to minimise their footprint. Regarding the ESG disclosure, normally high polluting firms are pushed by stakeholders to disclose more, alternatively probably firms with low emissions want to communicate their green initiatives.

Next, we run equation 10 with random effects model and we retain the coefficients and we use these coefficients for the non-disclosing firms in order to predict the $lnGHG$ values. These coefficients are reported in Table A.3 in the Online Appendix. For the sake of the estimation, we use as base year and industry the 2005 and Basic Materials, respectively. In order to generate coefficients for the year 2005 and Basic Materials, we rerun equation 10 by taking different base year (2006) and industry (Consumer Discretionary). This method increased our sample for more than 1,000 observations (from 2446 to 3453). The alternative measure of environmental performance is scaled by the market size and is calculated as shown: $\widehat{EP} = (\widehat{lnGHG/lnMV})^{-1}$.

[INSERT Table 11 HERE]

Table 11 presents the results based on panel regression estimations with other control variables. The new predicted EP variable appears strongly positive in relation to *Stock Return* (coef.=0.151, p<0.01). This result is in line with previous literature (Al-Tuwaijri et al., 2004; Trumpp and Guenther, 2017). Also, $\widehat{EP}$ is strongly negative for both *Total* (coef.=-0.3968, p<0.01) and *Idiosyncratic Risk* (coef.=-0.0718, p<0.01). This finding is line with our expectations and previous literature (Bouslah et al., 2013; Benlemlih et al., 2016; Tzouvanas et al., 2020b). From investors perspective this very important because it implies that higher diversification can be achieved by including environmental stocks in an investment portfolio. Moreover, the *Systematic Risk* is positively affected (coef.=0.045, p<0.05) by the $\widehat{EP}$. This should not be surprising. According to Sadorsky (2012), the cleantech revolution is a challenging task and unavoidably there are associated risks such as higher compliance costs, raising capital and increasing competition. Thus, our results are in line with those of (Benlemlih et al., 2016; Tzouvanas et al., 2020b), but are against the literature between CSR and systematic risk, which reports negative coefficients (Salama et al., 2011; Oikonomou et al., 2012).

Lastly, the $\widehat{EP}$ effect on *Sharpe Ratio* is strongly positive (coef.=0.0667, p<0.01), whereas *Alpha* is unaffected. Since both *Sharpe Ratio* and *Alpha* measure the relative performance of a portfolio, how would the former be improved, while the latter would not? Note that *Sharpe Ratio* is used to compare two different portfolios (i.e environmental vs non-environmental portfolios), while *Alpha* compares any portfolio with the benchmark index. Our 5 factors used to compute *Alpha* are retrieved from the entire U.S. market. Our sample is over-represented by large capitalization stocks (S&P500) and it is well documented in the literature that smaller firms exhibit higher stock returns (Fama and French, 1992). Therefore, an explanation is that environmental stocks matches the performance of small-capitalization stocks. This might be very important in the asset pricing literature because it implies that forming portfolio of environmental stock can potentially be used as an additional factor in the asset pricing models.

6 Conclusion

Over the past 25 years, a great deal of research has examined the effects of environmental friendly firms on financial performance. We extend earlier research and examine whether environmental stocks perform superior in terms of return and risk.

Our main findings suggest that firms with higher EP have also higher equity valuation, while benefit from lower associated risks and particularly lower idiosyncratic risk. We demonstrate that portfolio selection of EP firms is justified both in terms of market returns and risks. However, we also provide evidence that warrants caution on the relationship between between EP stocks and systematic risk as the latter shows persistence. When we control for firm specific characteristics and address endogeneity the main findings remain robust as environmental stocks perform better than non-environmental stocks. In addition, the panel VAR analysis reveals underling interlinkages as shocks in EP stocks would impact on total risk and vice versa. In particular, the VAR shows shocks in EP stocks would affect idiosyncratic risk, while shocks in systematic risk would affect EP stocks. Finally,opting for instrumental variable estimation EP confirms our findings.

Our findings reveal that EP stocks are value for money in the portfolio, while they contribute to the sustainability of the economy. Policy and regulation interventions towards environmental responsible 'green' investment are therefore justified and warranted in line with (Banerjee et al., 2019). It pays to invest on a portfolio of environmental stocks.

We would like to underline some financial and policy implications. Our analysis suggests that by investing in environmental stocks financial markets would improve in terms of efficiency (Liesen et al., 2017). In a typical min-variance portfolio analysis, environmental stocks should be selected. In terms of policy implications, there is justification for lower GHG emissions. Lowering GHG emissions would not only halt the environmental degradation, but would also benefit financial market's efficiency.

Further research could examine the role of scope 3 emissions as herein the focus has been on scope 1 and 2. In close relation to this, the *European Organisational Environmental Footprint* provide 14 different climate change impacts categories (Pelletier et al., 2012), which can potentially be considered in the measurement of environmental performance. Lastly, large number of world market indices could be employed, though controlling for the underlying heterogeneity, could a promising area for future research.

References

Aggarwal, R. and Dow, S. (2012). Corporate governance and business strategies for climate change and environmental mitigation. *The European Journal of Finance*, 18(3-4):311–331.

Al-Tuwaijri, S. A., Christensen, T. E., and Hughes, K. E. (2004). The relations among environmental disclosure, environmental performance, and economic performance: A simultaneous equations approach. *Accounting, Organizations and Society*, 29(5-6):447–471.

Albertini, E. (2013). Does Environmental Management Improve Financial Performance? A Meta-Analytical Review. *Organization and Environment*, 26(4):431–457.

Albuquerque, R., Koskinen, Y., and Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10):4451–4469.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance*, 61(1):259–299.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, 91(1):1–23.

Baker, M., Bergstresser, D., Serafeim, G., and Wurgler, J. (2018). Financing the response to climate change: The pricing and ownership of US green bonds. *National Bureau of Economic Research*.

Baltagi, B. (2008). *Econometric Analysis of Panel Data*. John Wiley & Sons.

Balvers, R., Du, D., and Zhao, X. (2017). Temperature Shocks and the Cost of Equity Capital: Implications for Climate Change Perceptions. *Journal of Banking and Finance*, 77:18–34.

Banerjee, R., Gupta, K., and Mudalige, P. (2019). Do environmentally sustainable practices lead to financially less constrained firms? International evidence. *International Review of Financial Analysis*.

Bansal, P. (2005). A Longitudinal Study of Corporate Sustainable Development. *Strategic Management Journal*, 26(3):197–218.

Becchetti, L., Ciciretti, R., and Hasan, I. (2015). Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *Journal of Corporate Finance*, 35:297–309.

Benlemlih, M., Shaukat, A., Qiu, Y., and Trojanowski, G. (2016). Environmental and Social Disclosures and Firm Risk. *Journal of Business Ethics*, pages 1–14.

Benz, L., Paulus, S., Scherer, J., Syryca, J., and Trück, S. (2019). Investor ownership and carbon-intensive stocks: Who holds the carbon risk bomb?

Blankenberg, A.-K. and Gottschalk, J. F. (2018). Is socially responsible investing (SRI) in stocks a competitive capital investment? A comparative analysis based on the performance of sustainable stocks.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143.

Boehme, R. D., Danielsen, B. R., Kumar, P., and Sorescu, S. M. (2009). Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets Miller (1977). *Journal of Financial Markets*, 12(3):438–468.

Boiral, O., Talbot, D., and Brotherton, M.-C. (2020). Measuring sustainability risks: A rational myth? *Business Strategy and the Environment*.

Bouslah, K., Kryzanowski, L., and M'Zali, B. (2013). The impact of the dimensions of social performance on firm risk. *Journal of Banking and Finance*, 37(4):1258–1273.

Broadstock, D. C., Collins, A., Hunt, L. C., and Vergos, K. (2018). Voluntary disclosure, greenhouse gas emissions and business performance: Assessing the first decade of reporting. *British Accounting Review*, 50(1):48–59.

Brzeszczyński, J. and McIntosh, G. (2014). Performance of portfolios composed of British SRI stocks. *Journal of business ethics*, 120(3):335–362.

Busch, T. and Lewandowski, S. (2017). Corporate carbon and financial performance: A meta analysis. *Journal of Industrial Ecology*.

Cai, L., Cui, J., and Jo, H. (2016). Corporate Environmental Responsibility and Firm Risk. *Journal of Business Ethics*, 139(3):563–594.

Carhart, M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1).

Chan, P. T. and Walter, T. (2014). Investment performance of "environmentally-friendly" firms and their initial public offers and seasoned equity offers. *Journal of Banking & Finance*, 44:177–188.

Chen, T., Dong, H., and Lin, C. (2020). Institutional shareholders and corporate social responsibility. *Journal of Financial Economics*, 135(2):483–504.

Cheung, A. W. K. (2016). Corporate social responsibility and corporate cash holdings. *Journal of Corporate Finance*, 37:412–430.

Clarkson, P. M., Li, Y., Pinnuck, M., and Richardson, G. D. (2015). The Valuation Relevance of Greenhouse Gas Emissions under the European Union Carbon Emissions Trading Scheme. *European Accounting Review*, 24(3):551–580.

Coban, S. and Topcu, M. (2013). The nexus between financial development and energy consumption in the EU: A dynamic panel data analysis. *Energy Economics*, 39:81–88.

Cormier, D. and Magnan, M. (2015). The Economic Relevance of Environmental Disclosure and its Impact on Corporate Legitimacy: An Empirical Investigation. *Business Strategy and the Environment*, 24(6):431–450.

Cumming, D., Henriques, I., and Sadorsky, P. (2016). 'Cleantech' venture capital around the world. *International Review of Financial Analysis*, 44:86–97.

Delmas, M. A., Nairn-Birch, N., and Lim, J. (2015). Dynamics of environmental and financial performance: The case of greenhouse gas emissions. *Organization and Environment*, 28(4):374–393.

Dimson, E., Karakaş, O., and Li, X. (2015). Active ownership. *The Review of Financial Studies*, 28(12):3225–3268.

Ding, D. K., Ferreira, C., and Wongchoti, U. (2016). Does it pay to be different? Relative CSR and its impact on firm value. *International Review of Financial Analysis*, 47:86–98.

Dyck, A., Lins, K. V., Roth, L., and Wagner, H. F. (2019). Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics*, 131(3):693–714.

Endrikat, J., Guenther, E., and Hoppe, H. (2014). Making sense of conflicting empirical findings: A meta-analytic review of the relationship between corporate environmental and financial performance. *European Management Journal*, 32(5):735–751.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216.

Fama, E. and French, K. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33:3–56.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Farag, H., Meng, Q., and Mallin, C. (2015). The social, environmental and ethical performance of chinese companies: Evidence from the shanghai stock exchange. *International Review of Financial Analysis*, 42:53–63.

Ferreira, M. A. and Laux, P. A. (2007). Corporate Governance, Idiosyncratic Risk, and Information Flow. *The Journal of Finance*, 62(2):951–989.

Ferrell, A., Liang, H., and Renneboog, L. (2016). Socially responsible firms. *Journal of Financial Economics*, 122(3):585–606.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, 91(1):24–37.

Galema, R., Plantinga, A., and Scholtens, B. (2008). The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking & Finance*, 32(12):2646–2654.

Griffin, P. A., Lont, D. H., and Sun, E. Y. (2017). The relevance to investors of greenhouse gas emission disclosures. *Contemporary Accounting Research*, 34(2):1265–1297.

Griffin, P. A., Neururer, T., and Sun, E. Y. (2018). Environmental performance and analyst information processing costs. *Journal of Corporate Finance*.

Grougiou, V., Leventis, S., Dedoulis, E., and Owusu-Ansah, S. (2014). Corporate social responsibility and earnings management in US banks. *Accounting Forum*, 38(3):155–169.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4):1029–1054.

Hart, S. and Ahuja, G. (1996). Does it pay to be green? An empirical examination of the relationship between emission reduction and firm performance. *Business strategy and the Environment*, 5(1996):30–37.

Humphrey, J. E., Lee, D. D., and Shen, Y. (2012). Does it cost to be sustainable? *Journal of Corporate Finance*, 18(3):626–639.

IPCC (2014). The Intergovernment Panel on Climate Change Fifth Assessment Report. Technical report.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jones, T. M. (1995). Instrumental stakeholder theory: A synthesis of ethics and economics. *Academy of Management Review*, 20(2):404–437.

Jung, J., Herbohn, K., and Clarkson, P. (2018). Carbon risk, carbon risk awareness and the cost of debt financing. *Journal of Business Ethics*, 150(4):1151–1171.

King, A. A. and Lenox, M. J. (2001). Does It Really Pay to Be Green? An Empirical Study of Firm Environmental and Financial Performance. *Journal of Industrial Ecology*, 5(1):105–116.

Konar, S. and Cohen, M. (2001). Does the Market Value Environmental Performance? *Review of Economics and Statistics*, 83(2):281–289.

Krueger, P., Sautner, Z., and Starks, L. T. (2019). The importance of climate risks for institutional investors. *Swiss Finance Institute Research Paper*, (18-58).

Lagoarde-Segot, T. and Paranque, B. (2018). Finance and sustainability: From ideology to utopia. *International Review of Financial Analysis*, 55:80–92.

Liang, H. and Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance*, 72(2):853–910.

Liesen, A., Figge, F., Hoepner, A., and Patten, D. M. (2017). Climate change and asset prices: are corporate carbon disclosure and performance priced appropriately? *Journal of business finance & accounting*, 44(1-2):35–62.

Lins, K. V., Servaes, H., and Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4):1785–1824.

Luo, L. and Tang, Q. (2014). Carbon tax, corporate carbon profile and financial return. *Pacific Accounting Review*, 26(3):351–373.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, pages 77–99.

Matsumura, E. M., Prakash, R., and Vera-Munoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *Accounting Review*, 89(2):695–724.

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, 42(3):483–510.

Misani, N. and Pogutz, S. (2015). Unraveling the effects of environmental outcomes and processes on financial performance: A non-linear approach. *Ecological Economics*, 109:150–160.

Mishra, S. and Modi, S. B. (2013). Positive and Negative Corporate Social Responsibility, Financial Leverage, and Idiosyncratic Risk. *Journal of Business Ethics*, 117(2):431–448.

Ng, A. C. and Rezaee, Z. (2015). Business sustainability performance and cost of equity capital. *Journal of Corporate Finance*, 34:128–149.

Nollet, J., Filis, G., and Mitrokostas, E. (2016). Corporate social responsibility and financial performance: A non-linear and disaggregated approach. *Economic Modelling*, 52:400–407.

Oikonomou, I., Brooks, C., and Pavelin, S. (2012). The Impact of Corporate Social Performance on Financial Risk and Utility: A Longitudinal Analysis. *Financial Management*, 41(2):483–515.

Orlitzky, M. and Benjamin, J. D. (2001). Corporate Social Performance and Firm Risk: A Meta-Analytic Review. *Business & Society*, 40(4):369–396.

Orlitzky, M., Schmidt, F. L., and Rynes, S. L. (2003). Corporate Social and Financial Performance : A meta-analysis. *Organization Studies*, 24(3):403–441.

Pelletier, N., Allacker, K., Manfredi, S., Chomkhamsri, K., and de Souza, D. M. (2012). Organisation Environmental Footprint (OEF) Guide.

Psillaki, M., Tsolas, I. E., and Margaritis, D. (2010). Evaluation of credit risk based on firm performance. *European Journal of Operational Research*, 201(3):873–881.

Qadan, M. (2019). Risk appetite, idiosyncratic volatility and expected returns. *International Review of Financial Analysis*, 65:101372.

Reinhardt, F. L. and Stavins, R. N. (2010). Corporate social responsibility, business strategy, and the environment. *Oxford Review of Economic Policy*, 26(2):164–181.

Roodman, D. (2009). Practitioners' corner: A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158.

Sadorsky, P. (2012). Modeling renewable energy company risk. *Energy Policy*, 40:39–48.

Salama, A., Anderson, K., and Toms, J. S. (2011). Does community and environmental responsibility affect firm risk? Evidence from UK panel data 1994-2006. *Business Ethics: A European Review*, 20(2):192–204.

Sharfman, M. P. and Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic management journal*, 29(6):569–592.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.

Sun, X. and Gunia, B. C. (2018). Economic resources and corporate social responsibility. *Journal of corporate finance*, 51:332–351.

Tamazian, A. and Bhaskara Rao, B. (2010). Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies. *Energy Economics*, 32(1):137–145.

Trumpp, C. and Guenther, T. (2017). Too Little or too much? Exploring U-shaped Relationships between Corporate Environmental Performance and Corporate Financial Performance. *Business Strategy and the Environment*, 26(1):49–68.

Tzouvanas, P., Kizys, R., Chatziantoniou, I., and Sagitova, R. (2020a). Environmental and Financial Performance in the European Manufacturing Sector: An Analysis of Extreme Tail Dependency. *The British Accounting Review*, 52(6):100863.

Tzouvanas, P., Kizys, R., Chatziantoniou, I., and Sagitova, R. (2020b). Environmental disclosure and idiosyncratic risk in the european manufacturing sector. *Energy Economics*, 87:104715.

US SIF (2018). *US SIF Trends Report*. Retrieved from: https://www.ussif.org/trends. Accessed: 17 Nov 2019.

Wagner, M. (2005). How to reconcile environmental and economic performance to improve corporate sustainability: Corporate environmental strategies in the European paper industry. *Journal of Environmental Management*, 76(2):105–118.

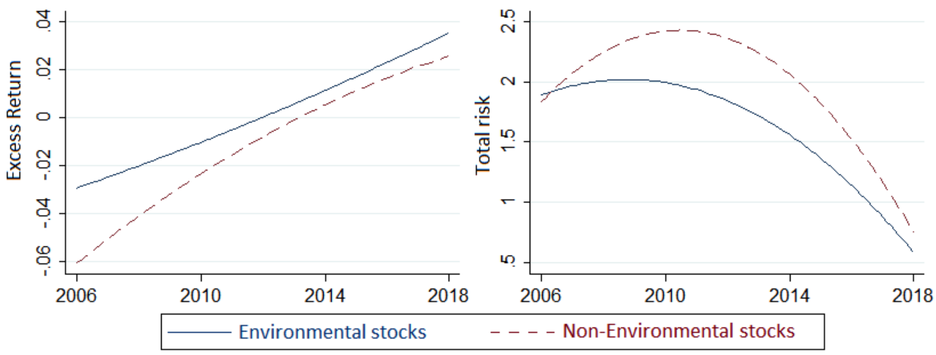
Wagner, M., Phu, N. V., Azomahou, T., and Wehrmeyer, W. (2002). The relationship between the environmental and economic performance of firms: An empirical analysis of the European paper industry. *Corporate social responsibility and Environmental Management*, 146(9):133–146.

Widyawati, L. (2019). A systematic literature review of socially responsible investment and environmental social governance metrics. *Business Strategy and the Environment*.

Windmeijer, F. (2005). A Finite Sample Correction for the Variance of Linear Two-Step Estimators. *Journal of econometrics*, 126(1):25–51.

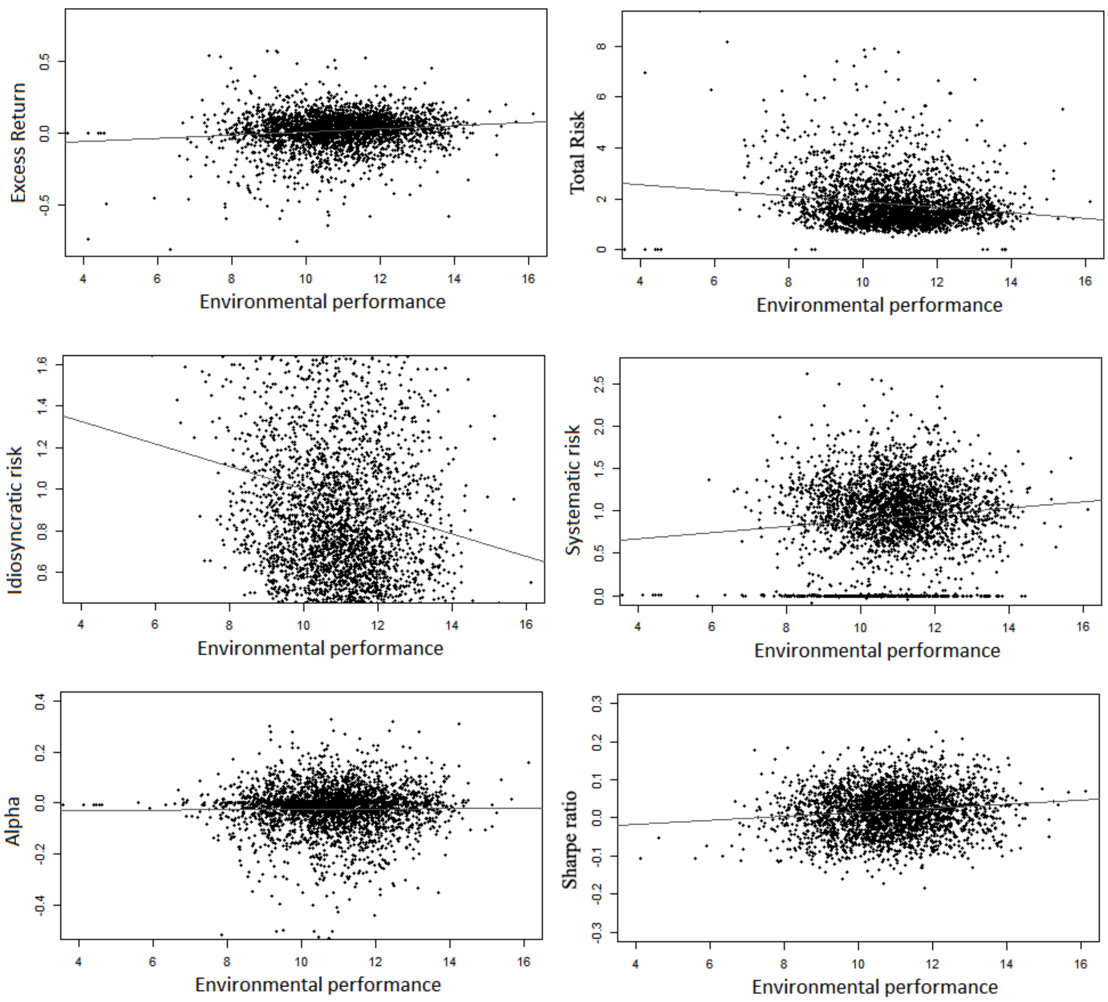
Zhang, D. and Broadstock, D. C. (2018). Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis*.

Figure 1: Time series



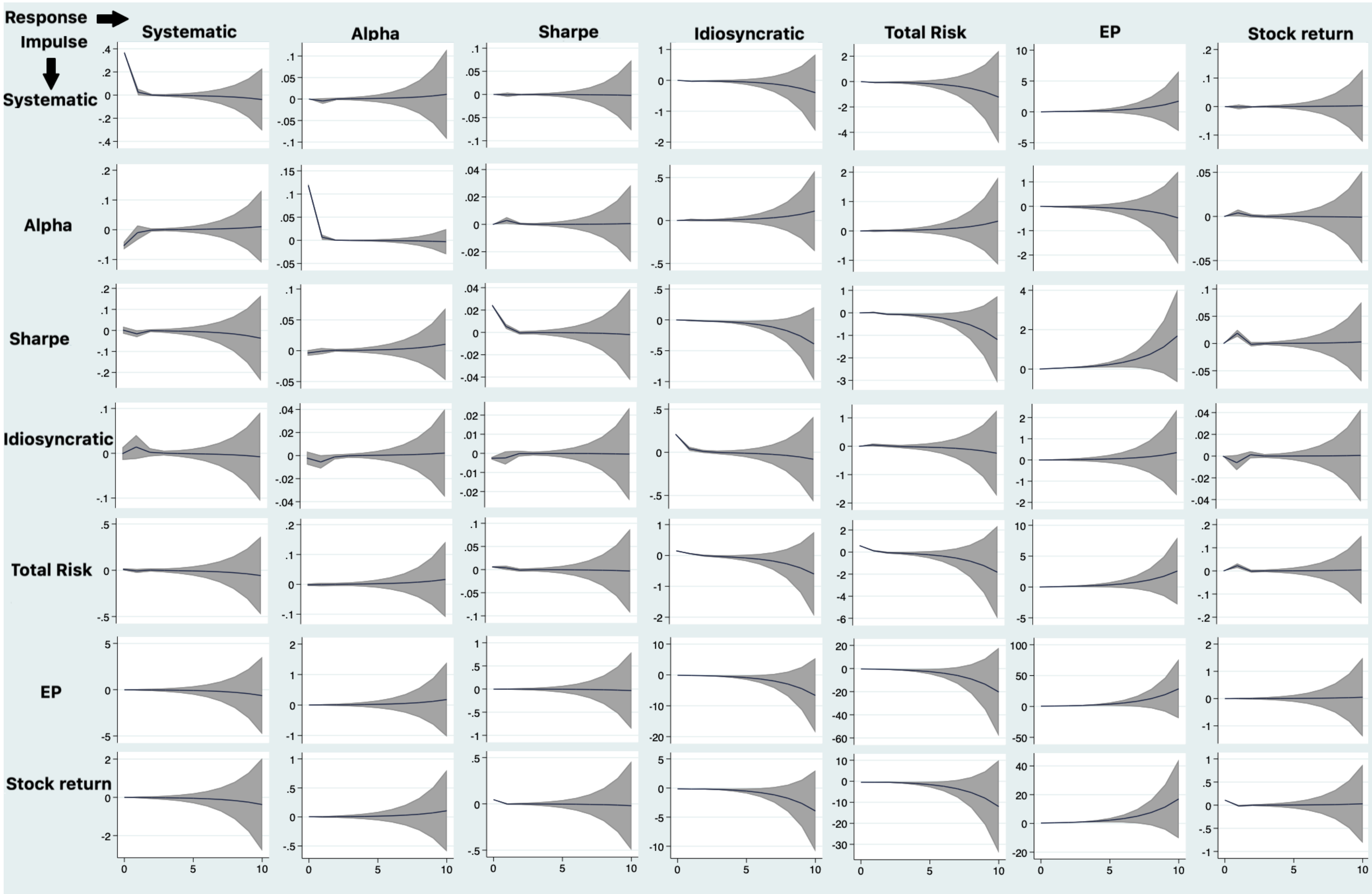
Notes: In this Figure environmental stocks are observations where EP is greater than its median, if EP is less than its median then they are considered non-environmental stocks.

Figure 2: Plot EP against market-based measures



Notes: The figure shows scatter plots and fitted lines between EP and other market-based financial performance measures.

Figure 3: Impulse response function



Notes: Grey area shows 5% confidence interval using errors generated by Monte Carlo with 1,000 replications.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnGHG	2,975	13.745	2.173	5.129	18.927
lnMV	5,437	16.467	1.275	9.632	20.581
EP	2,975	10.829	1.474	3.031	17.414
Stock Return	6,949	-0.001	0.157	-3.161	1.196
Total Risk	6,949	1.648	1.612	0.000	29.221
Systematic	6,930	0.861	0.523	-0.998	3.102
Idiosyncratic	5,902	0.984	0.435	0.446	1.896
Sharpe	5,920	-0.116	0.644	-4.882	0.226
Alpha	6,930	-0.023	0.113	-2.407	1.233
Idio(OLS)	6,930	1.223	1.224	0	22.861
smb	6,930	0.084	0.495	-4.328	7.042
hml	6,930	0.067	0.743	-4.505	7.529
rmw	6,930	0.003	0.841	-7.909	8.733
cma	6,930	0.202	0.875	-9.078	9.163
Lev	5,474	111.63	1096.87	-29125.81	34709.26
Spread (Bid-Ask)	4,995	-0.034	0.223	-9.750	0.040
lnVol	5,706	13.620	1.075	8.111	18.209
Liq	4,522	1.781	1.140	0.090	13.650
BMV	5,435	20.242	416.98	0.078	15536.29
Sales growth	4,996	0.098	3.961	-1.903	279.621
CT	5,283	0.138	0.345	0	1
lnTang	6,549	15.378	1.299	9.456	19.317
lnInta	5,010	14.493	1.799	5.951	19.552
lnEmp	5,404	10.078	1.323	4.3694	14.648
ESG	5,264	61.181	16.602	0	97.92
TQ	5,435	1.884	1.083	0.484	13.734
lnTa	5,476	16.728	1.467	11.893	21.949
$\widehat{EP}$	3,804	2.952	1.480929	-4.369	6.773

Notes: *lnGHG* is the natural logarithm of greenhouse gas emissions; *lnMV* the natural logarithm of market value; *EP*, environmental performance, calculated as shown in equation 1; *Stock Return* measured as shown in equation 2; *Total Risk* as shown in equation 4; *Systematic* risk is the coefficient of market premium ($\beta_{i,1}$) from equation 5; *Idiosyncratic* risk as shown in equation 6; Sharpe ratio, measures the stock performance adjusted for risk, as shown in equation 3; *Alpha*, measures the relative performance of the stock against the whole market, is the constant term (a_i) in equation 5; $Idio(OLS)$ is alternative measures of idiosyncratic risk, estimated by the annualised residuals of equation 5; *smb*, *hml*, *rmw*, *cma* the rest of the systematic risk factors as shown in equation 5; *Lev* is the total debt to total (shareholder) equity ratio; *Spread* is the bid minus the ask price of each stock; $lnVol$ the natural logarithm of the trading volume of each stock; *Liq* is the liquidity ratio (current ratio = current assets / current liabilities); *BMV* is the book to market value, *Sales growth* is the percentage increase in revenue from the last year; CT is dummy taking values of 1 if firms participate in Carbon Trading, 0 otherwise; *lnTang* and *lnInta* the natural logarithm of tangible and intangible assets of the firms, respectively; *lnEmp* the natural logarithm of total number of employees; *ESG* is a score taking values from 0 to 100, highest values denote high level of environmental social and governance disclosure by firms; *TQ* is accounting performance measure (Tobin's Q); *lnTa* is the natural logarithm of the total assets of the firms and $\widehat{EP}$ is the estimated environmental performance of firms as shown in equation 10.

Table 2: Sort by EP

	Low 1	2	3	4	5	High 6	6-1
Stock return	-0.0387	0.0061	0.0157	0.0216	0.0329	0.0353	0.0741
Idiosyncratic	1.3135	1.0067	0.9538	0.9089	0.8987	0.9048	-0.4087
Systematic	0.7363	0.8483	0.9426	0.9507	0.9703	0.9141	0.1777
Alpha	-0.0227	-0.0227	-0.0271	-0.0255	-0.0294	-0.01253	0.0102
Sharpe	0.0008	0.0119	0.0173	0.0224	0.0289	0.0298	0.0290
Total risk	2.6336	1.9247	1.8005	1.6858	1.6701	1.7696	-0.864

Notes: Quantile portfolios "1" to "6" from Low to High Environmental perfomance. Portfolios are sorted according to the EP distribution (q), with "1", "2", "3", "4", "5" and "6" correspond to $q \leq 5\%$, $5\% < q \leq 25\%$, $25\% < q \leq 50\%$, $50\% < q \leq 75\%$, $75\% < q \leq 95\%$, and $q > 95\%$, respectively. Portfolio "1-6" represents a strategy that goes long the highest EP quantile and short the lowest EP quantile.

Table 3: Panel regressions without control variables

	(1) Stock Return	(2) Total Risk	(3) Idiosyncratic	(4) Sharpe	(5) Alpha	(6) Systematic
EP	0.0306***	-0.1145***	-0.0863***	0.0159***	0.0004	0.0246**
	(0.0060)	(0.0333)	(0.0135)	(0.0020)	(0.0016)	(0.0110)
Constant	-0.3206***	2.8635***	1.8343***	-0.1658***	-0.0142	0.3725**
	(0.0660)	(0.3846)	(0.1484)	(0.0229)	(0.0207)	(0.1584)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	Yes	No	No	Yes	Yes
R^2	0.3272	0.4758	0.2899	0.2898	0.0083	0.0289
N	2953	2953	2953	2953	2953	2953
Hausman	69.30***	17.33	62.40***	50.12***	17.01	12.79

Notes: Random and fixed effects regressions between EP and financial performance measures with no other covariates. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses. Significant Hausman test indicates that the fixed effects estimator is more appropriate than the random effects estimator.

Table 4: Panel regressions with control variables

	(1) Stock Return	(2) Total Risk	(3) Idio.	(4) Sharpe	(5) Alpha	(6) Systematic
EP	0.0118	-0.0580**	-0.0556***	0.0087***	-0.0008	0.0122
	(0.0076)	(0.0236)	(0.0130)	(0.0029)	(0.0024)	(0.0132)
Lev	0.0001	0.0010	-0.0003	0.0001	-0.0001	0.0004
	(0.0002)	(0.0011)	(0.0004)	(0.0001)	(0.0001)	(0.0003)
Spread (Bid-Ask)	-0.3934***	-0.0568	-0.1402	-0.1248**	-0.0300	0.1369
	(0.1132)	(0.4568)	(0.2046)	(0.0494)	(0.0900)	(0.3854)
lnVol	0.0029	0.2253***	0.2712***	-0.0143***	0.0006	0.0556***
	(0.0094)	(0.0341)	(0.0232)	(0.0039)	(0.0024)	(0.0188)
Liq	0.0031	0.0159	-0.0022	0.0038*	-0.0020	0.0113
	(0.0038)	(0.0142)	(0.0084)	(0.0021)	(0.0033)	(0.0141)
BMV	-0.0293**	0.1243***	0.0176***	-0.0073	-0.0029**	-0.0015
	(0.0147)	(0.0388)	(0.0037)	(0.0046)	(0.0013)	(0.0054)
Sales growth	0.0174	-0.1117*	0.0067	0.0135**	0.0106	-0.0174
	(0.0144)	(0.0614)	(0.0303)	(0.0067)	(0.0122)	(0.0569)
Constant	-0.1254	-0.8274	-2.1871***	0.1226**	-0.0188	-0.2262
	(0.1232)	(0.5339)	(0.3466)	(0.0585)	(0.0406)	(0.3108)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	Yes	No	No	Yes	Yes
R^2	0.4154	0.5727	0.2208	0.3159	0.0120	0.0330
N	2446	2446	2446	2446	2446	2446

Notes: Random and fixed effects regressions between EP and financial performance measures with other covariates as shown in equation 7. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses.

Table 5: System-GMM regressions

	(1) Stock Return	(2) Total Risk	(3) Idio.	(4) Sharpe	(5) Alpha	(6) Systematic
$Y_{i,t-1}$	0.4870	0.6555	0.3838*	0.7822**	0.0305	0.0262
	(0.4208)	(0.4445)	(0.2041)	(0.3703)	(0.0343)	(0.2225)
EP	0.0345**	-0.0268	-0.0264***	-0.0014	-0.0006	-0.0008
	(0.0170)	(0.0646)	(0.0100)	(0.0016)	(0.0021)	(0.0131)
Lev	0.0002	-0.0003	-0.0002	0.0000	-0.0001	0.0005
	(0.0003)	(0.0009)	(0.0003)	(0.0001)	(0.0001)	(0.0006)
Spread	-0.6302***	0.5464	-0.1652	-0.0699	-0.0103	0.1670
	(0.1867)	(0.6470)	(0.2546)	(0.0521)	(0.0955)	(0.6136)
lnVol	0.0380	0.5031***	0.0198*	0.0012	-0.0015	0.0586**
	(0.0254)	(0.1181)	(0.0116)	(0.0011)	(0.0026)	(0.0243)
Liq	-0.0016	-0.0029	0.0312**	0.0013	-0.0017	0.0120
	(0.0068)	(0.0311)	(0.0149)	(0.0010)	(0.0030)	(0.0150)
BMV	-0.0605**	0.1765*	0.0342**	-0.0034	-0.0029*	-0.0150**
	(0.0243)	(0.0929)	(0.0149)	(0.0025)	(0.0017)	(0.0073)
Sales growth	-0.0366	-0.1980*	0.0015	-0.0176	0.0120	-0.0771
	(0.0531)	(0.1092)	(0.0319)	(0.0222)	(0.0118)	(0.0661)
Constantt	0.0056	-5.5571***	0.5344**	0.0221	0.0163	-0.0825
	(0.4982)	(1.9203)	(0.2104)	(0.0147)	(0.0426)	(0.3168)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	2446	2446	2446	2446	2446	2446
AR(1) p-value	0.0342	0.0688	0.0014	0.0021	0.0001	0.0315
AR(2) p-value	0.9592	0.5891	0.3658	0.1197	0.5946	0.8603
Hansen p-value	0.1917	0.0258	0.2185	0.7816	0.0174	0.1377
N of instruments	43	39	37	37	61	51

Notes: System GMM regressions between EP and financial performance measures with other covariates as shown in equation 8. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses. Insignificant AR(2) indicates that second order autocorrelation does not exist. Insignificant Hansen test indicates that the GMM instruments are valid.

Table 6: Panel VAR-Granger causality Wald test

Equation / Excluded		χ^2	df	P > χ^2
Stock return				
	EP	1.499	1	0.221
	Total risk	21.107	1	0.000
	Idiosyncratic	1.105	1	0.293
	Sharpe	36.760	1	0.000
	Alpha	2.250	1	0.134
	Systematic	0.111	1	0.739
	ALL	49.020	6	0.000
EP				
	Stock return	0.819	1	0.365
	Total risk	3.434	1	0.064
	Idiosyncratic	0.295	1	0.587
	Sharpe	8.304	1	0.004
	Alpha	0.363	1	0.547
	Systematic	3.439	1	0.064
	ALL	46.231	6	0.000
Total Risk				
	Stock return	18.103	1	0.000
	EP	31.221	1	0.000
	Idiosyncratic	2.957	1	0.085
	Sharpe	0.513	1	0.474
	Alpha	0.044	1	0.833
	Systematic	5.696	1	0.017
	ALL	81.623	6	0.000
Idiosyncratic				
	Stock return	8.624	1	0.003
	EP	18.354	1	0.000
	Total risk	11.173	1	0.001
	Sharpe	1.444	1	0.229
	Alpha	0.048	1	0.827
	Systematic	7.472	1	0.006
	ALL	90.891	6	0.000
Sharpe				
	Stock return	21.111	1	0.000
	EP	0.011	1	0.915
	Total risk	5.672	1	0.017
	Idiosyncratic	1.148	1	0.284
	Alpha	3.609	1	0.057
	Systematic	0.108	1	0.742
	ALL	36.745	6	0.000
Alpha				
	Stock return	0.015	1	0.902
	EP	0.080	1	0.777
	Total risk	1.039	1	0.308
	Idiosyncratic	2.777	1	0.096

	Sharpe	0.030	1	0.863
	Systematic	1.209	1	0.272
	ALL	5.073	6	0.535
Systematic				
	Stock return	3.623	1	0.057
	EP	0.201	1	0.654
	Total risk	1.223	1	0.269
	Idiosyncratic	1.227	1	0.268
	Sharpe	3.569	1	0.059
	Alpha	0.352	1	0.553
	ALL	7.538	6	0.274

Table 7: Forecast-error variance decomposition

Response	Impulse:	Stock return	EP	Total Risk	Idios.	Sharpe	Alpha	Systematic
Stock return								
	1	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	10	0.812	0.129	0.033	0.002	0.023	0.001	0.001
EP								
	1	0.212	0.788	0.000	0.000	0.000	0.000	0.000
	10	0.258	0.731	0.006	0.000	0.003	0.000	0.003
Total Risk								
	1	0.346	0.154	0.500	0.000	0.000	0.000	0.000
	10	0.258	0.730	0.007	0.000	0.003	0.000	0.003
Idiosyncratic								
	1	0.190	0.120	0.238	0.452	0.000	0.000	0.000
	10	0.258	0.729	0.006	0.001	0.003	0.000	0.003
Sharpe								
	1	0.767	0.001	0.013	0.002	0.217	0.000	0.000
	10	0.603	0.220	0.015	0.003	0.156	0.002	0.001
Alpha								
	1	0.001	0.000	0.000	0.000	0.001	0.997	0.000
	10	0.185	0.521	0.004	0.001	0.002	0.285	0.002
Systematic								
	1	0.000	0.001	0.001	0.000	0.000	0.021	0.977
	10	0.196	0.555	0.005	0.000	0.002	0.005	0.236

Notes: The complete FEVD Table, reporting all periods between 1 and 10, is available in Table A.2 in the Online Appendix

Table 8: Industry results

Industry:		(1) Return	(2) Total Risk	(3) Idio.	(4) Sharpe	(5) Alpha	(6) Systematic
Basic Materials	EP	0.015	-0.268	-0.099	0.004	0.023*	-0.017
		(0.029)	(0.239)	(0.097)	(0.010)	(0.011)	(0.087)
	R^2	0.513	0.624	0.369	0.480	0.014	0.037
	N	157	157	157	157	157	157
Consumer Discretionary	EP	0.045**	-0.321***	-0.126***	0.016***	0.003	-0.075**
		(0.019)	(0.119)	(0.029)	(0.005)	(0.006)	(0.032)
	R^2	0.338	0.362	0.373	0.321	0.027	0.001
	N	438	438	432	432	438	438
Consumer Staples	EP	0.014	-0.037	-0.039**	0.006	-0.000	0.014
		(0.009)	(0.066)	(0.015)	(0.003)	(0.010)	(0.038)
	R^2	0.393	0.349	0.366	0.401	0.028	0.041
	N	297	297	297	297	297	297
Energy	EP	0.031**	-0.291**	-0.142***	0.005	-0.002	-0.001
		(0.014)	(0.119)	(0.045)	(0.005)	(0.017)	(0.036)
	R^2	0.604	0.566	0.227	0.603	0.034	0.050
	N	191	191	191	191	191	191
Financials	EP	0.025**	-0.246	-0.094**	0.013***	0.010	0.076
		(0.010)	(0.159)	(0.037)	(0.004)	(0.014)	(0.079)
	R^2	0.570	0.752	0.759	0.643	0.034	0.048
	N	313	313	313	313	313	313
Health Care	EP	0.052***	-0.226**	-0.151***	0.032***	-0.005	-0.096
		(0.012)	(0.096)	(0.041)	(0.009)	(0.015)	(0.058)
	R^2	0.307	0.331	0.133	0.287	0.052	0.006
	N	314	314	314	314	314	314
Industrials	EP	0.031***	-0.115	-0.056	0.018***	-0.002	0.015
		(0.007)	(0.069)	(0.036)	(0.006)	(0.009)	(0.034)
	R^2	0.407	0.547	0.439	0.419	0.028	0.023
	N	496	496	496	496	496	496
Real Estate	EP	0.029	0.178	-0.118**	0.055**	-0.023	0.345*
		(0.026)	(0.216)	(0.037)	(0.020)	(0.030)	(0.145)
	R^2	0.555	0.724	0.552	0.113	0.092	0.001
	N	46	46	40	40	46	46
Technology	EP	0.030***	-0.004	-0.032	0.011***	0.015	0.080
		(0.009)	(0.067)	(0.040)	(0.004)	(0.013)	(0.052)
	R^2	0.423	0.404	0.288	0.425	0.059	0.009
	N	324	324	324	324	324	324
Telecom-munications	EP	0.045	-0.454*	-0.250	0.023	-0.017	-0.072
		(0.044)	(0.212)	(0.157)	(0.019)	(0.037)	(0.177)
	R^2	0.492	0.303	0.163	0.333	0.041	0.001
	N	86	86	86	86	86	86
Utilities	EP	0.005	0.331**	-0.016	0.019***	0.016	0.020
		(0.010)	(0.153)	(0.025)	(0.005)	(0.016)	(0.034)
	R^2	0.416	0.169	0.460	0.372	0.032	0.063
	N	291	291	282	282	291	291

Notes: Fixed effects regressions: $Y_{i,t} = a + bEP_{i,t} + \sum_{t=2}^{T} \delta_t Year_t + u_{i,t}$, constant and year dummies are not reported for brevity. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors in parentheses.

Table 9: Additional results: panel regressions without control variables

	(1) Idio(OLS)	(2) smb	(3) hml	(4) rmw	(5) cma
EP	-0.1137***	-0.0071	0.0050	-0.0028	0.0025
	(0.0311)	(0.0080)	(0.0119)	(0.0116)	(0.0118)
Constant	2.4825***	0.2419**	0.1261	0.0110	0.1285
	(0.3528)	(0.1008)	(0.1459)	(0.1448)	(0.1465)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	No	Yes	Yes	Yes
R^2	0.3038	0.0028	0.0088	0.0053	0.0070
N	2953	2953	2953	2953	2953
Hausman	9.43	37.26***	1.29	19.66	6.04

Notes: Random and fixed effects regressions between EP and systematic (idiosyncratic) risk measures with no other covariates. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses. Significant Hausman test indicates that the fixed effects estimator is more appropriate than the random effects estimator.

Table 10: Additional results: panel regressions with control variables

	(1) Idio(OLS)	(2) smb	(3) hml	(4) rmw	(5) cma
EP	-0.0539***	-0.0057	0.0080	0.0171	-0.0057
	(0.0187)	(0.0108)	(0.0165)	(0.0156)	(0.0153)
Lev	0.0009	-0.0001	0.0010	-0.0006	-0.0014*
	(0.0012)	(0.0007)	(0.0009)	(0.0010)	(0.0008)
Spread (Bid-Ask)	0.2313	0.2038	0.5801	1.7304***	-0.0478
	(0.2960)	(0.3431)	(0.8701)	(0.6655)	(0.7628)
lnVol	0.2403***	-0.0229	-0.0149	-0.0446**	0.0140
	(0.0292)	(0.0182)	(0.0216)	(0.0186)	(0.0213)
Liq	0.0107	-0.0027	0.0074	-0.0578***	0.0013
	(0.0121)	(0.0143)	(0.0194)	(0.0194)	(0.0187)
BMV	0.1142***	0.0062	0.0187	0.0192	-0.0229*
	(0.0309)	(0.0053)	(0.0193)	(0.0127)	(0.0137)
Sales growth	-0.1425***	0.0390	-0.0732	0.0196	-0.0409
	(0.0542)	(0.0678)	(0.0899)	(0.0888)	(0.0989)
Constant	-1.4314***	0.5680*	0.2433	0.5183	-0.0421
	(0.4512)	(0.2928)	(0.3546)	(0.3264)	(0.3518)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	No	Yes	Yes	Yes
R^2	0.3797	0.0190	0.0114	0.0123	0.0097
N	2446	2446	2446	2446	2446

Notes: Random and fixed effects regressions between EP and systematic (idiosyncratic) risk measures with other covariates as shown in equation 7. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses.

Table 11: Robustness checks

	(1) Stock Return	(2) Total Risk	(3) Idio.	(4) Sharpe	(5) Alpha	(6) Systematic
$\widehat{EP}$	0.1510***	-0.3968***	-0.0718***	0.0667***	-0.0014	0.0450**
	(0.0084)	(0.0387)	(0.0193)	(0.0030)	(0.0031)	(0.0187)
Lev	-0.0003**	0.0010	0.0001	-0.0000	0.0001	0.0001
	(0.0002)	(0.0015)	(0.0008)	(0.0001)	(0.0001)	(0.0010)
Spread (Bid-Ask)	-0.0625	-0.1185	0.1758**	-0.0110	-0.0198	0.1282
	(0.0459)	(0.1159)	(0.0745)	(0.0120)	(0.0231)	(0.0885)
lnVol	0.0101	0.2272***	0.2352***	-0.0081**	0.0012	0.0538***
	(0.0085)	(0.0253)	(0.0200)	(0.0033)	(0.0020)	(0.0162)
Liq	-0.0081***	0.0352***	0.0061	-0.0026**	0.0027	-0.0035
	(0.0028)	(0.0132)	(0.0082)	(0.0013)	(0.0021)	(0.0106)
BMV	-0.0020	0.0276**	-0.0007	0.0025***	0.0000	-0.0019
	(0.0031)	(0.0118)	(0.0030)	(0.0002)	(0.0008)	(0.0020)
Sales growth	-0.0107	-0.0419	0.0326	0.0001	0.0088	0.0120
	(0.0119)	(0.0399)	(0.0264)	(0.0051)	(0.0072)	(0.0382)
Constant	-0.5501***	-0.3930	-2.0224***	-0.0671	-0.0332	-0.1387
	(0.1159)	(0.3365)	(0.2838)	(0.0471)	(0.0275)	(0.2457)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	No	Yes	Yes	Yes	Yes
R^2	0.1669	0.6518	0.2515	0.1529	0.0098	0.0346
N	3453	3453	3451	3453	3451	3451

Notes: Random and fixed effects regressions between $\widehat{EP}$ and financial performance measures with other covariates as shown in equation 7. ***, ** and * denote 1%, 5% and 10% significant level, respectively. Robust standard errors are reported in parentheses.