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Corporate Sustainability Performance and Idiosyncratic Risk: A Global Perspective

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Abstract

Does investing in sustainability leaders affect portfolio performance? Analyzing two mutually exclusive leading and lagging global corporate sustainability portfolios (Dow Jones) finds that (1) leading sustainability firms do not underperform the market portfolio, and (2) their lagging counterparts outperform the market portfolio and the leading portfolio. Notably, we find leading (lagging) corporate social performance (CSP) firms exhibit significantly lower (higher) idiosyncratic risk and that idiosyncratic risk might be priced by the broader global equity market. We develop an idiosyncratic risk factor and find that its inclusion significantly reduces the apparent difference in performance between leading and lagging CSP portfolios.

Keywords: sustainability, corporate social performance, corporate financial performance, idiosyncratic risk, global evidence, best of sector

JEL Classifications: G11, G30, Q56

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1. Introduction

The rapidly changing dynamics of the modern world suggest that socially responsible investing (SRI) or corporate sustainability are becoming increasingly popular with investors and corporations (Grant, Buttle, McKenzie and Veale, 2002). Indeed, recent statistics suggest that U.S. $2.49 trillion of the $24.4 trillion (i.e., around 10%) of total assets under professional management in the United States are managed according to SRI criteria and that 94% of the *Business Week* global 1,000 companies believe corporate sustainability can deliver real business benefits (Grant, Buttle, McKenzie and Veale, 2002; Social Investment Forum, 2005). Furthermore, banks representing 80% of the world's source of project finance have signed up to the Equator Principles while the United Nations Principles of Responsible Investment boasts more than 160 signatories representing U.S. $10 trillion in assets under management (UNEP, 2007). Although SRI has experienced strong growth, little is known about SRI and corporate sustainability investing (Cerin and Dobers, 2001; Hamid and Sanford, 2002; Beloe, Scherer and Knoepfel, 2004). Accordingly, our primary goal is to present new evidence on how stock markets view corporate sustainability, taking a global perspective.

We argue that prior studies seeking to analyze portfolio performance by using SRI mutual fund data provide an imperfect picture due to the intervention of other factors, such as fees, transaction costs, and other non-SRI-related characteristics. For example, Brammer, Brooks and Pavelin (2006) argue that analyzing fund data requires disentangling corporate social performance (CSP) from fund manager performance. To overcome this limitation, we analyze the stock price performance of passively managed leading and lagging corporate sustainability portfolios relative to an unrestricted market index (see also Statman, 2000, 2006). Leading (lagging) CSP portfolios contain firms with superior (inferior) CSP profiles. We also compare the performance of a passively managed leading corporate sustainability portfolio relative to its lagging counterpart. We use the Dow Jones Sustainability Index (DJSI) as our CSP proxy and apply a range of controls for country, industry, size, style (value or growth), momentum (country, industry, and stock), idiosyncratic risk, and corporate sustainability industry ranking.

We also argue that the single CSP proxy measures, which are frequently used in other SRI studies, present nontrivial limitations with regard to their interpretation and reliability. A major concern is the assumption that a single proxy (e.g., environmental reporting) provides sufficient information to assess a company's broader commitment to corporate sustainability activities. Given that the DJSI takes a multidimensional view of sustainability, we believe that it is more appropriate than the single-dimensional proxies in the prior literature.

SRI and corporate sustainability have attracted a great deal of attention, manifesting in the ongoing debate among professional and private investors, trustees, government bodies, and scholarly and professional academics. For example, an increasing number of market participants argue that a socially responsible business strategy enables firms to reap substantial economic rewards (Herremans, Akathaporn and McInnes, 1993; Waddock and Graves, 1997; Derwall, Guenster, Bauer and Koedijk, 2005). On the other hand, others argue that an SRI strategy is inconsistent with modern portfolio theory and the maximization of shareholder wealth (Langbein and Posner, 1980). This school of thought argues that the rejection of profitable business and investment strategies only because of CSP concerns must harm economic performance (Aupperle, Carroll and Hatfield, 1985). Another body of research suggests that a neutral CSP-CFP (corporate social performance-corporate financial performance) link should exist. For example, Ullmann (1985) argues there is a large number of intervening variables between the social and financial performance of companies. A neutral association could also be explained by the financial market's inability to value and, thus, price CSP (see Statman, 2000).

A negative CSP-CFP relation might not necessarily indicate a destruction of shareholder value but, rather, demonstrate a price premium (i.e., return discount) afforded to leading CSP firms. An investor's expected return is a function of the risks associated with that investment, so lower risk equates to lower expected returns. Therefore, if we are willing to pay comparatively more for firms with lower risk due to their superior CSP performance, then the future income streams derived from these firms are expected to be comparatively lower than their riskier counterparts. Indeed, standard asset pricing models might not be able to capture a CSP-induced lower risk price premium, and in such circumstances SRI researchers could erroneously interpret a negative alpha as evidence of underperformance. We provide empirical support for the idea that idiosyncratic risk is being priced, and this price is reflected in the return differentials of leading and lagging CSP portfolios. Consequently, one of the main benefits of having a leading CSP profile is that a firm is able to reduce its business risk relative to lagging CSP firms and secure a lower cost of equity capital.

2. SRI and the empirical research

The SRI literature is divided across two major themes. The first seeks to analyze SRI at the firm level while the second focuses on (managed) portfolio performance with both types being characterized by studies using either a specific or a broad-based measure of CSP. This current discussion focuses on firm-level prior research because our analysis uses firm-level data.

A majority of SRI studies at the firm level find a positive CSP-CFP link (see Griffin and Mahon, 1997; Orlitzky, Schmidt and Ryes, 2003). For example, a recent study by Filbeck, Gorman and Zhao (2009) find that a portfolio of newly listed Top 100 *Business Ethics* companies outperforms both the S&P 500 and a matched sample. Austin and Sauer (2002) examine the effect of climate policies (i.e., carbon taxes) on company performance and find that performance is affected by at least 10% for some companies. However, Brammer, Brooks and Pavelin (2006) show a negative link between CSP and CFP in a sample of U.K. firms. Notably, they attribute this result primarily to firms having good CSP on the environmental front.

Wood and Jones (1995) argue that a more comprehensive measure of CSP is required if a robust CSP-CFP relation is to be found. One such view suggests that the CSP-CFP relation is best analyzed with regard to the strong theoretical underpinnings of stakeholder theory. With this in mind, Herremans, Akathaporn and McInnes (1993) use *Fortune* magazine's annual surveys of corporate reputations to assess a company's broader CSP. The seventh attribute of the survey, "responsibility to the community and the environment," is used as their measure of CSP. They find that the market-adjusted returns for leading CSP firms outperform lagging CSP firms and that leading CSP firms exhibit significantly lower risk.

Another body of SRI research seeks to create SRI portfolios comprising leading and lagging CSP firms. In the United States, SRI research of this type often uses KLD (Kinder, Lydenburg, and Domini) CSP ratings data. Using KLD data, Guerard (1997) finds no significant difference in the returns of portfolios screened according to KLD criteria relative to portfolios not applying CSP screens. Derwall, Guenster, Bauer and Koedijk (2005) analyze two mutually exclusive portfolios formed from leading and lagging eco-efficiency-rated U.S. stocks. They find that portfolios with better eco-efficiency rankings provide higher risk-adjusted returns with results remaining robust to numerous variants of the pricing model including size, book-to-market (BM), momentum, and industry controls.

In this study, we enhance this literature by using a broad-based measure of CSP across a large sample of global firms while using a robust performance assessment method, which also seeks to assess and control for idiosyncratic risk pricing factors.

3. Measuring CSP

Two dominant contemporary SRI screening practices are negative and positive SRI screens. Negative screens are the most common SRI screening method, representing more than 80% of all screened portfolios in the eco-efficiency-rated United States (Social Investment Forum, 2005). Negative CSP screens frequently exclude firms engaged in the business of alcohol, tobacco, firearms, gambling, nuclear power, and military weapons while heavily overweighting financial services, healthcare, and technology stocks (Hamid and Sanford, 2002). Modern portfolio theory indicates that SRI screens, most notably negative screens, increase portfolio risk because the exclusions of stocks, sectors, and countries can result in a significant reduction in diversification benefits (Langbein and Posner, 1980).

We seek to overcome some of the inherent problems associated with research based on negative screens by using CSP ratings from the DJSI Group.[1] The DJSI is a prominent index seeking to track the performance of leading sustainability firms on a global basis. The DJSI derives its investment universe from the Dow Jones Global

[1] The DJSI's corporate sustainability rankings of firms are provided by SAM Group GmbH.

Index (DJGI) with both indexes using the same method for calculation, review, and publication.[2]

The DJSI assesses five main areas of corporate sustainability. The first is strategy, which assesses a firm's ability to integrate long-term economic, environmental, and social strategies into their business plans while maintaining global competitiveness and brand reputation. The second is the financial ability of a firm to lead its respective industry in meeting its shareholders' demands for sound financial returns, long-term economic growth, open communication, and transparent financial accounting. The third area requires leading CSP firms to foster loyalty by investing in customer relationship management and product and service innovation that focuses on technologies and systems, all of which use financial, natural, and social resources in an efficient, effective, and economic manner over the long term. The fourth area of assessment demands the highest standards of corporate governance and stakeholder engagement, including corporate codes of conduct and public reporting. Finally, leading CSP firms must manage human resources to maintain workforce capabilities and employee satisfaction (DJSI, 2002).

Opportunities and risks for each company, within their respective industries, are then assessed across three equally weighted economic (including financials), environmental, and social dimensions. Sustainability risks focus on the defensive component of sustainable management to mitigate sustainability costs and risks (i.e., risk management). Sustainability opportunities focus on a firm's ability to harness the market's demand for sustainability products and services (DJSI, 2002). A composite CSP score is then calculated for each of the DJGI firms with leading CSP firms representing those firms with the best (i.e., highest) composite corporate sustainability score. The best of sector (BOS) leading sustainability approach is then used to rank all firms within each of the DJGI 51 industry groups, spanning some 34 countries. Once completed, the DJSI index consists of approximately 200 to 300 companies, which approximates the top 10% of the leading sustainability companies that form part of the DJGI.

The primary source of information is a company questionnaire with more than 70 multiple-choice questions, which is endorsed by a senior member of management from each DJSI-rated company as a means of ensuring its accountability and accuracy. The remainder of the ratings information is subsequently sourced from company-specific documentation and direct dialogue between the analyst and company and by media and Internet research. The DJSI's BOS corporate sustainability approach is a special type of positive screen whereby the DJSI selects firms with the best

[2] The DJGI is a global equity index that covers more than 4,500 firms and represents 95% (80% prior to June 2000) of the world's free-float equity market (DJGI, 2002). The DJGI, Morgan Stanley Capital International, and Financial Times Stock Exchange World indexes are highly similar, with an average correlation coefficient in excess of 0.99, which indicates that the DJGI is a suitable proxy for the global equity markets.

economic, social, and environmental performance within each economic region and sector (DJSI, 2002; Social Investment Forum, 2005).

A major strength of the DJSI is that it is one of the few SRI indexes to be fully checked and verified by an independent auditor (Beloe, Scherer and Knoepfel, 2004). The DJSI also satisfies the inherent qualities of a suitable SRI benchmark in that it is comprehensive, consistently applied, flexible, and investable. The DJSI should not be confused with the other CSP indexes, such as the Domini Social Index 400 (DSI400), since the latter is more akin to an ethical or moral index than a sustainability index. Ethical indexes, such as the DSI400, apply negative screens and exclude firms engaged in alcohol, tobacco, firearms, gambling, nuclear power, and military weapons (KLD, 2007). The DJSI does not seek to exclude any of these sectors but rather assesses each firm's ability to manage the business opportunities and risks associated with its particular sector.

4. Empirical analysis

All firms forming part of the DJSI and DJGI are matched against companies in the Compustat global database. All returns are denominated in U.S. dollars. The first stage of the portfolio formation process requires an annual filtering of the DJGI universe of approximately 5,000 companies to represent the largest 2,500 DJGI companies. The latter represents the sample universe from which the DJSI then selects approximately 10% of what their research deems the "most sustainable" group of companies.

Similar to Derwall, Guenster, Bauer and Koedijk (2005), we construct two mutually exclusive portfolios with differing CSP profiles using constituent firm data from the DJGI 2,500 and CSP firm data from the DJSI.[3] As a result, two data sets (i.e., portfolios) are derived from the DJGI 2,500 sample universe. The first represents a portfolio of leading CSP firms that are brought together to form the DJSI portfolio data set while the second portfolio represents the DJGI 2,500 sample universe once the DJSI firms have been removed. The latter portfolio consisting of the lagging CSP group of firms is labeled "DJGI Unmatched."[4] To ensure greater homogeneity between the leading and lagging CSP portfolios, we also create a DJGI matched portfolio. To accomplish this objective, we randomly match each leading CSP (DJSI) firm against a lagging CSP (DJGI unmatched) firm according to one of the 34 countries in which they are primarily listed and then to one of the 51 industries with which they belong. Of these firms, the final match is achieved by ensuring the smallest absolute difference in size. Thus, the matching process alleviates the influence of country, industry, size, fiscal reporting periods, and other heterogeneous

[3] Like Derwall, Guenster, Bauer and Koedijk (2005) we use a short period of back-dated data and find that these data do not influence the findings.

[4] Throughout the paper, leading and lagging refer to cross-firm corporate sustainability comparisons, not time series leads and lags.

factors commonly reported in the literature as detracting from prior SRI research efforts.

In light of Herremans, Akathaporn and McInnes (1993) reporting a CSP industry effect on the performance of leading CSP firms, the second portfolio formation process seeks to control for the way in which different industries could be influenced by CSP. Employing proprietary CSP industry-ranking data sourced from the DJSI, we create leading and lagging CSP industry formed portfolios for each of the 51 DJGI industry groups. A CSP industry score is calculated using the following approach. First, an aggregated cluster score for each firm is derived from the economic, environmental, and social dimensions used to assess firms. The cluster score represents a firm's management (i.e., governance) ability with regard to tackling sustainability issues within their respective industry. Second, a weighted average of firms comprising each industry provides an industry-specific CSP score. We then rank each of the 51 CSP industry scores from highest to lowest. The 26 highest CSP industry scores and their constituent firms form the leading CSP industry portfolio with the balance (25) making up the lagging CSP industry portfolio.

Using the leading and lagging industry portfolios, we then repeat the portfolio formation process as outlined above. Consequently, for the leading CSP industry-sorted portfolio we then divide our sample into two portfolios: the first represents our sample of leading CSP firms and the second represents our sample portfolio of lagging CSP firms. The portfolio formation process is repeated each year. The DJSI, DJGI unmatched, and DJGI matched portfolios represent an equal-weighted monthly return series covering the period 1998–2002.

Table 1 presents the descriptive statistics for both the leading and lagging equal-weighted CSP formed portfolios. Panels A, B, and C indicate that both the monthly mean returns and Sharpe ratios for leading CSP (DJSI) portfolios, including those across each of the CSP industry formed portfolio types, are lower than their lagging CSP (DJGI) counterparts. In addition, DJSI portfolios, with the exception of the leading CSP industry portfolio, generally exhibit lower risk (Panel B, column 3) when compared to lagging CSP portfolios. Panel D is also shown to highlight the performance of the broader market, large stocks, and small stocks over the 1998–2002 analysis period.

4.1. Basic results

We use a six-factor model in preference to the one-, three- and four-factor models that are commonly used in the literature. The results are robust to this choice. The model is

$$\begin{aligned}(R_{p,t} - R_{f,t}) = \alpha_p &+ \beta_{i,1}(R_{m,t} - R_{f,t}) + \beta_{i,2}SMB + \beta_{i,3}HML \\ &+ \beta_{i,4}UMD_{DJGI\_Stock} + \beta_{i,5}UMD_{DJGI\_Industry} \\ &+ \beta_{i,6}UMD_{DJGI\_Country} + \varepsilon_{i,t}, \qquad (1)\end{aligned}$$

Table 1

Descriptive statistics of equal-weighted leading/lagging CSP portfolios

Results are derived from the 1998–2002 sample period. Return and risk values are presented as monthly percentages with the exception of the Sharpe ratio, which is the ratio of the mean excess return to the standard deviation of return over the full period. The base portfolios reported are the Dow Jones Sustainability Index (DJSI) and the Dow Jones Global Index (DJGI).

	Mean return	Risk (Std dev)	Sharpe ratio	Maximum	Minimum
Panel A: Equal-weighted portfolios—no industry sort					
DJSI world	0.191	5.279	−0.028	11.729	−14.485
DJGI unmatched	1.270	5.285	0.176	10.508	−14.703
DJGI matched	0.816	5.294	0.091	11.070	−14.559
Panel B: Equal-weighted portfolios—leading CSP industries					
DJSI world	0.169	5.183	−0.033	11.938	−14.220
DJGI unmatched	0.980	4.824	0.133	10.735	−13.971
DJGI matched	0.852	5.140	0.100	11.814	−13.502
Panel C: Equal-weighted portfolios—lagging CSP industries					
DJSI world	0.281	5.454	−0.010	11.413	−14.887
DJGI unmatched	1.523	5.661	0.209	10.382	−15.263
DJGI matched	0.843	5.568	0.091	10.100	−15.523
Panel D: Dow Jones benchmark indices					
DJGI broad	0.011	5.161	−0.063	9.089	−14.066
DJGI large cap	−0.038	5.240	−0.072	9.260	−13.151
DJGI small cap	0.227	5.692	−0.019	10.060	−17.704

where $R_{p,t}, R_{m,t}, R_{f,t}$ are the returns of portfolio p, the market portfolio (DJGI), and the risk-free proxy (three-month U.S. Treasury bill) at time t, respectively. Here, HML (SMB) is the Fama-French high minus low (HML) book-to-market (small minus big [SMB]) mimicking portfolio in month t. The SMB factor is calculated using the DJGI large-cap and DJGI small-cap indexes while the HML factor follows Elton, Gruber and Blake (1996) whereby the MSCI World Growth and Value indexes are used. UMD_{DJGI_Stock}, $UMD_{DJGI\_Industry}$, and $UMD_{DJGI\_Country}$ represent the Scowcroft and Sefton (2005) self-financing (6,1,1) firm, industry, and country momentum factors, respectively. The intercept term represents the portfolio's abnormal return.

The results of the basic times-series regression (in which the portfolio has no CSP industry sorting) presented in Table 2, Panel A, show several features. First, we see that the six-factor alpha for the DJSI portfolio is statistically close to zero, suggesting that it neither outperforms nor underperforms the DJGI equity market. Second, both the DJGI unmatched and matched portfolios slightly outperform the broader equity market at an economically and statistically significant level as reflected by their six-factor alphas. Third, the six-factor alphas for Panel A's difference portfolios indicate that the DJSI provides lower realized returns relative to both the DJGI unmatched

Most likely universe mismatch, as DJGI unmatched with outperformance DJGlobalIndex broad with 4,500 comapnies (Should apply, if only a few 100 funds in DJSI - DJSI seems to have about 222 firms

Table 2

Regression of six-factor model for DJSI, DJGI unmatched and DJGI matched portfolios

This table reports the estimation of Model (1) as shown in the main text. The dependent variable is the excess return on various (passive) Dow Jones sustainability-related portfolios (monthly returns for the DJSI, DJGI unmatched and DJGI matched portfolios). DJSI represents the leading CSP firms while the lagging CSP firms form part of the DJGI unmatched and DJGI matched portfolios. Independent variables comprise: the market portfolio (DJGI Broad); HML (SMB), which is the Fama-French high minus low book-to-market (small minus big) mimicking portfolio; and three UMD factors for country, industry, and stock momentum (Scowcroft and Sefton, 2005). All regressions apply a Newey-West (1987) correction for heteroskedasticity and autocorrelation. Columns one to three represent an analysis of the individual portfolio while columns four and five represent the difference portfolios.

	DJSI		DJGI unmatched		DJGI matched		DJSI-DJGI unmatched		DJSI-DJGI matched	
	B	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Panel A: No industry sort										
6-factor alpha	0.002	0.167	0.012**	0.000	0.007**	0.000	−0.010**	0.000	−0.005**	0.000
DJGI broad	0.971**	0.000	0.979**	0.000	0.967**	0.000	−0.009	0.783	0.004	0.909
HML	0.229*	0.020	0.002	0.962	0.098	0.382	0.227**	0.002	0.131**	0.007
SMB	0.116	0.238	0.455**	0.000	0.377**	0.003	−0.339	0.000	−0.261**	0.000
UMD country	0.125**	0.008	0.075	0.032	0.086	0.133	0.051	0.295	0.039	0.347
UMD industry	0.183*	0.024	0.132	0.002	0.099	0.244	0.051	0.420	0.084*	0.034
UMD stock	−0.354**	0.002	−0.241	0.000	−0.207	0.110	−0.113	0.220	−0.147**	0.005
R^2 (Adj)	0.92		0.98		0.92		0.48		0.45	
No. of observations	60		60		60		60		60	

(*continued*)

Table 2 (*continued*)

Regression of six-factor model for DJSI, DJGI unmatched and DJGI matched portfolios

	DJSI		DJGI unmatched		DJGI matched		DJSI-DJGI unmatched		DJSI-DJGI matched	
	B	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Panel B: Leading CSP industries										
6-factor alpha	0.002	0.457	0.009**	0.000	0.008**	0.004	−0.007**	0.001	−0.006**	0.002
DJGI broad	0.948**	0.000	0.900**	0.000	0.934**	0.000	0.049	0.224	0.014	0.716
HML	0.368**	0.001	0.115**	0.005	0.254*	0.031	0.253**	0.003	0.115*	0.031
SMB	0.001	0.993	0.325**	0.000	0.263*	0.024	−0.324**	0.001	−0.262	0.000
UMD country	0.111*	0.044	0.136**	0.000	0.099	0.186	−0.025	0.641	0.013	0.813
UMD industry	0.209*	0.012	0.201**	0.000	0.107	0.280	0.007	0.910	0.102*	0.047
UMD stock	−0.334**	0.004	−0.340**	0.000	−0.196	0.150	0.006	0.954	−0.138*	0.023
R^2 (Adj)	0.89		0.97		0.87		0.31		0.29	
No. of observations	60		60		60		60		60	
Panel C: Lagging CSP industries										
6-factor alpha	0.003*	0.023	0.014**	0.000	0.008**	0.000	−0.011**	0.000	−0.005**	0.009
DJGI broad	0.981**	0.000	1.032**	0.000	0.992**	0.000	−0.052	0.134	−0.012	0.765
HML	0.112	0.250	−0.042	0.485	0.015	0.902	0.154*	0.019	0.097	0.114
SMB	0.229*	0.020	0.531**	0.000	0.409**	0.002	−0.302**	0.000	−0.180**	0.002
UMD country	0.158**	0.007	0.026	0.560	0.112	0.187	0.132**	0.003	0.046	0.387
UMD industry	0.158	0.065	0.098	0.080	0.119	0.239	0.060	0.325	0.039	0.467
UMD stock	−0.377**	0.002	−0.174*	0.028	−0.252	0.103	−0.203*	0.020	−0.126	0.133
R^2 (adj)	0.92		0.97		0.89		0.54		0.27	
No. of observations	60		60		60		60		60	

**, * indicate statistical significance at the 0.01 and 0.05 level, respectively.

and DJGI matched portfolios by 1% (p-value < 0.001) and 0.5% (p-value < 0.001) per month, respectively.

The results in Panel B of Table 2 for leading-lagging CSP industry-sorted portfolios provide similar results to those for nonindustry-sorted portfolios. Consequently, the leading CSP portfolio of companies (i.e., DJSI) within the leading CSP industry group provide returns commensurate with the broader market while slightly underperforming the lagging CSP (i.e., DJGI) unmatched and matched portfolios. The results for those companies comprising lagging CSP industries are in Panel C, Table 2. Most notable is that the DJSI now provides statistically significant and positive abnormal returns of 0.3% per month. However, the DJSI portfolio continues to provide lower realized returns relative to the DJGI unmatched and DJGI matched portfolios.[5]

Examining the various style characteristics of the leading and lagging equally weighted portfolio is best done in the form of the difference portfolios as presented in Table 2, columns "DJSI-DJGI unmatched" and "DJSI-DJGI matched." First, the results for both difference portfolios (unmatched and matched), in Panel A, indicate no significant difference in the systematic risk between leading and lagging CSP firms. These results are also consistent for both the leading and lagging CSP industry-sorted portfolios. Second, the HML factor in Panel A indicates that leading CSP portfolios exhibit a statistically and substantively significant value style when compared to both the unmatched (0.227, p-value of 0.002) and matched portfolios (0.131, p-value of 0.007). This relation is also consistent across leading and lagging CSP industry-sorted portfolios with the exception of the lagging CSP industry matched portfolio.

Third, the SMB factor demonstrates that leading CSP firms exhibit a significant large cap bias relative to lagging CSP firms irrespective of the portfolio formation process. Fourth, there is little difference in momentum effects for the DJSI-DJGI unmatched difference portfolios with the exception of the lagging CSP industry-sorted portfolio (Panel C). However, we observe some significant differences with regard to momentum for DJSI-DJGI matched difference portfolios. For example, the DJSI portfolio in Panel A has a significant industry momentum effect when compared to the matched portfolio although this is not observed for the lagging CSP industry portfolio in Panel C.

Finally, we observe that all portfolio types appear to exhibit a negative coefficient on the stock UMD factor, which is found to be more pronounced for the DJSI portfolios. This observation would indicate that the equally weighted portfolios exhibit a contrarian investment style. While puzzling for the DJGI portfolios, it is not

[5] The underperformance of leading CSP firms relative to lagging CSP firms is argued to reflect a price premium (i.e., return discount) afforded to leading CSP firms. It is unlikely that this underperformance provides a takeover opportunity for lagging CSP firms. On the other hand, the lower prices (i.e., return premium) of lagging CSP firms might provide leading CSP firms with an incentive to acquire these "cheaper" lagging CSP firms. However, this potential acquisition is only viable if lagging CSP firm prices are below "fair" market value. We thank an anonymous referee for bringing these issues to our attention.

unexpected for the DJSI given that it exhibits a value investment style, which has strong contrarian implications.

4.2. Why do lagging CSP firms outperform leading CSP firms?

The results above are contrary to the findings of prior SRI studies, such as those by Derwall, Guenster, Bauer and Koedijk (2005) and Herremans, Akathaporn and McInnes (1993). Why? One possible explanation is the use of different measures of CSP. Given the earlier discussion that our measure, having a broad scope, is more suited to gauge a business' entire commitment to CSP, we argue that these results are derived from a superior measure of CSP. Accordingly, they highlight a serious concern regarding prior SRI research efforts and question the validity of theories arguing that leading CSP firms should provide superior market returns.

Traditional asset pricing models propose that only systematic risk matters—expected return is an exclusive function of this risk and idiosyncratic risk is not priced.[6] However, the activities of leading CSP firms are likely to have a downward influence on their unsystematic (idiosyncratic) risk. For example, this lower risk can happen because they have happier, more stable employees, lower fines, good production levels, and all the other business-related virtues bestowed on leading CSP firms. On the other hand, lagging CSP companies could simply be adept at engaging in less socially responsible business strategies while engaging in business activities that continue to make them equally competitive in the current market.

Like Derwall, Guenster, Bauer and Koedijk (2005), we argue that the extent to which CSP screens influence investment returns depends on two main factors. The first requires financial markets to possess the ability and inclination to factor into current share prices the economic consequences of CSP. The second requires that market valuation models have the ability to price CSP. If the performance models are correctly specified, then no abnormal returns should exist. If abnormal returns continue, the model itself might not be correctly specified, thereby ensuring that CSP cannot be explained by current asset pricing models. Alternatively, it might signal that financial markets are continually mispricing leading CSP firms.

While every effort has been made with regard to correcting for investment styles, such as size, BM, UMD, and industry and country biases, like Derwall, Guenster, Bauer and Koedijk (2005), we are not able to fully explain the anomalous return behavior of leading and lagging CSP firms. Consequently, two distinct questions arise. First, does a firm's CSP profile result in a return discount or premium not accounted for in current performance models? Second, is this anomaly simply the result of a continued mispricing of leading CSP firms by capital markets? These questions capture the essence of the well-known joint test dilemma: it is possible that

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[6] However, Fletcher (2007) finds that many asset pricing models have difficulty correctly pricing idiosyncratic risk.

our results either reflect an incomplete asset pricing model or are the result of the market's inability to correctly price CSP (i.e., market inefficiency) or both.

In this research, we argue that financial markets do value CSP information and that current asset pricing models are not able to fully capture the influence of CSP on security valuations. One possible explanation is that leading-lagging CSP firms exhibit lower or higher idiosyncratic (business) risk and that this is being priced into security valuations by financial markets for which conventional models are not able to account (Campbell, Lettau, Malkiel and Xu, 2001).

4.3. What about idiosyncratic risk?

With the exception of Boutin-Dufresne and Savaria (2004), there is little to no research focusing on the nonsystematic or idiosyncratic business risk of leading and lagging CSP companies. This lack of research is surprising given that many SRI advocates argue that firms exhibiting a strong CSP profile are able to reduce their (company specific) business risk by adopting a leading CSP strategy (see, for example, Herremans, Akathaporn and McInnes, 1993; DJSI, 2002; Boutin-Dufresne and Savaria, 2004; Social Investment Forum, 2005; UNEP, 2007). Business risks might include adverse events arising from lawsuits, strikes, brand and reputation erosion, and boycotts, all of which could materially influence a firm's profitability and overall risk profile.

Leading CSP firms should, all else being equal, exhibit lower idiosyncratic risk. While such risk is clearly irrelevant when using the capital asset pricing model (CAPM) or similar asset pricing models, recent evidence supporting the role of idiosyncratic risk in asset pricing suggests the CSP effect could be risk related. The viability of this risk explanation is best reflected in a body of research providing growing evidence that idiosyncratic (i.e., diversifiable) risk does matter and that these risks are, in fact, now being priced by the market despite asset pricing models failing to predict their importance (see Campbell, Lettau, Malkiel and Xu, 2001; Malkiel and Xu, 2001; Fletcher, 2007). Malkiel and Xu (1997), using a Fama and French (1996) portfolio formation approach, find that lower stock returns, most notably for larger firms, are associated with lower idiosyncratic risk. Goyal and Santa-Clara (2003) also find a significant and positive relation between average stock volatility (which they deem largely idiosyncratic) and the return on the market, with the market variance itself having no forecasting power.

Malkiel and Xu (1997) argue why idiosyncratic risk is relevant when pricing equity. First, they argue that the size effect found by Fama and French (1992) could be a proxy for the varying idiosyncratic risks of small and large firms. Second, they postulate that "portfolio managers may well demand an extra risk premium on individual issues that are perceived to carry extraordinary specific risk" (Malkiel and Xu, 1997, p. 12). This argument is especially plausible in segments of the market that are less compliant with the perfect capital market assumption; that is, in those situations in which market frictions are particularly evident. Malkiel and Xu (1997) concede that idiosyncratic risk could proxy for broader risk factors, such as those associated with the factor sensitivities of the arbitrage pricing theory.

Also believers in their own outperformance dillute their Alpha by diversification

Another related explanation argues that idiosyncratic risks attract compensation because investors, for exogenous reasons, are prevented from fully diversifying their portfolios. These reasons might include frictions arising from transaction costs and taxes or exogenous legal or regulatory constraints, such as employee compensation plans that give workers shares in the firm but restrict their capacity to sell their holdings. For example, Benartzi and Thaler (2001) find people hold disproportionate amounts of their pension plans in the shares of their employers. Furthermore, Goetzmann and Kumar (2004) and Barber and Odean (2000) find that U.S. investors are underdiversified with regard to their portfolio holdings.

The CSP return discount that we observe above is also consistent in principle with the ideas behind the incomplete information model of Merton (1987). He presents the view that firms with larger firm-specific variance will have larger alphas and that a stock's return is a function of both market risk and total variance. Furthermore, the model recognizes that the dissemination of information by firms has significant value to investors, especially in the presence of information asymmetries. Merton (1987) recognizes that a standard CAPM might not fully value some securities when faced with incomplete information sets, especially for small neglected stocks. This model is consistent with the argument that the market values the risk management and transparency practices of leading CSP firms, especially with regard to how these practices can influence a firm's overall risk.

Collectively, the evidence suggests investors seek to be compensated for these idiosyncratic risks. Thus, investors wishing to invest in firms that help reduce idiosyncratic risk (e.g., CSP firms), all other things being equal, are called on (and willing) to relinquish some of their return, in effect creating an SRI discount. Initial evidence supporting a lower expected idiosyncratic risk for leading CSP companies is reported by Boutin-Dufresne and Savaria (2004). They analyze a relatively small sample of Canadian firms over the 1995–1999 period. They find those firms with higher social responsibility have significantly lower idiosyncratic risk when compared to firms with lower social responsibility. Herremans, Akathaporn and McInnes (1993) and McGuire, Sundgren and Schneeweis (1988) also find evidence of lower risks in leading CSP firms.

4.4. Idiosyncratic risk results

Based on the previous discussion, one would expect leading CSP firms to exhibit lower idiosyncratic risk. This research seeks to explore this proposition by first undertaking a simple analysis of differences in idiosyncratic risk between leading (DJSI) and lagging (DJGI) CSP firms when using the CAPM. We then follow Malkiel and Xu (1997) and Boutin-Dufresne and Savaria (2004) and use the CAPM to estimate a firm's idiosyncratic risk. A second measure of idiosyncratic risk is also calculated whereby we use our six-factor market model (Equation (1)). Idiosyncratic risk is

Idiosyncratic risk formula should be right, as Alpha does not capture any variance ... --> Their use of variance is great, as it this level, idiosyncratic and systematic component are additive (see Bennett and Sias)

have somewhat of a look ahead bias, as the DJSI was not founded before 1999

Table 3

Idiosyncratic risks of leading-lagging CSP companies

This table presents the average idiosyncratic risk for the six-factor model for both the matched and unmatched portfolios over the 1998–2002 period. Tests of significant differences in means are undertaken using a bootstrap method as described in the text. The bootstrap p-value is the proportion of the 10,000 simulations in which the simulated difference in idiosyncratic risk exceeds the actual difference reported.

	DJSI	DJGI unmatched			DJGI matched		
Period (1998–2002)	Mean	Mean	*Diff*	*% Diff*	Mean	*Diff*	*% Diff*
All industries	0.1813	0.2427	−0.0614**	34%	0.2212	−0.040**	22%
(No. of obs)	*1,110*	*11,479*			*1,110*		
Leading CSP industries	0.1534	0.2292	−0.0758**	49%	0.2043	−0.051**	33%
(No. of obs)	*602*	*5,881*			*602*		
Lagging CSP industries	0.2146	0.2569	−0.0423**	20%	0.2413	−0.027**	12%
(No. of obs)	*508*	*5,598*			*508*		

** indicates statistical significance at the 0.01 level.

Diff calculated from DJSI

calculated using annual time series regressions with the process repeated for each of the five years of data.[7] Accordingly, an estimate of each firm's idiosyncratic risk is taken from the square root of the residual variance as captured by each model.

To test whether the reported difference in idiosyncratic risk between leading (DJSI) and lagging (DJGI) CSP firms is nonzero, the following bootstrap procedure is undertaken (the bootstrap results for the CAPM are similar).[8] Under the null hypothesis, the idiosyncratic risk of DJSI stocks and non-DJSI stocks is identical. Accordingly, the sample estimates of risk are pooled to obtain a combined sample of 11,479 observations (1,110 DJSI and 10,369 non-DJSI). From the combined sample, 1,110 observations are drawn at random to represent the bootstrap sample of DJSI firms. Similarly, 1,110 observations are sampled to represent the non-DJSI firms. The mean idiosyncratic risk of each bootstrapped sample is calculated and the difference recorded. This bootstrap procedure is repeated 10,000 times.

The idiosyncratic risk test results for the six-factor model in Table 3 provide strong evidence that leading CSP (i.e., DJSI) companies exhibit both substantively and statistically significant differences with regard to idiosyncratic risk. Under the null hypothesis that idiosyncratic risk is equal for leading and lagging CSP firms,

[7] Annual periods are employed to avoid the issue of overlapping observations. However, we also examine the relation based on a three-year time frame (details not reported here) and find results consistent with those presented here.

[8] We also employ a t-test and nonparametric Wilcoxon signed-rank analysis of differences in means between the lead and lag CSP firms. All results (details not reported here) indicate highly significant differences (at the 1% level) between all leading and lagging CSP firms across all portfolios types. However, in light of some limitations associated with the t-test and the nonparametric Wilcoxon signed-rank test, we report only the bootstrap results. We would like to thank an anonymous referee for suggesting the bootstrap approach.

Which software to use for bootstrap?

Table 3 shows that the likelihood of observing differences of the magnitude reported purely by chance is virtually zero (significant at the 1% level). When observing the "all industries" portfolios, the lagging CSP DJGI unmatched and DJGI matched firms have approximately 34% and 22%, respectively, more idiosyncratic risk than the DJSI's leading CSP firms (significant at the 1% level). These results are robust to industry, country, and size factors given the firm matching process applied throughout this research.

Results are also robust to the influence of leading and lagging CSP industries and indicate that leading CSP companies in leading CSP industries exhibit lower company-specific risks compared to lagging CSP industries. The results are consistent with those of Boutin-Dufresne and Savaria (2004) and clearly demonstrate strong empirical evidence to support the hypothesis that leading CSP firms exhibit significantly lower idiosyncratic risk than lagging CSP firms. Furthermore, our findings expand on those of Boutin-Dufresne and Savaria (2004), who only analyze Canadian firms, as we provide evidence of a significant CSP-idiosyncratic risk link at the global level for both models.

lagging industries generally higher risk

4.5. What of the relation between idiosyncratic risk, firm size, returns, and CSP?

Consistent with the size-idiosyncratic relation, as hypothesized by Malkiel and Xu (1997) above, it is important to ascertain if the lower idiosyncratic risks of leading CSP firms are driven by a size bias rather than a CSP firm-specific effect. We run a similar regression to that of Malkiel and Xu (1997) as a means of determining if firm size and idiosyncratic risk have the same significant negative relation in our data.

Furthermore, we extend Malkiel and Xu's (1997) approach to provide a greater understanding and robustness to our results in several ways. First, idiosyncratic risk is estimated when using both the CAPM and six-factor models. An analysis of the CAPM, when calculating a firm's idiosyncratic risk, enables us to compare the substantive nature of our results with that of Malkiel and Xu (1997). By observing the results of the six-factor model, we are also able to better control for other factor biases that might be contributing to a firm's idiosyncratic risk. Second, we undertake the analysis for the entire period of the study and for each year individually to ascertain the stability of this relation over the period analyzed. Third, we incorporate a return variable to establish if there is any evidence of a relation between a firm's idiosyncratic risk and its total return. Fourth, we control for possible panel data issues due to the repeated cross-sectional sampling of the data over time. Fifth, an analysis over a longer three-year time frame using three-year returns (unreported) provides similar results. Finally, we repeat our tests including a dummy variable for leading CSP firm (DJSI) firms. This additional testing provides an analysis of the relation between idiosyncratic risk, firm size, returns, and CSP. The regression model takes the form

$$\sigma_{i,t} = \alpha + \beta_1 \ln MCap_i + \beta_2 D_{DJSI} + \beta_3 Return + e_{i,t}, \tag{2}$$

where $\sigma_{i,t}$ is the idiosyncratic risk as derived from either the CAPM or six-factor model, ln$MCap_i$ is the size variable measured by the natural log of market capitalization for firm i, *Return* is the one-year return for each firm, and D_{DJSI} is a dummy variable that takes the value of unity if the firm is in the DJSI and zero otherwise.

The results presented in Table 4 are consistent with those of Malkiel and Xu (1997) and indicate that larger firm size is indeed negatively related to ~~lower~~ idiosyncratic risk (significant at the 1% level). Our results are robust to both the CAPM and six-factor models and across all periods analyzed. Perhaps the most important finding is that a firm's idiosyncratic risk is positively and significantly related to a firm's return. This finding remains across all cases, including the full period, with the only exception being 2002.

An alternative view might suggest that both size and CSP firm characteristics are interrelated in that leading CSP firms are typically large firms and have lower idiosyncratic risk. Consequently, we need to examine the relation between a firm's return, whether it be a leading or lagging CSP firm, and its idiosyncratic risk while controlling for firm size. The regression results also shown in Table 4, which now include a dummy variable for leading CSP firms, empirically support the argument that leading CSP firms have lower idiosyncratic risk even after controlling for size. As hypothesized, large firms and leading CSP firms are clearly characterized by lower idiosyncratic risk and that a predominately positive relation between idiosyncratic risk and one-year returns exists. These findings would suggest that leading CSP firms, even after controlling for size, would be characterized by lower returns, which could be due to their lower relative idiosyncratic risk. An obvious question is whether these findings influence the performance of those portfolios that comprise leading and lagging CSP firms as presented in Table 2 above. This issue is considered in the following section.

4.6. *Influence of an idiosyncratic risk factor on leading-lagging portfolio performance*

To examine the influence of idiosyncratic risk on the returns of the portfolios presented in Table 2, we construct an idiosyncratic risk-mimicking portfolio in the spirit of SMB and HML. First, we rank all firms in our sample based on their idiosyncratic risk. We then build low- and high-idiosyncratic risk portfolios, applying an annual rebalancing. Each year, low (high) idiosyncratic risk portfolios are characterized by those firms below (above) the 10th (90th) percentile of idiosyncratic risk. We then create an equal-weighted five-year return series for the low (high) idiosyncratic risk portfolio. The monthly returns of the high idiosyncratic risk portfolio are subtracted from that of the monthly returns of low idiosyncratic risk portfolio, thus producing our ("low minus high") idiosyncratic risk factor-mimicking portfolio (denoted *MID*). We then augment our six-factor model with *MID* and repeat the analysis previously find idiosyncratic risk to be lower for CSP firms and priced in terms of return! [Hence in their sample irresponsible firms do well as reward for idiosyncractic risk.] Use whoever of the idiosyncratic risk guys proposed that first and add as fifth factor in models.

Table 4

Cross-sectional regression of idiosyncratic risk on returns, firm size and CSP

This table reports the estimation of Model (2) as shown in the main text for annual periods, as well as the full five-year sample. The regression approach used here uses the full sample consisting of both the DJSI and DJGI unmatched firms (the DJGI unmatched group also includes the DJGI matched subset of firms). Panels A and B have as the dependent variable idiosyncratic risk from the CAPM and six-factor modes, respectively. We correct for possible heteroskedasticity via a White's (1980) modified adjustment.

	1998		1999		2000		2001		2002		Full period	
Panel A: 1-factor idiosyncratic risk												
One-year return	0.062**	0.061**	0.039**	0.039**	0.092**	0.091**	0.060**	0.059**	−0.006	−0.007	0.039**	0.039**
Firm size	−0.076**	−0.075**	−0.078**	−0.076**	−0.063**	−0.059**	−0.068**	−0.062**	−0.064**	−0.060**	−0.074**	−0.072**
Bin (DJSI = 1, 0 otherwise)		−0.006		−0.023**		−0.036**		−0.040**		−0.024**		−0.021**
Constant	0.894**	0.890**	0.983**	0.966**	0.908**	0.874**	0.970**	0.914**	0.876**	0.842**	−0.971**	0.950**
Adjusted R^2	0.183	0.183	0.260	0.265	0.175	0.178	0.076	0.081	0.063	0.066	0.113	0.114
No. of obs	2,256	2,256	2,260	2,260	2,267	2,267	2,317	2,317	2,379	2,379	11,479	11,479
Panel B: 6-factor idiosyncratic risk												
One-year return	0.062**	0.061**	0.037**	0.037**	0.011**	0.010**	0.047**	0.046**	0.008	0.007	0.035**	0.035**
Firm size	−0.054**	−0.053**	−0.066**	−0.064**	−0.061**	−0.058**	−0.074**	−0.071**	−0.065**	−0.063**	−0.063**	−0.061**
Bin (DJSI = 1, 0 otherwise)		−0.014**		−0.026**		−0.027**		−0.017*		−0.012	0.832**	−0.017**
Constant	0.687**	0.675**	0.867**	0.848**	0.850**	0.824**	0.964**	0.940**	0.840**	0.822**		0.814**
Adjusted R^2	0.135	0.136	0.224	0.226	0.057	0.059	0.101	0.101	0.075	0.075	0.108	0.109
No. of obs	2,256	2,256	2,260	2,260	2,267	2,267	2,317	2,317	2,379	2,379	11,479	11,479

**, * indicate statistical significance at the 0.01 and 0.05 level, respectively.

undertaken in Table 2. This process provides us with some indication as to whether idiosyncratic risk is being priced and thus reflected in our leading-lagging CSP formed portfolios. The model is

$$\begin{aligned}(R_{p,t} - R_{f,t}) = \alpha_p + \beta_{i,1}(R_{m,t} - R_{f,t}) + \beta_{i,2}SMB + \beta_{i,3}HML \\ + \beta_{i,4}UMD_{DJGI\_Stock} + \beta_{i,5}UMD_{DJGI\_Industry} \\ + \beta_{i,6}UMD_{DJGI\_Country} + \beta_{i,7}MID + \varepsilon_{i,t}. \quad (3)\end{aligned}$$

Malkiel and Xu (1997) suggest that the SMB factor might be a proxy for idiosyncratic risk.[9] We find that the SMB and the MID factors have a −0.279 correlation, which does not seem high enough either to support their argument or to raise serious concerns of multicollinearity. We expect the *MID* regression coefficient will be positive or negative for leading-lagging CSP portfolios. This prediction arises because of the positive relation we find between idiosyncratic risk and return (confirming Malkiel and Xu, 1997). However, the most important prediction relates to the alpha term for the difference portfolio (DJSI-DJGI). Specifically, if idiosyncratic risk is an important factor explaining the "sustainability effect," then the difference alphas should become statistically insignificant (or at least statistically weaker) in Equation (3) when compared to their counterparts from Table 2. The results are in Table 5.

All panels of Table 5 clearly indicate that, as hypothesized, the *MID* idiosyncratic risk-mimicking portfolio is significant and typically in the expected direction. For example, in Panel A, the MID regression coefficient for the DJSI portfolio is 0.094 (p-value of 0.034). Notably, the DJSI now exhibits a statistically significant alpha. While the DJSI's returns as seen in Panel A are still lower than those of the DJGI unmatched and matched portfolios, the gap has narrowed. Indeed, when we observe the results for the difference portfolios, relative to the matched case, the difference alpha is now statistically insignificant (5% level). These results provide some empirical support for the view that a firm's' idiosyncratic risk is reflected in stock prices and is more apparent for firms classified as leading sustainability outfits. We also find that the DJSI's underperformance as captured by the difference portfolios (Panel A) has decreased by more than 30% relative to the results in Table 2. Also, there is a sizeable reduction in the statistical significance in the alpha of the DJSI-matched difference portfolio.

The results in Panels B and C of Table 5 for the leading-lagging CSP industry-sorted portfolios are similar to those found for the non-CSP industry-sorted portfolios. Most notable is that the difference portfolios again demonstrate lower estimates of alpha with weakening statistical significance (compared to Table 2). Indeed, for the unmatched case in Panel B and for the matched case in Panel C, the difference alphas

[9] A variety of other linkages between variables in this model have been explored in the literature. For example, Arena, Haggard and Yan (2008) investigate the association between idiosyncratic volatility and price momentum.

All outperform, which indicates universe mismatch!

Table 5

Regression of multifactor model including idiosyncratic risk for DJSI and DJGI portfolio returns

This table reports the estimation of Model (3) as shown in the main text. The dependent variable is the excess return on various (passive) Dow Jones sustainability-related portfolios (monthly returns for the DJSI, DJGI unmatched and DJGI matched portfolios). DJSI represents the leading CSP firms while the lagging CSP firms form part of the DJGI unmatched and DJGI matched portfolios. Independent variables comprise: the market portfolio (DJGI Broad); HML (SMB), which is the Fama-French high minus low book-to-market (small minus big) mimicking portfolio; three UMD factors for country, industry, and stock momentum (Scowcroft and Sefton, 2005); and a mimicking portfolio capturing "low minus high" idiosyncratic risk (MID). All regressions apply a Newey-West (1987) correction for heteroskedasticity and autocorrelation. Columns one to three represent an analysis of the individual portfolio while columns four and five represent the difference portfolios.

	DJSI		DJGI unmatched		DJGI matched		DJSI-DJGI unmatched		DJSI-DJGI matched	
	B	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Panel A: No industry sort										
6-factor alpha	0.005*	0.031	0.011**	0.000	0.009**	0.001	−0.006**	0.005	−0.003	0.055
DJGI broad	1.003**	0.000	0.970**	0.000	0.979**	0.000	0.034	0.369	0.024	0.461
HML	0.143	0.100	0.028	0.571	0.066	0.482	0.115	0.135	0.076	0.253
SMB	0.192*	0.023	0.432**	0.000	0.405**	0.000	−0.241**	0.002	−0.214**	0.001
UMD country	0.128	0.033	0.074*	0.030	0.087	0.182	0.054	0.306	0.041	0.373
UMD industry	0.147*	0.030	0.143**	0.000	0.086	0.241	0.005	0.939	0.061	0.235
UMD stock	−0.315**	0.001	−0.252**	0.000	−0.192	0.060	−0.063	0.444	−0.122	0.090
MID	0.094*	0.034	−0.028	0.258	0.035	0.466	0.122**	0.003	0.059	0.084
R^2 (adj)	0.93		0.98		0.91		0.56		0.47	
No. of observations	60		60		60		60		60	

(*continued*)

Table 5 (*continued*)

Regression of multifactor model including idiosyncratic risk for DJSI and DJGI portfolio returns

	DJSI		DJGI unmatched		DJGI matched		DJSI-DJGI unmatched		DJSI-DJGI matched	
	B	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*	*B*	*p-value*
Panel B: Leading CSP industries										
6-factor alpha	0.005*	0.045	0.010**	0.000	0.011**	0.000	−0.004	0.077	−0.006*	0.012
DJGI broad	0.992**	0.000	0.906**	0.000	0.975**	0.000	0.086*	0.040	0.017	0.681
HML	0.252*	0.014	0.098	0.070	0.145	0.192	0.154	0.071	0.107	0.203
SMB	0.103	0.282	0.340**	0.000	0.359**	0.001	−0.237**	0.005	−0.255**	0.002
UMD country	0.115	0.097	0.137**	0.000	0.102	0.184	−0.022	0.706	0.013	0.819
UMD industry	0.161*	0.040	0.194**	0.000	0.062	0.467	−0.033	0.608	0.099	0.129
UMD stock	−0.282**	0.010	−0.332**	0.000	−0.147	0.217	0.050	0.577	−0.135	0.134
MID	0.126*	0.015	0.018	0.497	0.118*	0.039	0.108*	0.014	0.008	0.845
R^2 (adj)	0.90		0.97		0.87		0.38		0.28	
No. of observations	60		60		60		60		60	
Panel C: Lagging CSP industries										
6-factor alpha	0.005	0.055	0.013**	0.000	0.006*	0.045	−0.008**	0.001	−0.001	0.562
DJGI broad	0.998**	0.000	1.014**	0.000	0.972**	0.000	−0.016	0.681	0.026	0.489
HML	0.066	0.485	0.006	0.926	0.069	0.536	0.060	0.461	−0.004	0.962
SMB	0.270**	0.004	0.489**	0.000	0.361**	0.001	−0.219**	0.006	−0.092	0.218
UMD country	0.160*	0.016	0.025	0.584	0.111	0.153	0.135*	0.018	0.049	0.357
UMD industry	0.139	0.059	0.118*	0.025	0.141	0.107	0.021	0.737	−0.002	0.971
UMD stock	−0.357**	0.001	−0.196**	0.008	−0.276*	0.025	−0.161	0.067	−0.080	0.331
MID	0.050	0.291	−0.052	0.123	−0.059	0.299	0.103*	0.014	0.110**	0.007
R^2 (adj)	0.92		0.96		0.89		0.58		0.36	
No. of observations	60		60		60		60		60	

**, * indicate statistical significance at the 0.01 and 0.05 level, respectively.

are now statistically insignificant (at the 5% level) whereas in Table 2 they were strongly significant.

Collectively, the most important aspect of these findings is that the alphas for both the industry- and nonindustry-sorted portfolios demonstrates that the difference portfolio, in all cases, head in the right direction (i.e., are closer to zero). All the difference portfolio alphas are now found to be statistically weaker, and in half the cases the alpha changes from being statistically significant to insignificant at the 5% level. The results for the DJSI-matched portfolio are especially important given that they seek to control for industry, country, and size differences, which could influence the results. In a nutshell, our *MID*-enhanced regressions provide a plausible explanation as to why we observe the relatively lower realized returns of the DJSI in Table 2 above.[10]

4.7. Does survivorship bias affect our analysis?

The DJGI, like most indexes (e.g., S&P 500), has liquidity, size, and other requirements that could create survivorship concerns. Additionally, it might be the case that the inappropriate treatment of terminal returns (see, e.g., Shumway, 1997) induces a bias in the recorded returns for high idiosyncratic risk stocks, which in some way drives our results. While we acknowledge that a potential survivorship bias from these two sources warrants serious consideration, there is no reason to believe that the DJGI would suffer to a greater degree than any other comparable index. There are a range of considerations that suggest that the bias is unimportant in our study.

First, the DJGI that we use represents a global portfolio of more than 2,500 stocks; clearly, it is not a small portfolio of high idiosyncratic risk stocks. Thus, it is implausible to believe that a (relatively small) subsample of delisted firms could drive our results. The portfolios that we use are just too large and the typical stocks included in our analysis are predominantly very large in size (i.e., for the most part they are unlikely to be distressed stocks) for the Shumway argument to materially influence our analysis.

Second, all DJSI firms are derived from the DJGI investment universe with firm deletions (i.e., failure to survive) from the DJGI resulting in the same firm being deleted from the DJSI's eligible investment universe. Third, any such survivorship bias in our data (the extent to which it exist) is likely to bias against our empirical findings. For example, Shumway (1997) indicates that the negative effect on returns from the delisting bias is more pronounced for small firms vis-à-vis large firms. If we recognize that high idiosyncratic risk firms are typically smaller firms, as shown in Table 4 (and

[10] In effect, we jointly explore whether: (1) idiosyncratic risk is priced and (2) the lower returns of leading CSP firms can be explained by lower idiosyncratic risk. Accordingly, while we believe our analysis is strongly suggestive of the linkage between sustainability performance and idiosyncratic risk, we caution readers against drawing unqualified support for this proposition.

also in Malkiel and Xu, 1997), and that these firms are generally biased downward in returns, our high idiosyncratic risk portfolio will have overstated returns. Since MID is defined as a "low minus high" portfolio, the (positive) divergence in returns between our low- and high-idiosyncratic risk portfolios is currently understated. As a result, the current construction of the *MID* factor makes it harder for it to be empirically successful in our analysis; the fact that it is successful renders our findings all the more persuasive.[11]

5. Conclusion

This study examines the CSP-CFP link. We investigate the relative performance of firms classified into leading or lagging CSP portfolios within a BOS ratings approach. This study contrasts the prior research based on CSP ratings derived from negative screens or those that use single CSP proxy measures (e.g., executive remuneration). Specifically, we choose the DJSI as our CSP proxy. The DJSI includes firms that lead their respective industries with regard to economic, social, and environmental risk management strategies. This approach is largely compatible with the ideas underlying modern portfolio theory. Accordingly, the DJSI is likely to be more acceptable to a wider range of investors and trustees with fiduciary responsibilities when compared to the more restrictive negatively screened SRI approaches.

Our main findings are summarized as follows. The initial tests indicate a leading CSP portfolio underperforms its lagging counterpart (see Brammer, Brooks and Pavelin, 2006), which is in contrast to the large body of research supporting a positive CSP-CFP link (e.g., Orlitzky, Schmidt and Ryes, 2003; Derwall, Guenster, Bauer and Koedijk, 2005). One explanation is that higher returns for lagging CSP firms compensates for higher idiosyncratic risk. We provide empirical evidence in support of this view. We examine the influence of idiosyncratic risk on various portfolio returns by constructing an idiosyncratic risk-mimicking portfolio in the spirit of SMB and HML. Our results suggest that a significant proportion of the return difference of leading and lagging CSP firms or portfolios is plausibly explained by differences in idiosyncratic risk. Accordingly, this study suggests that future researchers should seriously consider the potential merits of using an idiosyncratic risk factor when assessing the performance of leading and lagging CSP firms or portfolios.

This study is just the tip of the iceberg when analyzing the BOS corporate sustainability process. Substantial follow-up research opportunities exist that might use different databases, regions, and periods. Indeed, given the global focus of this study, readers should exercise caution when interpreting our results and implying any relation to specific market contexts. For example, further work would be worthwhile in the U.S. context to establish whether our findings for the performance-idiosyncratic risk linkage are robust to that single country setting. Future researchers also need to

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[11] We thank an anonymous referee for drawing the question of survivorship bias to our attention.

better understand the stability of the supposed link between leading CSP factors and CFP. There is a need to further explore and disentangle the performance of large-cap firms from that of leading CSP firms. Finally, future researchers need to better understand the linkage between idiosyncratic risk and a firm's return and particularly whether an idiosyncratic risk factor deserves a role in future asset pricing models motivated by sustainability forces.

No a single indication to diversification

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