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Investors' Reaction to Environmental Performance: A Global Perspective of the Newsweek 's "Green Rankings"

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Keywords
Environmental ranking, event study, newsweek magazine

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INVESTORS' REACTION TO ENVIRONMENTAL PERFORMANCE: A GLOBAL PERSPECTIVE OF *NEWSWEEK*'S "GREEN RANKINGS"

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Keywords: Environmental ranking, event study, *Newsweek* magazine

JEL Codes: M14, G02, G14, G24, Q51, Q56.

1. Introduction

Socially Responsible Investing, an investment strategy that favors corporate practices promoting environmental stewardship, consumer protection, human rights, and diversity, represents 12% of the $25.2 trillion in total world assets under professional management (Social Investment Forum 2010). Socially Responsible Investing has become a dynamic research area in recent years (Geczy *et al*. 2003; Kurtz 1997; Sauer 1997; Cummings 2000; Abramson and Chung 2000; Bauer *et al*. 2002; Mill 2006; Lobe, Roithmeier and Walkshausl 2009).[1] The popularity of Socially Responsible Investing has led to the development of indexes like the Dow Jones Sustainability Index (DJSI), in which environmental responsibility weights 9.2% (Fowler and Hope 2007).

A specific environmental index created in 2009 targeting the Socially Responsible Investing audience is *Newsweek*'s "Green Rankings." Its first edition included the "US 500 List," which comprises the 500 largest publicly-traded US companies. Its second edition, released online on October 18th, 2010 at 8 a.m. US East coast time, added the "Global 100 List," involving the 100 largest publicly traded companies worldwide. These *Newsweek's* rankings mostly use existing information about hundreds of environmental indicators and models. Nevertheless, they provide new information by presenting a clear unique measure of environmental performance for each company. This publicly available measure may help coordinate expectations about how the market weights all of the environmental data available. It also gives small investors access to costly environmental information, and increases public awareness about the largest companies' environmental performance.

The present study applies financial tools to assess whether stock values reacted across world markets to the announcement of indexes that synthesize the environmental performance of the world's largest publicly-traded companies. The environmental index selected for this purpose is the "Global 100 Ranking" (G100), a ranking of the 100 largest public companies by market

[1] Kitzmueller and Shimshack (2012) provide an extensive review of this literature.

capitalization. The G100 comprises stocks traded in nine different exchanges across the world, which allows us to study whether there are differences in the reactions of investors operating within and outside the US stock market.[2] Specifically, we analyze (a) whether there are changes in the value of an equal-weight portfolio of the companies on the ranking; (b) whether a company's ranking position affects its stock value; (c) whether there are differences in the reactions to the ranking of US-traded companies compared to non-US-traded companies; and (d) whether the reactions to the ranking differ across industry sectors.

The present study contributes to the literature in four aspects. First, it adds a world market dimension to environmental rankings and the response of investors. This is true because the G100 includes stocks traded in nine different exchanges (NYSE, London, Paris, Frankfurt, Switzerland, Hong Kong, Shanghai, South Korea, and Tokyo) from companies based in most of the continents (e.g., the US and Brazil in America; the United Kingdom, France, Italy, Germany, Spain, and Russia in Europe; and China, South Korea, and Japan in Asia). Second, the study quantifies the marginal effects of the ranking on stock prices. By employing cross-sectional models of abnormal returns against rankings, we are able to determine marginal effects that cannot be computed from the cumulative abnormal return statistics typically used in event studies. Third, we investigate the impact of rankings on returns by industry sectors. Finally and most importantly, to our knowledge it provides the first evidence of the existence of heterogeneity among investors in regard to their interest in past performance and managerial quality as predictors of future environmental performance.

Previous studies have analyzed the impact of environmental news and rankings on stock markets, with results showing positive correlation between economic and environmental performance (Murphy 2002). Environmental news studies have included the Toxic Release Inventory of US firms (Khana, Quimio, and Bojilova 1998), pollution information of S&P 500 companies (Konar and Cohen 2001), explosions on chemical plants worldwide (Capelle-

[2] We use the G100 because, unlike the "US 500 List" and other environmental indexes, it includes both US- and non-US-traded firms. The "US 500 List" has been analyzed by Anderson-Weir (2010), Murguia (2010), Blumenshine and Wunnava (2010), van Iwaardenl *et al*. (2010), and Lyon and Shimshack (2011).

Blancard and Laguna 2010), and carbon disclosure (see Busch and Hoffmann 2011 for an extended literature review). Some of these studies found significant effects (Capelle-Blancard and Laguna 2010; Konar and Cohen 2001), whereas other studies uncovered significant effects only when repeated information was released (Khana, Quimio, and Bojilova 1998). Busch and Hoffmann (2011) report that, for companies in the Global 2500 Dow Jones, corporate environmental performance pays off when using carbon emissions as an outcome-based measurement. Margolis, Elfenbein and Walsh (2007) provide an extensive review of the literature linking corporate financial performance to corporate social performance.

Studies involving environmental news and rankings have been performed for Japan (Nagayama and Takeda 2007, Yamaguchi 2008, and Takeda and Tomozawa 2008) and the US. For the US, some studies used the KLD ranking (Plumlee *et al*. 2010; Walter 2009; Dawkins and Fraas 2011),[3] whereas others focused on *Newsweek's* ranking (Anderson-Weir 2010; Murguia 2010; Blumenshine and Wunnava 2010; van Iwaardenl *et al*. 2010; Lyon and Shimshack 2011). In the case of *Newsweek's* ranking, Anderson-Weir (2010), Murguia (2010) and van Iwaardenl *et al*. (2010) found no significant effects of *Newsweek*'s "Green Ranking 2009" on the returns of S&P 500 stocks, whereas Lyon and Shimshack (2011) did.[4] Blumenshine and Wunnava (2010) found that companies with high environmental rankings have higher market capitalization values. They concluded that either investors include environmental factors when pricing stocks, or that a high environmental rank indicates other intangible variables that contribute to a company's value.

Succinctly, our results indicate that the market reacted to the G100 by changing the relative prices of the stocks included in it, but not the value of the equal-weight portfolio of such stocks. Specifically, increasing ten positions in the ranking improved the value of a stock by

[3] In general, these papers find a positive relationship between environmental performance and voluntary climate change disclosure.

[4] The differences in results may be due to the event windows selected, and the methods employed for estimating abnormal returns. Murguia (2010) analyses one and two days (the event day and the next one), Anderson-Weir (2010) three days (the day previous to the event plus the event day and the day after), van Iwaardenl *et al*. (2010) one year, and Lyon and Shimshack (2011) three and four days (starting the day of the event).

0.0994%, or 113 million dollars for the average company capitalization. There is also evidence of a stronger reaction for non-US-traded stocks compared to US-traded stocks, and a more robust one for stocks in the non-heavy sector compared to the ones in the heavy sector. Non-US- and US-traded stocks reacted different also with respect to past environmental performance and environmental managerial quality. In particular, US-traded stock returns appear to be affected by past performance and managerial quality, whereas non-US-traded stock returns seem to respond only to managerial quality.

2. Theoretical Framework

Why should investors care about Corporate Social Responsability (CSR)? Chatterji, Levine, and Toffel (2009) propose four possible motivations for investors to desire transparency about both past social performance and current managerial decisions that influence future social performance. The first motivation is based on the idea that socially responsible companies may perform better financially by attracting socially responsible consumers, reducing the thread of regulation, and reducing concerns from activists and non-governmental organizations. The second motivation is the driving force underlying “deontological” investors, who do not want to profit from unethical behaviors. Deontological investors care about past performance because they want to ensure that current profits were not earned from previous unethical behavior, and they also care about current management to avoid future scandals which would taint future profits. The third motivation is associated with “consequentialist” investors, who are driven by a desire to reward good behavior and decrease the market share of environmental irresponsible firms. The fourth and final motivation corresponds to “expressive” investors, who want to show to themselves or others that they are socially responsible.

Kitzmueller and Shimshack (2012) discuss extensively the existing CSR theories and the supporting evidence. Regardless of the motives behind CSR, [5] there are investors who seek

[5] Ditlev-Simonsen and Midttun (2011) provide a partial answer in this regard. In a survey of corporate leaders they find that branding, stakeholders, and value maximization are assumed to be key motivators of CSR by senior

transparency in social rankings, in the sense of combining an accurate summary of past performance, and a careful evaluation of current managerial actions likely to influence future environmental performance (Chatterji, Levine, and Toffel 2009).

Chatterji, Levine, and Toffel (2009) suggest that future research should examine how the holding of socially responsible funds changes as stakeholders are provided with more transparency about corporate social performance; and argue that stakeholders might be heterogeneous in their responses to higher-quality information. To the best of our knowledge, the present study is the first one to provide evidence of the latter, in the form of US-traded stocks reacting differently to the G100 announcement compared to non-US-traded stocks. We also provide evidence about what investors look for in practice, which might be beneficial for the construction of environmental indexes. We find that investors in US-traded stocks are interested on past environmental performance and managerial quality, while for investors in non-US-traded stocks only managerial quality is relevant. Our results for US-traded firms are consistent with Chatterji, Levine, and Toffel (2009), who found that KLD pollution prevention scores predicted pollution or regulation violations for companies regulated by the US Environmental Protection Agency.

According to Chatterji, Levine, and Toffel (2009), measures of (environmental) managerial quality are relevant when they contain little noise and have substantial incremental information about future environmental outcomes not contained in history alone. They present a theoretical model based on these ideas for the selection of the optimal weight in a social index. In our study, managerial quality is represented by its environmental policies and its reputation (the correlation between both is 0.51), which have a correlation with environmental performance of 0.35 and 0.03, respectively. It is possible then that managerial quality might be relevant for predicting future environmental performance, provided it is not too noisy.

managers of the 20 largest Norwegian corporations. They also report that corporate leaders believe sustainability and branding should be the key motivators of CSR by senior managers of the 20 largest Norwegian corporations.

Errors in CSR measures, and particularly in environmental rankings, may cause market inefficiencies and explain different results regarding their impact on stock performance (Chatterji, Levine, and Toffel 2009). Noisy measures may be the reason why some studies find little correlation between CSR metrics and financial performance. Alternatively, if consumers or investors are misled by the errors, studies finding a positive correlation may overestimate the true relationship between actual CSR and financial performance. These limitations must be taken into account when evaluating the results of the present study, because measurement errors are likely to affect the indexes employed for the analysis.

3. Data

Data in the present study include the G100, stock returns, nine stock exchange indexes, and Fama-French indexes. A detailed explanation follows.

3.1. *Newsweek*'s "Global 100 Ranking"

The G100 consists of a ranking of the world's 100 largest (by market capitalization) companies according to *Newsweek*'s "Green Score." The Green Score is a weighted sum of three component scores that are designed to complement each other, namely, the "Environmental Impact Score" (EIS) with 45% weight, the "Green Policies Score" (GPS) with 45% weight, and the "Reputation Survey Score" (RSS) with 10% weight. The raw component scores were first converted to standardized values called Z scores, which reflect how individual companies performed relative to the average. The Green Score, as well as each component score, is published on a scale from 1 (worst performing) to 100 (best performing) (*Newsweek* 2010).

The EIS is an index of past environmental performance based on data compiled by Trucost. It measures the total environmental impact of a corporation's global operations (90 %) and the disclosure of those impacts (10 %). The EIS incorporates more than 700 metrics, including emissions of nine key greenhouse gases, water use, solid-waste disposal, and emissions that contribute to acid rain and smog. When publicly disclosed environmental data are available, they are used to evaluate a company performance for each impact metric. An economic input-output model is used to calculate direct-company and supply-chain impacts in cases where data are unavailable (*Newsweek* 2010).

The companies are classified into 15 sectors according to the FTSE/Dow Jones Industry Classification Benchmark. Therefore, to fairly assess impacts for companies operating in more than one industry, a benchmarking system was used. To make it possible to compare companies of different size, this system calculates environmental impact in dollars per dollar of sales. This accounts for 90% of the raw EIS; the remaining 10 % measures the disclosure of usable data. In the case of investing firms, rankings are adjusted to take into account the impact of the equity under management (*Newsweek* 2010).

The GPS is a managerial performance index based on models provided by MSCI, and assesses how a company manages its environmental footprint. To estimate the GPS, MSCI created a model that measures the quality of each company's environmental reporting, policies, programs, and initiatives. More than 70 indicators are incorporated into the GPS, and categorized into five issues, namely, (a) climate-change policies and performance, (b) pollution policies and performance, (c) product impact, (d) environmental stewardship, and (e) management of environmental issues. They address, respectively, how well each company manages its carbon emissions; how well each company manages its non-carbon emissions to air, water, and land; the life-cycle impacts of each company's products and services; how well each company manages and uses its local resources; and the quality of each company's track record of managing environmental risks. Data on regulatory compliance, lawsuits, controversies, and community impacts are also among the indicators taken into account within each category (*Newsweek* 2010).

The RSS is another managerial index, but based on an opinion survey of CSR professionals, academics, and other environmental experts who subscribe to *CorporateRegister.com*. A total of 14,921 surveys were sent out asking each respondent to rate a random sample of 15 companies on a sliding scale (1 to 100) from "laggard" to "leader" in three key green areas: environmental performance, commitment, and communications. Of those surveyed, 2,480 were environmental sector specialists that were only asked to score companies in their sector of expertise. The survey's response rate was 12 %, twice the rate for the 2009 reputation survey. Chief-executive scores, sector specialists, and other participants were given a weight of three, two, and one, respectively. Each company's performance, commitment, and communications scores were then averaged to produce its raw RSS (*Newsweek* 2010).

Companies that appear on both the US and Global lists in the 2010 edition have different Green Scores and component scores because normalizations are different. Moreover, it is not possible to compare company scores over time due to the changes in the methods used to construct them (*Newsweek* 2010).

3.2. Stock Returns and Indexes

Values of stocks and market indexes adjusted by splits and dividends were obtained from Yahoo Finance.[6] When a company's stock data were not available for the period under study, the company's web site was used as the source of information. In three instances (Nissan Motor, Toshiba, and Lukoil), pink-sheet data (i.e., over-the-counter transactions in the US) were used as a last resource.

Seventy one of the companies in the G100 are traded in the US. Out of the remaining 29 companies not traded in the US, 25 are traded in Europe and four are traded in Asia. For companies trading in more than one stock market and currency, the market selected was the one with the highest average daily volume. Since the companies in the ranking are traded in nine different stock markets, the indexes used include NYA (New York, 1,900 largest stocks), the SSE Composite Index (Shanghai, all stocks), the Hang Seng Index (Hong Kong, 50 largest stocks), the TOPIX (Japan, all stocks), the Kospi Composite Index (Korea, all stocks), the SBF250 (Paris, CAC-All Tradeables) (France, all stocks), CDAX (Frankfurt, all stocks), SMI

[6] Yahoo Finance web page for US and Asian stocks, and United Kingdom Yahoo Finance web pages for European stocks.

Expanded (Switzerland, 95% of the market capitalization), and the FTSE All-Share (United Kingdom, 98% of the market capitalization).

For each stock in the G100 and the nine market indexes, daily excess returns were calculated by subtracting the risk-free rate (measured as the interest rate on the one-month Treasury bill, downloaded from French's web page (French 2011)) from the respective rate of return. Following the literature (Fama and French 1998; Griffin 2002; Hou, Karolyi, and Kho 2011; Fama and French 2012), rates of return for the 29 non-US-traded stocks and the market indexes other than NYA, were computed by first converting the values denominated in foreign currencies into US dollars.[7] For this purpose, the corresponding daily exchange rates from Oanda (2012) were used.

Fama-French factors for US-traded stocks were downloaded from French's web page (French 2011). The Fama-French factors are the small-minus-big factor ($\mathrm{SMB_t}$), the high-minus-low factor ($\mathrm{HML_t}$), and the factor consisting of the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios at time *t* ($\mathrm{MOM_t}$). SMB_t is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks at time *t*, whereas HML_t is the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks at time *t*. Unfortunately, to the best of our knowledge, local analogs of the $\mathrm{SMB_t}$, HML_t, and $\mathrm{MOM_t}$ factors for non-US-traded stocks are not available on a daily basis (Ken French personal communication).[8]

4. Methods

[7] This procedure ignores exchange rate risk (Fama and French 1998; Griffin 2002; Hou, Karolyi, and Kho 2011; Fama and French 2012). It implies purchasing power parity, and that the stocks considered cannot be used to hedge exchange risk (Fama and French 2012).

[8] Fama and French (2012) constructed monthly factors for 23 different countries to study their effect on international stock returns. Kubota and Takehara (1997) also constructed monthly factors for Japan. Exeter University has factors calculated with a monthly frequency for the United Kingdom (http://xfi.exeter.ac.uk/researchandpublications/portfoliosandfactors/index.php). For Canada there are daily factors, but the series has been updated only until 2009 (http://expertise.hec.ca/professorship_information_financiere_strategique/fama-french-canadian-factors/).

Based on the previous discussion, it is hypothesized that the publication of the G100 may have impacted the listed firms in two ways, namely, (a) by affecting the overall value of the firms comprised in the G100 relative to firms not included in the index, and/or (b) by inducing changes in the relative prices of the G100 firms according to their respective rankings. A third testable hypothesis is whether investors were more interested in past environmental performance or present managerial skills.

The first hypothesis is tested by analyzing the significance of the abnormal return of the equal-weight portfolio of firms in the G100 when the index was released. The second and third ones are tested by regressing the companies' abnormal returns against their respective rankings (cross-section OLS models). Both methods are explained in detail in the following subsections. Finding out that the aforementioned cross-section OLS models are statistically significant would support the idea that the market reacted to the G100 announcement. These findings cannot explain how the market used the information released,[9] but might provide evidence regarding whether investors care more about managerial practices or past performance, and whether there is homogeneity across stocks in this regard. In contrast, the statistical insignificance of these OLS models would indicate that there was no evidence of the G100 release affecting the market during the event window.

In this paper event studies methods are applied to assess whether the release of the G100 had an impact on the values of the firms included in it.[10] Event studies rely on the estimation of each firm's abnormal returns ($AR_{i,\tau}$) at date τ, which are a measure of the unexpected change in security holders' wealth associated with the event. Abnormal returns are calculated as

$$(1) \qquad AR_{i,\tau} = R_{i,\tau} - E\left(R_{i,\tau} | \underline{X_\tau}\right),$$

[9] Our tests do not distinguish among the possible theoretical motivations (presented earlier in section 2) underlying investors' reaction to the G100. For example, investors may react because the ranking contains new information. Alternatively, they may react because the release of the ranking helps coordinate how to interpret the large amount of information condensed in the G100, even though the basic information might not be new.

[10] Event studies in financial markets examine the behavior of firms' stock prices around a specific event (see MacKinlay (1997) for a detailed explanation of event study methods).

where $R_{i,\tau}$ denotes company i's excess return at time τ, and $E\left(R_{i,\tau} | \underline{X_\tau}\right)$ is company i's expected excess return at time τ conditional on the value of the vector of variables $\underline{X_\tau}$. Here, the conditional expected return $E\left(R_{i,\tau} | \underline{X_\tau}\right)$ is estimated by means of two alternative models, namely, the market model (2), and an extended version of the Fama-French Four Factor Model (FFFM) (3)[11]

$$(2) \qquad R_{i,t} = \alpha_i + \underline{\beta_i}\, \underline{\underline{\mathrm{MARKETRF}_t}} + \eta_{i,t},$$

$$(3) \qquad R_{i,t} = \alpha_i + \underline{\beta_i}\, \underline{\underline{\mathrm{MARKETRF}_t}} + s_i\, \mathrm{USSMB}_t + h_i\, \mathrm{USHML}_t + m_i\, \mathrm{USMOM}_t + \epsilon_{i,t},$$

where $\underline{\underline{\mathrm{MARKETRF}_t}}$ is a vector comprising the excess rates of return on the nine market indexes; USSMB_t, USHML_t, and USMOM_t are Fama-French factors for US-traded stocks; α_i, $\underline{\beta_i}$, s_i, h_i, and m_i are regression coefficients; and $\eta_{i,t}$ and $\epsilon_{i,t}$ are regression residuals.

The nine market returns comprised in $\underline{\underline{\mathrm{MARKETRF}_t}}$ are included as explanatory variables, because the existing literature on integrated international asset pricing indicates that it is more appropriate to use factors specific to the markets where stocks are listed than global factors (Karolyi and Stulz 2003, Griffin 2002, Fama and French 2012).[12] The estimation using nine market factors improves identification. Although it would be desirable for the market returns in regressions (2) and (3) to exclude the companies in the ranking, such data were not available. The second best option is to use a portfolio for each stock market that includes the companies of interest, but whose performance is not strongly affected by such companies. This is achieved by

[11] FFFM is the result of the work of Fama and French (1993) and Jegadeesh and Timman (1993). FFFM extends the traditional single factor market model to explain abnormal returns that the latter model was unable to account for.

[12] We thank an anonymous referee for this suggestion. Fama and French (2012) examined local versions of the factor models in which the returns to be explained are from the same region, and found that global models perform poorly compared to local ones. Their results are in line with Griffin (2002), who found that country-specific factors explain returns better for portfolios and individual stocks in the cases of US, United Kingdom, Canada and Japan. Hybrid models including both local and global factors have been found to add no explanatory power compared to their purely local counterparts (Griffin 2002, Fama and French 2012). Interestingly, we find that local market factors from markets other than the one where the stock is traded are significant in explaining returns (e.g., US market affects European and Asian traded stocks, and Asian markets affect Asian-based companies trading in the US).

employing market portfolios that comprise a large number of other companies, causing a dilution effect.[13]

Ideally, the set of explanatory variables in regression (3) should also include local Fama-French factors for the non-US-traded stocks (Fama and French 2012). That is not possible, however, because daily SMB, HML and MOM local factors are available only for US-traded stocks. Hence, rather than omitting the US Fama-French factors, they are included because they may help explain non-US-traded stock returns. Proceeding in this manner creates no estimation problems; in fact, it greatly facilitates the estimation from a computational point of view, as for the case of the companies it reduces a 100-equation SUR to an OLS estimation problem.[14]

Based on the length of the estimation periods typically employed in the previous literature (MacKinlay 1997), regressions (2) and (3) were estimated using data for dates t = 10/5/2009 through t = 10/4/2010. This period excluded the 10 trading days before the release of the information, to avoid biases from potential information leaks close to the event (MacKinlay 1997). The selected interval resulted in 250 observations for US-traded companies and some non-US-traded firms. For other non-US-traded companies the number of observations was slightly different from 250, due to differences in holidays and other non-trading days across countries over the fixed calendar period. Given the estimates of regressions (2) and (3), abnormal returns for the date of interest τ are respectively computed from equations (4) and (5), respectively:

[13] The dilution effect is important in all stock markets. For example, only 71 out of 1,900 firms in the NYA are included in the G100, representing 34% of the market capitalization of the New York Stock Exchange. Stocks in other markets have even lower relative market capitalizations.

[14] It seems unlikely that including local SBM, HML, and MOM factors would change the general results of the present study. This is true because the cross section models for the 71 US-traded stocks yield very similar results whether the Fama-French factors are included or not (see tables 8 and A4). The effect of not including local SMB, HML and MOM factors might be negligible especially due to the size of the firms. Fama and French (2012) find that SMB, HML and MOM vary with firm size, with the exception of Japan. While they do not find size premiums in any region studied, there are value premiums in all regions and momentum premiums in all but Japan. Previous studies have also reported the lack of momentum in Japan (Assness, Moskiwitz, and Pedersen 2009; Chui, Titman, and Wei 2010; Kubota and Takehara 1997). Interestingly, both value and momentum premiums are smaller for larger firms (Fama and French 2012).

$$(4) \qquad AR_{i,\tau} = R_{i,\tau} - \left(\underline{\widehat{\alpha}_i} + \underline{\widehat{\beta}_i}\ \underline{\underline{\mathrm{MARKETRF}_\tau}} \right) = \widehat{\eta}_{i,\tau},$$

$$(5) \qquad AR_{i,\tau} = R_{i,\tau} - \left(\underline{\widehat{\alpha}_i} + \underline{\widehat{\beta}_i}\ \underline{\underline{\mathrm{MARKETRF}_\tau}} + \hat{s}_i\ \mathrm{USSMB}_\tau + \hat{h}_i\ \mathrm{USHML}_\tau + \widehat{m}\ \mathrm{USMOM}_\tau \right) = \hat{\epsilon}_{i,\tau}.$$

Using abnormal returns $AR_{i,\tau}$ resolves the potential problem of reverse causality (i.e., the G100 may be correlated with financial performance simply because more profitable firms in the past were able to invest more in CSR). That is, here correlation can be interpreted as the G100 impacting abnormal returns, because we control for past performance when estimating expected returns.

4.1. Equal-Weight Portfolio's Abnormal Return Test Statistic

To assess whether the release of the information increased the value of the entire set of companies on the list, the following test statistic was employed

$$(6) \qquad J_1 \equiv \frac{\overline{AR}_\tau}{\sigma_{\overline{AR}_\tau}} \sim N(0,1),$$

where $\overline{AR}_\tau \equiv \sum_{i=1}^{i=100} AR_{i,\tau}/100$, $\sigma_{\overline{AR}_\tau}$ is the corresponding standard deviation, $N(0,1)$ is the standard normal distribution, and τ is the day of the online release of the G100, i.e., October 18th, 2010.[15] That is, the test statistic J_1 is the equally-weighted portfolio's abnormal return normalized by its standard deviation.

4.2. Cross Sectional Models

The test statistic J_1 is not recommended to test whether the G100 release affected relative stock prices according to their ranking performance. There are at least two reasons why this is the case.

[15] The independence assumption of individual firms' abnormal returns is violated in the present application, because the event time is perfectly clustered due to the fact that information was released at the same time for all companies. A solution is to estimate the abnormal returns of a portfolio of companies (MacKinlay 1997).

First, there is a loss in estimation efficiency, because the sample must be split into company groups according to ranking positions (e.g., high-, medium-, and low-ranked firms) to assess the effect of the ranking position using J_1. Second and more importantly, finding out statistically significantly different J_1s would only allow us to sign the marginal effect of the rankings. For these reasons, we apply a cross-sectional approach to analyze whether the market reacted by changing the relative price of the stocks comprised in the G100.

The advocated procedure consists of a cross-section OLS regression of each firm's abnormal returns ($AR_{i,\tau}$) based on equations (4) or (5), against the respective firm’s ranking (GREENRANKING_i):

$$(7) \qquad AR_\tau = \alpha_{GR,\tau} + \beta_{GR,\tau}\,\text{GREENRANKING} + \varphi_{GR,\tau},$$

where $\varphi_{GR,\tau}$ is a regression residual, and τ is October 18th, 2010 (i.e., the day of the online release of the G100). To further investigate the firm-specific impact of the G100, cross-sectional OLS regressions (8) through (10) were fitted, as well:

$$(8) \qquad AR_\tau = \alpha_{GS,\tau} + \beta_{GS,\tau}\,\text{GREENSCORE} + \varphi_{GS,\tau},$$

$$(9) \qquad AR_\tau = \alpha_{EGR,\tau} + \beta_{EGR,\tau}\,\text{EIS} + \beta_{EGR,\tau}\,\text{GPS} + \beta_{EGR,\tau}\,\text{RSS} + \varphi_{EGR,\tau},$$

$$(10) \qquad AR_\tau = \alpha_{ER,\tau} + \beta_{ER,\tau}\,\text{EISRSS} + \varphi_{ER,\tau},$$

where GREENSCORE, EIS, GPS, and RSS are respectively the firm-specific Green Score, EIS, GPS, and RSS, and EISRSS = EIS – RSS. Robust standard errors were computed for all regressions.[16]

[16] Regression (10) corrects EIS by RSS, to control for previously available information.

To investigate the robustness of the findings, cross-sectional regressions analogous to (6)-(10) were also fit using each firm's cumulative abnormal returns over the two-day event window consisting of October 18th and 19th, 2010 (i.e., the day of the G100 release plus the following day, to account for time zone differences across countries). That is, the dependent variable in such regressions consists of

(10) $$CAR_{i,(\tau_1:\tau_2)} \equiv \sum_{\tau=\tau_1}^{\tau=\tau_2} AR_{i,\tau},$$

where τ_1 and τ_2 are respectively October 18th and 19th, 2010. Further, cross-sectional regressions were also estimated separately for eight different sets of companies, namely, (a) all of the companies, (b) G100 top 50 companies, (c) G100 bottom 50 companies, (d) heavy sector companies,[17] (e) non-heavy sector companies, (f) US-traded companies, (g) non-US-traded companies, and (h) non-heavy sector US-traded companies. A total of 128 cross-sectional models were estimated, 64 with $AR_{i,\tau}$ as the explanatory variable, and the other 64 with $CAR_{i,(\tau_1:\tau_2)}$ instead.

5. Results and Discussion

The next two subsections discuss the findings regarding the impact of the G100 on both the general and the relative value of the firms included in it.

5.1. The Impact of the G100 on the General Value of the Listed Firms

Result 1. The release of the ranking did not increase the price of the equal-weight portfolio of companies in the G100.

[17] Industries are classified as belonging to the heavy sector if they are potentially highly pollutant. The heavy sector includes basic materials; consumer products and cars; general industrials, industrial goods, oil and gas; transport and aerospace; and utilities. The non-heavy sector consists of banks and insurance; food and beverage; media, travel, and leisure; pharmaceuticals; retail; and technology.

The test statistic J_1 is statistically non-significant for the equal-weight portfolio. Thus, the release of the ranking did not affect the price of the portfolio of companies in the G100, provided that there are no other confounding effects. One may argue that there is no reason for an improvement on the value of the portfolio, because the new information allows only for a comparison among the companies on the list. A change in the value of the portfolio would have implied that a comparison with companies not included in the G100 was possible.

Event studies analyzing one firm or a small number of firms often check for confounding effects, especially when testing the significance of the test statistic J_1. It may happen that other "new information" affects the performance of the company on the day the information of interest is released, leading to incorrect conclusions. On the day the G100 was released, the major news were related to higher-than-expected earnings from Citigroup, and an improvement in the housing sector that pushed prices up (cnn.money.com a). Companies in the banking sector were among that day's top performers, with average abnormal returns of 0.0091%, or 0.58 standard deviations higher than the average of all companies in the ranking (table 1). This may have caused the price of the portfolio to go up, creating a positive bias on the estimation of the effect of being in the G100.

In some cross-sectional models the next-day information is also used. The stock market declined the day after the release of the G100, due to reports that a group of bondholders were trying to force Bank of America to repurchase bad mortgages. There was also a surprise rate hike by the Chinese government, and mixed data on the housing market and corporate results (cnn.money.com b).[18] Not analyzing these confounding effects might bias the estimates of the marginal effect of the G100 if the "new information" is correlated with the ranking. However, it is difficult to find plausible reasons for such kind of correlation to exist.

Confounding effects can be ignored for the remainder of the study, because of the use of cross-sectional models and the methodology used to construct the G100. If on the day of the

[18] In particular, Bank of America reported a third-quarter net loss of $7.3 billion, Goldman Sachs disclosed a 40% plunge in profit for the third quarter, J&J stated a dip in sales, Yahoo reported less than expected sales, and Intel announced an up to $8 billion investment.

G100 release another event(s) affected returns across all firms, its impact would be controlled for by the constant in the cross-sectional models.[19] This would also be true for any event affecting a group of companies, provided the distribution of such group in the G100 is similar to the distribution of all the companies in the list. In particular, since the G100 is constructed to make the ranking comparable across industries, any event affecting firms in a specific industry should only affect the constant of the estimated cross-sectional models.[20]

5.2. The Impact of the G100 Release on the Relative Prices of the Listed Firms

Key statistics for the cross-sectional models' first estimation step are presented in Table 2. Out of the 100 estimated FFFMs, the F-test indicates that 97 of them are statistically significant at the 95% confidence level, with a median explanatory power of 46%. For the 97 significant models, the market index in which the stock is traded is typically significantly different from zero, whereas indexes for other markets besides US are not. The coefficient corresponding to the NYA market index is significantly different from zero in 92 of the models (66 US-traded stocks, 25 European-traded stocks, and one Asian-traded stock), and has a median value of 0.8851, a 95th percentile of 1.5084 and a 5th percentile of 0.2734.

Asian stock exchange indexes affected American companies and some Asian and European companies. The coefficients corresponding to Shanghai's SSE Composite Index and Hong Kong's Hang Seng Index are significant in six of the models.[21] Japanese and Korean stock exchange indexes affected US and European stocks. The coefficient corresponding to Japan's

[19] For example, the news about improvement in the housing sector might have pushed prices up in general, which would affect the constant, but not the slope, of the cross sectional models.

[20] In the case of banks and insurance (the industry involving most of the news on the day of the G100 release), the ranking of the companies ranges from 9 to 89, covering almost all of the ranking range.

[21] The SSE Composite Index coefficient is significant for one Korean company traded in Seoul, three US-traded stocks, and one European stock. It has a median value of -0.0121, a 95th percentile of 0.1419, and a 5th percentile of -0.2239. The Hang Seng Index coefficient is significant for one US-traded company, and surprisingly none of the four Chinese companies traded in Hong Kong. It has a median value of -0.0180, a 95th percentile of 0.0852 and a 5th percentile of -0.1304.

Topix Index is significant in 4 of the models,[22] and the one corresponding to South Korea's Kospi Composite Index is significant at the 95% confidence level in 9 of the models.[23]

European indexes are significant in models of European stocks and US-traded stocks of European and US companies. The coefficient for France's CAC-All (SCB250) is significant in seven of the models,[24] for Germany's CDAX in seven,[25] for Switzerland's SMI Expanded Index in nine,[26] and for the United Kingdom's FTSE All-Share Index coefficient in 4 of the models.[27]

The Fama-French factors SMB, HML and UMD are significantly different from zero in a considerable proportion of the US-traded stock models, whereas they are non-significant for most of non-US-traded stocks. SMB is significantly different from zero for 16 companies –all of them US-traded–, HML is significant for 31 companies (26 US-traded, four Europe- and one Asia-traded), and UMD is significant for 17 companies (14 US-traded, and three Europe-traded). The likely explanation for the lack of significance of the SMB, HML, and UMD daily factors in the models for non-US-traded stocks is that such factors are US-based. Ideally, the models should include exchange-specific SMB, HML, and UMD factors, but as explained earlier they were not available at a daily frequency for the period and stock exchanges of interest.

Given the similarity of the results obtained from the 128 cross-sectional models fitted in the second step, only the 64 models estimated using the FFFM abnormal returns are reported here. The other models are presented as tables A1 through A8 in the Appendix. All tables in the paper have the same structure. Models numbered 1 to 4 have as independent variable the Green

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[22] The Topix Index coefficient is significant for four US-traded stocks. It has a median value of 0.0132, a 95th percentile of 0.1885 and a 5th percentile of -0.1541.

[23] The Kospi Composite Index coefficient is significant for one Chinese stock traded in Hong Kong; seven US-traded stocks, and one European, and has a median value of 0.0213, a 95th percentile of 0.2208 and a 5th percentile of -0.3617.

[24] The SBF250 coefficient is significant for seven US-traded stocks. It has a median value of -0.0473, a 95th percentile of 0.4322 and a 5th percentile of -0.4741.

[25] The CDAXX Index coefficient is significant for one European traded stocks, and six US-traded stocks –two of European companies–. It has a median value of -0.0350, a 95th percentile of 0.3732 and a 5th percentile of -0.5910.

[26] SMI Expanded Index coefficient is significant for 8 US-traded stocks –five of European companies- and one Asian. It has a median value of 0.0800, a 95th percentile of 0.4355, and a 5th percentile of -0.3255.

[27] The FTSE All-Share Index coefficient is significant for two Europe-traded stocks, one of which correspond to a company based in the United Kingdom with stocks traded in London; and two US-traded stocks, both of which consist of European companies. It has a median value of 0.0344, a 95th percentile of 0.4078, and a 5th percentile of -0.3255.

Score, Green ranking, green components (EIS, GPS, and RSS), and EIS minus RSS (EISRSS), respectively. Version (a) of the models denotes the case where abnormal returns are measured only on the day of the information release, whereas version (b) corresponds to the case where abnormal returns are evaluated over both the day of release and the next day.

Result 2: An eleven million dollar step: Getting one position closer to the top of Newsweek's G100 increases the value of an average firm in the list by 11.4 million dollars.[28]

Ranking position and the Green Score affected stock prices on the day the information was released in the expected direction: negative for the ranking position, and positive for the Green Score (see Figure 1). Table 3 shows that at least 5.7% of the abnormal returns on the event day were explained in three different models by the Green Score (model 1-a), ranking position (model 2-a), and Green Score components (model 3-a), respectively. According to these results, moving ten positions closer to the top of the ranking increases the value of a company by 0.0994% with a 99% confidence level (model 2-a). By comparison, the absolute value of the daily return of the companies in the G100 during the estimation period (i.e., 10/5/2009 through 10/4/2010) was 0.014% on average.

Result 3: G100's top 50 performers reacted more strongly to the ranking than the bottom 50 performers.

We tested for the presence of non-linearities, and found that the top 50 performers reacted more strongly than the bottom 50 performers to the Green Score, the ranking position, and the components in both event windows. Tables 4 and 5 show respectively the results of the models for the top and bottom performers. There is a proportionally larger participation of heavy sector stocks in the bottom 50 performers (22 companies), which reacted more weakly to the ranking. To test for this confounding effect, we estimated regressions of the bottom 50 performers by

[28] The average capitalization of a firm in the list was 115 billion dollars as of September 2010. As a consequence, moving up one position in the ranking, which increases the value of a stock by 0.00994%, represents 11.4 million dollars.

sector. Results are omitted to save space, but they show that bottom 50 heavy sector stocks were not affected by being in the ranking (none of the models are significant). In contrast, non-heavy sector stocks in the bottom 50 did react to the EIS on the day the information was released (the coefficient estimate equals 1.542 and is significantly different from zero at the 10% level). The difference between the top and bottom companies may be explained in part by the weaker reaction of heavy sector stocks, presented later in the paper.

Result 4: Green Score components explain better the market reaction than the Green Score itself: EIS has a positive effect on stock prices, whereas RSS does not have a significant effect.

The explanatory power is higher using the components of the Green Score than employing the Green Score itself (model 3-a versus model 1-a on table 3). Out of the three components, the only one significantly different from zero is the EIS. The RSS coefficient is non-significant in either event window, which may be reasonable because it reflects the market expectations regarding the environmental performance of the firms. The non-significance may be explained by the efficient market hypothesis: the release provided information that had already been incorporated into the prices. The GPS is not significantly different from zero either, suggesting that neither the companies' reputation nor their policies were relevant new market information. Adding two non-significant components to the EIS to calculate the Green Score seems to distort the EIS signal, reducing the explanatory power of the Green Score model compared to the components' model.

Stocks in the non-heavy sector reacted fast to the G100, and took into account only the EIS (table 6). In contrast, stocks in the heavy sector were neither significantly affected by the G100 nor by the individual scores (table 7). Only there was a close to significant reaction to the Green Score (at a 90% confidence level) on a two day window. Ranking position and the Green Score impacted non-heavy stock prices on the day of the information release in the expected direction: negative for the ranking position and positive for the Green Score. According to the results, moving up ten positions in the ranking and improving the Green Score by ten points increased the expected value of a non-heavy sector company by 0.12% and 0.20%, respectively (table 6, models 1-a and 2-a). Increasing the EIS by ten points raised a company's abnormal returns by 0.129%.

Result 5: Non-US traded stocks exhibit a stronger and "more prolonged" reaction compared to US-traded stocks.

The reaction to the release of G100 of non-US traded stocks in the two-day event window was significantly different from zero, and larger than the one- and two-day reactions of US-traded stocks (tables 8 and 9). The reaction of US-traded stocks was in most cases slightly smaller than, but not significantly different from, the reaction of non-US stocks for the one-day event window. According to these results, moving ten positions closer to the top of the ranking increases the expected value of a US traded company by 0.113% with a 99% confidence level (model 2-a table 8), for the one event window. Within US-traded stocks, non-heavy sector companies were the ones that significantly reacted to the G100 (table 10); moving ten positions closer to the top of the ranking increased the value of a US-traded company in the non-heavy sector by 0.150%. The effect was driven by the EIS rather than GPS or RSS (Model 3-a table 10). For non-US traded companies, the corresponding expected increase is 0.323% (model 2-b table 9, 95% confidence level), for the two-day event window. The apparently slower and more prolonged reaction for non-US traded stocks may be explained by differences in time zones, as 8am US Eastern Time Zone corresponds to 2pm in Europe and afterhours trading in Asian exchanges.

One possible explanation for the different behavior of US- vs. non-US traded companies is the well-documented home bias puzzle.[29] European and Asian investors trade more non-US stocks due to the equity home bias (Sercu and Vanpee 2007). Also, European (French and

[29] The equity home bias is the difference between the relative weight of domestic equity in the portfolio of country *j* and the relative weight of country *j* in the total world market. The equity home bias of the market portfolio in 2004 was 0.81 for the US, 0.77 for EMU members, and 0.79 non-EMU EU members (Schoenmaker and Bosch 2008); and in 2005 was 0.78 for Hong Kong, 0.79 for Japan, and 0.96 for Korea (Sercu and Vanpee 2007). An extended literature review of home bias puzzle is available in Karolyi and Stulz (2003), and a list of home bias by country is available in table 1 of Sercu and Vanpee (2007).

German) consumers are more willing to support CSR than Americans (Maignan 2001). Another possible explanation for the higher reaction of non-US traded stocks is that more of the released information was relevant for the market, which is plausible because some of the US-traded companies had been assessed the previous year in the "US 500 List" (table 9).

The Green Score components explain 22% and 26% of the non-US traded stocks abnormal returns in the one- and two-day event window models, respectively (models 3-a and 3-b in table 9). The GPS is significant in the one- and two-day event window with similar coefficients while the EIS is only jointly significant in the two-day event window. Interestingly, the RSS coefficient is negative, a sign of investors' adjusting for existing information.[30] Significant cross-sectional models using FFFM abnormal returns had lower explanatory power than the ones excluding the US Fama-French factors, e.g., 5.7% vs. 9.7% in model 1-a, and 6.4% vs. 9.7% in model 2-a in tables 3 and A1, respectively. The sign and magnitude of the coefficients of cross-sectional models based on the market factor model abnormal returns are consistent with the significant cross-sectional models based on the FFFM abnormal returns. One difference is that more models become also significant in the two-day event window. In this sense, the results presented here are the most conservative ones.

Why did the estimated market factor model abnormal returns outperform the FFFM ones in the cross-sectional models? We expected the opposite because the FFFMs have higher explanatory power, as they include the US Fama-French factors in addition to the market returns. However, in most instances the additional factors in the FFFM were non-significant (table 2), and including them added noise to our estimation of expected returns. Therefore, the FFFM model is likely to incorporate unwarranted noise. This may end up being reflected in the predicted abnormal returns for the day of the event, thereby making the FFFM-based cross-sectional models lose explanatory power and even turn non-significant, especially in the two-day event window case.

[30] The reaction of non-US traded stocks in the two-day window EISRSS model (model 4-b in table 9) is significant at the 10% level and positive as expected. For each ten point difference in EISRSS, the expected abnormal returns of a foreign traded company in the two-day event window increases by 0.2091%.

Previous results support the idea that a new “green” process which affects a company's relative G100 performance will impact the firm's stock price. Consequently, the G100 becomes a tournament that (provided its information is correct) enhances the efficiency of investments in environmental performance by creating an extra incentive to improve environmental performance.[31] This occurs because firms that are able to improve their position in the G100 ranking at the lowest cost are the ones most likely to end up doing so. This result is independent of which mechanism is behind the investors’ reaction.

6. Conclusions

The present study adds a world market dimension to environmental rankings and the response of investors, quantifies the marginal effects of the G100 on stock prices, and investigates the impact of rankings on returns by industry sectors. Further, to the best of our knowledge it is the first study providing evidence of the existence of heterogeneity among investors regarding their interest in past performance and managerial quality as predictors of future environmental performance, which has implications for the construction of optimal environmental indexes (Chatterji, Levine, and Toffel 2009).

Our results indicate that the market reacted to the G100 by changing the relative prices of the stocks included in it, but not the value of the equal-weight portfolio of such stocks. The magnitude of the effect was sizeable: moving one position closer to the top of Newsweek’s G100 raised the value of an average firm in the list by 11.4 million dollars. This represents an increase in the stock price of 0.0994%, or seven times the average of the absolute daily rate of return of the companies in the G100 during the estimation period (i.e., 10/5/2009 through 10/4/2010). There is also evidence of a stronger reaction to the ranking position for top 50 companies in the G100 compared to bottom 50, for non-US-traded stocks compared to US-traded stocks, and of a more robust reaction for stocks in the non-heavy sector compared to the ones in the heavy sector.

[31] It must be noted that the methodology framework applied in this paper cannot account for the dynamic dimension of green investments.

The finding that the equal-weight portfolio return was not affected by the G100 release was expected, because the presence of the companies on the G100 list was only defined by their size. The use of a two-step procedure allowed us to identify a market effect that the standard event study method using only statistics of cumulative abnormal returns for the entire set might have ignored. The new information for the market was the performance of each company relative to the other ones in the set, and that is why the cross section in the second step was able to identify that effect in the firms' stock prices. The cross section also allowed us to estimate marginal effects.

The G100's top 50 performers reacted more strongly to the ranking release than the bottom 50 ones. The existence of this nonlinearity may be explained in part by a larger presence of heavy sector companies (which reacted less to the ranking) in the bottom 50.

Stocks of companies in the non-heavy sector had a more robust reaction to the G100 release than their heavy sector counterparts. Unlike heavy sector stocks, non-heavy sector stocks reacted significantly across all model specifications. One possible reason for this finding is that firms in the non-heavy sector might be closer to final consumers, and consequently pay more attention to consumers' reactions to environmental performance. Another plausible explanation is that heavy sector firms have an input matrix of raw materials and energy that has low elasticity of substitution, whereas companies in the non-heavy sector might have better more opportunities to improve their environmental performance at lower cost. For example, it might be easier to reduce energy consumption per unit of sales for a retail company (by replacing electric appliances with efficient ones, buying more locally, etc.) than for an iron company that basically consumes energy.

Across all model specifications, non US-traded stocks had a stronger reaction for a one-day event windows than US-traded stocks. In the case of a two-day event window, US-traded stocks had no significant reaction, whereas non-US-traded stocks exhibited a stronger reaction than with a one-day window. There are at least three possible explanations for this result. One explanation is that US-traded companies reacted as expected according to the efficient market hypothesis, and extending the event window only dilutes the effect making it non-significant. A second possible reason is that non-US-traded companies were included in a public environmental ranking for the first time, whereas some US-traded companies had already been in the “US 500 List” published in 2009. A third explanation is that most of the non-US-traded companies are European, for which GPS might provide better predictions about future performance. Given the different regulatory history and environment in Europe, expectations about future regulation might motivate investors' hedging behavior.

The use of stocks traded in international markets allowed us to find evidence of heterogeneity among investors with regard to their interest in past performance and managerial quality as predictors of future environmental performance. In particular, US-traded stock returns were jointly affected by past performance (EIS) and one of the measures of managerial quality (GPS), contrasting with non-US-traded stock returns which responded only to managerial quality (GPS). These results have implications for the construction of optimal environmental rankings (Chatterji, Levine, and Toffel 2009), suggesting that the weight on past performance and managerial quality used to construct indexes environmental performance should differ across stock markets.

Provided the measurement errors in the G100 are relatively small, the robustness of the findings not only implies that the G100 had relevant information for the market, but also supports the idea that companies should account for the effect on stock prices when making decisions about environmental policies that might affect their position in the G100. Whether the reason for such reaction is branding (to build a positive reputation and brand image), stakeholding (to satisfy different stakeholders), sustainability (to contribute to long-term sustainable development), or ethics/morals (to do the ‘right thing’), among other possible theoretical explanations, is an issue to be addressed in future research.

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Table 1. Event day abnormal returns statistics for different company groups

	average	median	max	min	Std. dev.
All	0.0025	0.0023	0.0343	-0.0277	0.0114
US	0.0006	0.0009	0.0343	-0.0277	0.0098
Non-US	0.0072	0.0092	0.0340	-0.0213	0.0133
Heavy	0.0002	0.0024	0.0151	-0.0196	0.0091
Non-Heavy	0.0036	0.0022	0.0343	-0.0277	0.0122
Banks	0.0091	0.0087	0.0343	-0.0213	0.0148

Table 1. Summary statistics of the hundred estimated FFFMs by regression (3).

	R-sq	nya	000001_ss	hsi	topix	ks11	sbf250	cdax	smiexc_sw	ftas	us-smb	us-hml	us-umd	_cons
95 percentile	0.7397	1.5084	0.1419	0.0852	0.1885	0.2208	0.4322	0.3732	0.4355	0.4078	0.0040	0.0095	0.0074	0.0012
75 percentile	0.6172	1.1315	0.0356	0.0238	0.0648	0.0899	0.1959	0.1009	0.1881	0.1401	0.0011	0.0009	0.0025	0.0003
median	0.4585	0.8851	-0.0121	-0.0180	0.0132	0.0213	-0.0473	-0.0350	0.0800	0.0344	-0.0006	-0.0023	0.0005	-0.0002
mean	0.4596	0.8906	-0.0203	-0.0015	0.0034	-0.0114	-0.0296	-0.0573	0.0676	0.0434	-0.0004	-0.0010	0.0009	-0.0002
25 percentile	0.3218	0.6684	-0.0485	-0.0634	-0.0652	-0.0861	-0.2292	-0.2694	-0.0708	-0.0788	-0.0020	-0.0046	-0.0013	-0.0007
5 percentile	0.1267	0.2734	-0.2239	-0.1304	-0.1541	-0.3617	-0.4741	-0.5910	-0.3255	-0.2664	-0.0039	-0.0070	-0.0053	-0.0018
Percentage of models 95% significant	97	92	5	1	4	9	7	7	9	4	16	31	17	2

The variables on the table are: SSE Composite Index (000001_SS), Hang Seng Index (hsi), Topix (topix), Kospi Composite Index (ks11), CAC-All (sbf250), SMI Expanded (smiexc_sw), FTSE All-Share Index (ftas), US SMB (us-smb), US HML (us-hml), US UMD (us-umd), and the respective model constant (_cons).

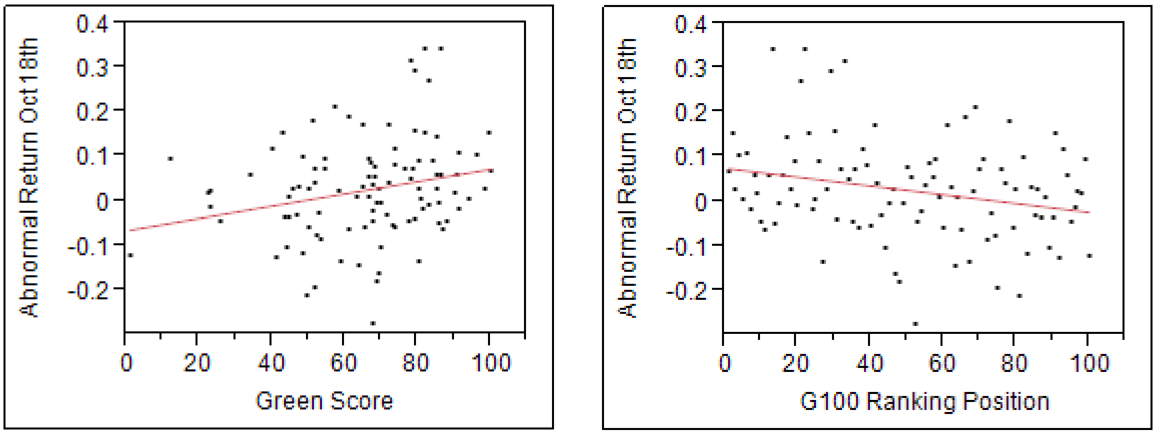

Figure 1. One-day window regressions for the 100 companies (Left: equation (8), Right equation (7)).

Table 2. Robust OLS regressions using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.379***	6.546						
	(0.476)	(4.583)						
Ranking			-0.994***	-4.951				
			(0.347)	(3.691)				
Environmental impact score					0.772*	-2.999		
					(0.449)	(4.718)		
Green policies and performance score					0.909	11.14		
					(0.676)	(10.195)		
Reputation survey score					0.0499	-0.490		
					(0.633)	(1.527)		
Env. Impact – Rep Survey							0.504	-1.889
							(0.368)	(3.201)
Intercept	-66.23**	-458.5	74.91***	223.2**	-70.70**	-504.9	27.96**	-39.08
	(31.977)	(380.179)	(21.751)	(111.529)	(34.215)	(425.466)	(12.504)	(102.038)
Observations	100	100	100	100	100	100	100	100
R2	0.057	0.025	0.064	0.031	0.087	0.060	0.024	0.006
AIC	1228.356	1625.604	1227.649	1625.014	1229.160	1625.990	1231.852	1627.496
Prob >F	0.005	0.156	0.005	0.183	0.022	0.158	0.175	0.556

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 3. Robust OLS regressions for top 50 performers in the G100 using estimated abnormal returns from FFFM for top 50 performers in the G100

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.923*	2.343						
	(1.496)	(2.426)						
Ranking			-1.706*	-1.366				
			(0.955)	(1.485)				
Environmental impact score					1.557**	2.399**		
					(0.773)	(1.057)		
Green policies and performance score					1.833*	1.636		
					(1.089)	(1.631)		
Reputation survey score					-0.656	-1.788		
					(1.095)	(1.909)		
Env. Impact – Rep Survey							1.183*	2.134**
							(0.664)	(0.986)
Intercept	-187.5	-103.2	93.73***	122.2**	-146.3	-78.11	47.27***	81.97***
	(125.549)	(197.117)	(28.083)	(47.116)	(103.063)	(179.111)	(15.532)	(22.087)
Observations	50	50	50	50	50	50	50	50
R2	0.045	0.013	0.044	0.013	0.131	0.148	0.087	0.132
AIC	619.961	659.524	619.981	659.530	619.224	656.211	617.687	653.094
Prob >F	0.057	0.339	0.08	0.362	0.088	0.115	0.081	0.035

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 4. Robust OLS regressions for bottom 50 in the G100 using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	0.324	6.063						
	(0.900)	(5.074)						
Ranking			-0.119	-10.84				
			(1.011)	(10.535)				
Environmental impact score					0.232	-7.845		
					(0.657)	(9.348)		
Green policies and performance score					-0.460	19.08		
					(1.035)	(19.282)		
Reputation survey score					0.885	-3.592		
					(0.756)	(5.649)		
Env. Impact – Rep Survey							-0.183	-6.038
							(0.422)	(6.362)
Intercept	-17.22	-447.4	8.153	677.1	-31.87	-549.0	-3.653	-234.2
	(44.514)	(405.690)	(81.045)	(642.647)	(41.549)	(500.485)	(17.898)	(254.980)
Observations	50	50	50	50	50	50	50	50
R2	0.002	0.007	0.000	0.019	0.024	0.081	0.004	0.040
AIC	609.971	848.260	610.070	847.622	612.887	848.366	609.867	846.552
Prob >F	0.720	0.238	0.907	0.309	0.664	0.741	0.667	0.347

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000. 22 of the bottom 50 companies are in the heavy sector.

Table 5. Robust OLS regressions for non-heavy sector using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.007**	14.76						
	(0.819)	(13.382)						
Ranking			-1.215**	-8.804				
			(0.513)	(7.840)				
Environmental impact score					1.287**	-2.178		
					(0.513)	(4.143)		
Green policies and performance score					1.100	19.46		
					(0.971)	(18.139)		
Reputation survey score					0.394	-0.441		
					(0.850)	(2.844)		
Env. Impact – Rep Survey							0.663	-2.374
							(0.448)	(3.843)
Intercept	-106.5*	-1093.9	89.38***	340.5	-134.6**	-1122.7	35.06**	-37.84
	(59.253)	(1069.415)	(27.795)	(228.181)	(64.829)	(1022.288)	(14.562)	(116.028)
Observations	66	66	66	66	66	66	66	66
R2	0.065	0.053	0.068	0.054	0.125	0.102	0.037	0.007
AIC	821.047	1098.872	820.882	1098.850	820.706	1099.400	823.044	1102.012
Prob >F	0.017	0.274	0.021	0.266	0.028	0.317	0.144	0.539

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 6. Robust OLS regressions for heavy sector using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	0.538	1.996						
	(0.639)	(1.201)						
Ranking			-0.421	-1.274				
			(0.477)	(0.924)				
Environmental impact score					-0.894	0.367		
					(1.073)	(1.705)		
Green policies and performance score					0.972	1.332		
					(0.847)	(1.385)		
Reputation survey score					0.105	0.330		
					(0.882)	(1.747)		
Env. Impact – Rep Survey							-0.565	-0.232
							(0.671)	(1.419)
Intercept	-28.07	-106.9	28.79	85.71	-25.00	-91.59	-11.19	-1.183
	(39.066)	(75.920)	(33.391)	(59.274)	(38.443)	(69.964)	(21.551)	(40.070)
Observations	34	34	34	34	34	34	34	34
R2	0.018	0.084	0.018	0.057	0.060	0.058	0.027	0.002
AIC	406.310	440.875	406.302	441.871	408.814	445.815	405.988	443.797
Prob >F	0.406	0.106	0.384	0.177	0.523	0.428	0.406	0.871

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 7. Robust OLS regressions for US traded stocks using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.645***	10.31						
	(0.473)	(8.101)						
Ranking			-1.130***	-7.192				
			(0.306)	(5.595)				
Environmental impact score					0.564''	-7.829		
					(0.532)	(7.941)		
Green policies and performance score					0.819''	16.77		
					(0.632)	(14.169)		
Reputation survey score					0.339	0.107		
					(0.584)	(2.124)		
Env. Impact – Rep Survey							0.248	-5.187
							(0.386)	(5.538)
Intercept	-107.5***	-816.9	58.14***	226.6	-91.83***	-756.6	7.473	-148.0
	(32.222)	(665.857)	(19.939)	(153.682)	(32.021)	(595.928)	(13.323)	(153.712)
Observations	71	71	71	71	71	71	71	71
R2	0.096	0.041	0.111	0.048	0.101	0.116	0.006	0.029
AIC	849.688	1175.291	848.516	1174.717	853.297	1173.515	856.393	1176.124
Prob >F	0.001	0.207	0	0.203	0.02	0.573	0.522	0.352

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. ’’ represents 95% jointly significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 8. Robust OLS regressions for non-US traded stocks using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.112*	4.709**						
	(1.053)	(1.701)						
Ranking			-1.710*	-3.235**				
			(0.978)	(1.495)				
Environmental impact score					-0.104	1.615’’		
					(0.812)	(1.245)		
Green policies and performance score					4.482**	4.828’’		
					(2.031)	(3.361)		
Reputation survey score					-2.568	-3.023		
					(1.693)	(2.895)		
Env. Impact – Rep Survey							0.740	2.091*
							(0.697)	(1.067)
Intercept	-53.25	-106.6	174.6**	366.5***	-16.55	-0.538	74.08***	178.8***
	(62.343)	(99.587)	(66.266)	(100.294)	(119.485)	(144.280)	(25.967)	(38.507)
Observations	29	29	29	29	29	29	29	29
R2	0.110	0.212	0.115	0.159	0.224	0.262	0.054	0.168
AIC	366.695	390.574	366.537	392.447	366.703	392.658	368.455	392.154
Prob >F	0.055	0.01	0.092	0.039	0.102	0.082	0.298	0.061

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. ’’ represents 95% jointly significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 9. Robust OLS regressions for US traded stocks in non-Heavy sectors using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.636***	27.94						
	(0.665)	(23.707)						
Ranking			-1.500***	-15.60				
			(0.424)	(13.162)				
Environmental impact score					1.235**	-7.599		
					(0.575)	(7.751)		
Green policies and performance score					1.018	36.40		
					(0.799)	(28.496)		
Reputation survey score					0.665	0.932		
					(0.756)	(4.814)		
Env. Impact – Rep Survey							0.603	-6.042
							(0.459)	(6.893)
Intercept	-181.9***	-2241.2	71.54***	434.1	-168.5***	-2207.9	13.91	-165.6
	(47.612)	(1925.961)	(25.191)	(343.148)	(58.698)	(1698.705)	(16.110)	(181.229)
Observations	44	44	44	44	44	44	44	44
R2	0.131	0.117	0.128	0.110	0.168	0.234	0.035	0.028
AIC	533.299	746.675	533.433	747.001	535.373	744.433	537.922	750.918
Prob >F	0	0.245	0.001	0.242	0.021	0.612	0.196	0.386

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Appendix

Table 10. Robust OLS regressions using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.989***	1.373**						
	(0.520)	(0.673)						
Ranking			-1.359***	-1.099**				
			(0.389)	(0.486)				
Environmental impact score					0.834	0.757		
					(0.509)	(0.736)		
Green policies and performance score					1.538**	1.177		
					(0.733)	(1.315)		
Reputation survey score					-0.429	-0.451		
					(0.569)	(1.168)		
Env. Impact – Rep Survey							0.699	0.656
							(0.422)	(0.445)
Intercept	-121.8***	-64.48	77.94***	81.53***	-99.12***	-55.96	13.84	30.28*
	(32.848)	(45.981)	(25.706)	(29.827)	(34.291)	(56.568)	(14.112)	(18.221)
Observations	100	100	100	100	100	100	100	100
R2	0.097	0.026	0.097	0.035	0.114	0.043	0.037	0.018
AIC	1244.714	1310.939	1244.694	1309.944	1246.842	1313.143	1251.117	1311.705
Prob >F	0	0.044	0.001	0.0260	0.008	0.144	0.101	0.143

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 11. Robust OLS regressions for non-heavy sectors using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.862***	2.415**						
	(0.929)	(1.132)						
Ranking			-1.724***	-1.522**				
			(0.575)	(0.718)				
Environmental impact score					1.473**	1.814**		
					(0.597)	(0.692)		
Green policies and performance score					1.891*	0.521		
					(1.091)	(1.520)		
Reputation survey score					-0.00377	0.974		
					(0.774)	(1.142)		
Env. Impact – Rep Survey							0.877*	0.851
							(0.493)	(0.560)
Intercept	-186.0***	-129.1	92.94***	109.2***	-191.5***	-157.1	16.00	41.14*
	(64.745)	(84.436)	(33.243)	(35.500)	(71.067)	(99.181)	(16.656)	(20.920)
Observations	66	66	66	66	66	66	66	66
R2	0.099	0.047	0.101	0.053	0.150	0.094	0.048	0.030
AIC	838.356	868.103	838.170	867.699	838.451	868.810	841.992	869.278
Prob >F	0.003	0.037	0.004	0.038	0.014	0.044	0.08	0.134

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 12. Robust OLS regressions for heavy sectors using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.306*	-0.155						
	(0.684)	(1.039)						
Ranking			-0.829	-0.000780				
			(0.513)	(0.852)				
Environmental impact score					-0.404	-2.935		
					(0.876)	(2.295)		
Green policies and performance score					1.573*	2.490		
					(0.847)	(2.007)		
Reputation survey score					-0.504	-1.267		
					(0.929)	(1.530)		
Env. Impact – Rep Survey							-0.0889	-0.804
							(0.739)	(0.991)
Intercept	-79.90*	1.869	45.78	-6.719	-46.49	26.99	-9.299	-25.35
	(39.797)	(55.752)	(36.135)	(66.537)	(31.927)	(87.210)	(18.999)	(44.977)
Observations	34	34	34	34	34	34	34	34
R2	0.121	0.001	0.081	0.000	0.101	0.162	0.001	0.019
AIC	398.193	443.790	399.710	443.807	402.934	441.789	402.538	443.167
Prob >F	0.065	0.882	0.116	0.999	0.282	0.601	0.905	0.423

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 13. Robust OLS regressions for US-traded stocks using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.988***	1.952*						
	(0.593)	(0.983)						
Ranking			-1.343***	-1.489**				
			(0.402)	(0.583)				
Environmental impact score					0.807’’	-0.0864		
					(0.742)	(1.007)		
Green policies and performance score					1.241’’	1.894		
					(0.828)	(1.584)		
Reputation survey score					-0.214	-0.233		
					(0.585)	(1.266)		
Env. Impact – Rep Survey							0.598	0.0199
							(0.567)	(0.582)
Intercept	-133.9***	-136.8*	65.26**	66.60**	-101.0***	-101.3	7.370	-2.526
	(38.426)	(71.135)	(26.923)	(31.946)	(35.628)	(68.621)	(17.871)	(21.413)
Observations	71	71	71	71	71	71	71	71
R2	0.089	0.052	0.100	0.074	0.097	0.051	0.023	0.000
AIC	882.069	920.383	881.247	918.702	885.435	924.494	887.051	924.187
Prob >F	0.0013	0.051	0.001	0.013	0.036	0.356	0.296	0.973

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. ’’ represents 95% jointly significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 14. Robust OLS regressions for non-US traded stocks using estimated abnormal returns from market model

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	2.647**	2.025**						
	(1.046)	(0.922)						
Ranking			-1.982*	-1.550*				
			(0.998)	(0.842)				
Environmental impact score					0.199	0.900’’		
					(0.761)	(0.858)		
Green policies and performance score					4.224**	2.894’’		
					(1.901)	(2.030)		
Reputation survey score					-2.067	-2.311		
					(1.528)	(1.810)		
Env. Impact – Rep Survey							0.803	1.352*
							(0.671)	(0.660)
Intercept	-131.0**	-23.29	144.8**	189.7**	-93.43	25.03	28.12	100.9***
	(59.912)	(43.152)	(68.073)	(68.595)	(110.493)	(111.093)	(25.199)	(32.111)
Observations	29	29	29	29	29	29	29	29
R2	0.177	0.059	0.158	0.055	0.235	0.150	0.065	0.106
AIC	363.693	383.823	364.351	383.943	365.565	384.881	367.372	382.347
Prob >F	0.018	0.037	0.057	0.077	0.114	0.051	0.242	0.051

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. ’’ represents 95% jointly significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 15. Top 50 FF9FM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	3.569**	5.685*						
	(1.543)	(2.928)						
Ranking			-2.157**	-3.533**				
			(0.935)	(1.743)				
Environmental impact score					1.874**	1.411		
					(0.893)	(1.009)		
Green policies and performance score					2.304**	3.924		
					(0.975)	(2.435)		
Reputation survey score					-0.850	-1.045		
					(1.043)	(1.919)		
Env. Impact – Rep Survey							1.442*	1.162
							(0.718)	(0.781)
Intercept	-248.8*	-414.0*	96.49***	138.5***	-198.3*	-266.6*	37.87**	45.51*
	(127.529)	(243.894)	(31.200)	(45.493)	(107.809)	(145.600)	(17.956)	(22.791)
Observations	50	50	50	50	50	50	50	50
R2	0.048	0.085	0.051	0.096	0.142	0.128	0.094	0.043
AIC	635.909	651.756	635.748	651.174	634.700	653.381	633.458	654.045
Prob >F	0.025	0.058	0.025	0.048	0.022	0.058	0.05	0.143

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table 16. Bottom 50 FF9FM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	1.294	-0.134						
	(0.936)	(1.495)						
Ranking			-0.994	0.114				
			(1.109)	(1.958)				
Environmental impact score					0.0861	0.553		
					(0.694)	(1.184)		
Green policies and performance score					0.467	-1.583		
					(1.301)	(1.905)		
Reputation survey score					0.129	1.007		
					(0.801)	(1.045)		
Env. Impact – Rep Survey							-0.0882	0.134
							(0.484)	(0.600)
Intercept	-88.25*	10.41	52.24	-4.937	-53.04	5.751	-24.20	5.716
	(46.548)	(66.628)	(87.308)	(160.300)	(40.464)	(89.348)	(18.405)	(30.228)
Observations	50	50	50	50	50	50	50	50
R2	0.036	0.000	0.019	0.000	0.007	0.019	0.001	0.001
AIC	607.899	659.485	608.763	659.488	613.392	662.547	609.685	659.449
Prob >F	0.173	0.929	0.374	0.954	0.915	0.760	0.856	0.825

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.

Table A8. Robust OLS regressions for US traded stocks in non-Heavy sectors using estimated abnormal returns from FFFM

	Model 1-a	Model 1-b	Model 2-a	Model 2-b	Model 3-a	Model 3-b	Model 4-a	Model 4-b
Green Score	3.378***	3.582**						
	(1.046)	(1.484)						
Ranking			-1.924***	-2.209**				
			(0.637)	(0.857)				
Environmental impact score					1.618*	1.096		
					(0.831)	(0.927)		
Green policies and performance score					1.620	0.886		
					(1.405)	(1.706)		
Reputation survey score					0.0657	2.115*		
					(0.850)	(1.083)		
Env. Impact – Rep Survey							1.046	0.0423
							(0.681)	(0.727)
Intercept	-242.6***	-253.3**	82.26**	97.65**	-201.5**	-239.6*	8.311	12.77
	(75.559)	(112.512)	(35.657)	(39.222)	(89.391)	(127.966)	(21.541)	(23.274)
Observations	44	44	44	44	44	44	44	44
R2	0.117	0.120	0.115	0.138	0.150	0.137	0.057	0.000
AIC	560.572	564.677	560.677	563.764	562.894	567.810	563.491	570.294
Prob >F	0.002	0.020	0.004	0.014	0.049	0.156	0.132	0.954

Note: "a" and "b" denote models estimated using one- and two-day windows, respectively.*, ** and *** represent 90, 95 and 99% significance. Standard deviations are shown between parentheses for each coefficient. Coefficients and standard deviations are multiplied by 10,000.