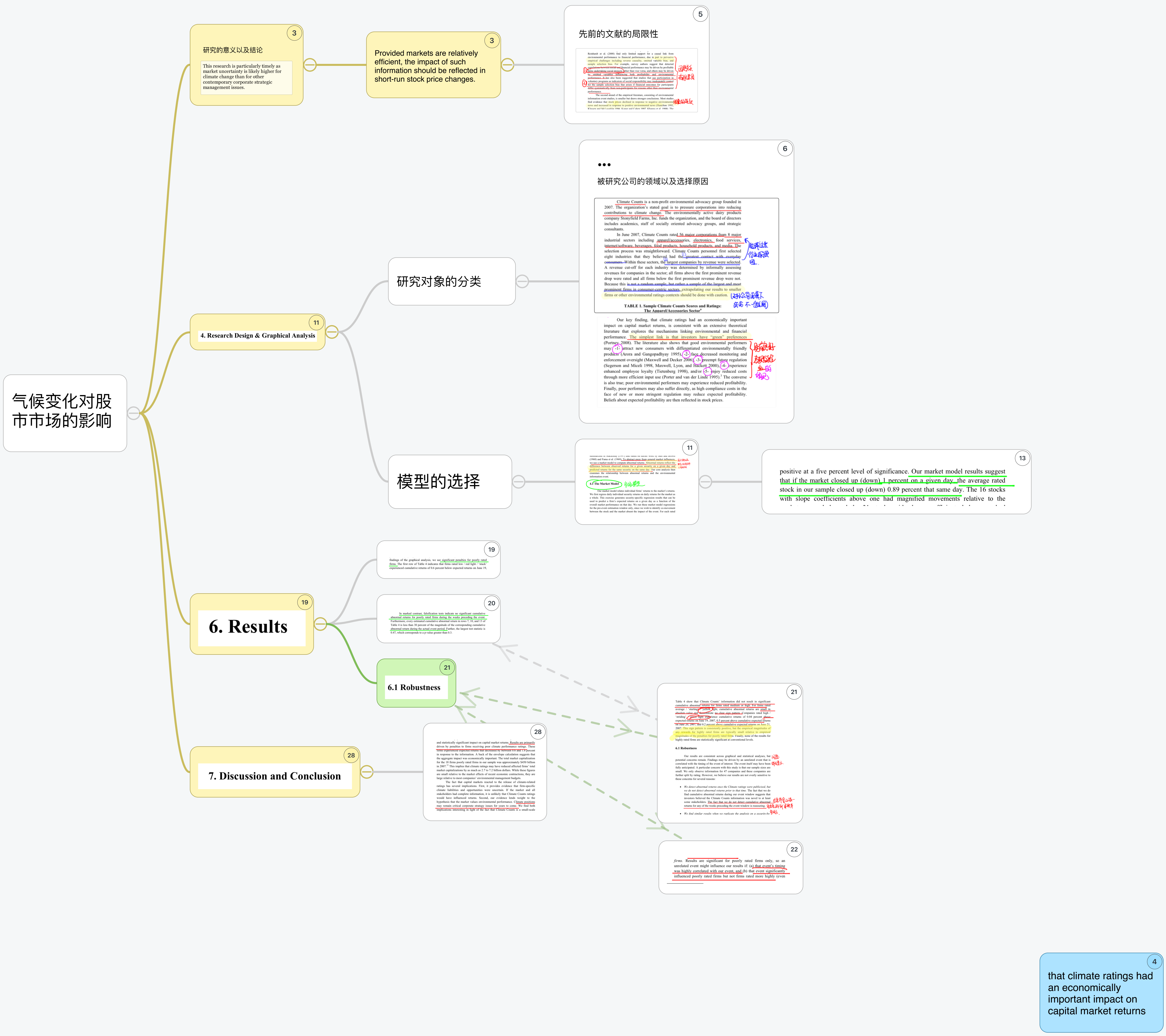
气候变化对股市市场的影响
研究的意义以及结论
This research is particularly timely as market uncertainty is likely higher for climate change than for other contemporary corporate strategic management issues.
Provided markets are relatively efficient, the impact of such information should be reflected in short-run stock price changes.
先前的文献的局限性
4. Research Design & Graphical Analysis
研究对象的分类
被研究公司的领域以及选择原因
模型的选择
positive at a five percent level of significance. Our market model results suggest that if the market closed up (down) 1 percent on a given day, the average rated stock in our sample closed up (down) 0.89 percent that same day. The 16 stocks with slope coefficients above one had magnified movements relative to the
6. Results
6.1 Robustness
7. Discussion and Conclusion
that climate ratings had an economically important impact on capital market returns

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The Impact of Climate Change Information: New Evidence from the Stock Market

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The Impact of Climate Change Information: New Evidence from the Stock Market

Abstract

On June 19, 2007, a non-profit organization released ratings of companies' plans for measuring, reporting, and reducing their greenhouse gas emissions. We explore the capital market impacts of this information event. In contrast to much of the related literature, our study examines climate change information and a plausibly exogenous event. We find that the information had an economically important and statistically significant impact on capital market returns. Poorly rated firms suffered market penalties. In contrast, we find limited benefits for firms receiving good ratings. We also uncover suggestive evidence that the economic mechanism driving our results is not a direct consumer demand effect.

KEYWORDS: Climate Change, Environmental Information, Corporate Social Responsibility, Corporate Environmental Behavior

1. Introduction

The challenges and opportunities to industry from climate change are large. On the costs side, anticipated legislation may increase regulatory burdens. For example, the Congressional Budget Office projected that a recently proposed climate bill would cost firms more than 100 billion dollars annually.[1] On the benefits side, "green" markets may generate new profit sources. The relative magnitudes of firms' climate-related net benefits, as well as which companies win and lose, are largely unknown. This paper contributes to the discussion by measuring the effect of climate change information on corporation's capital market performance. Provided markets are relatively efficient, the impact of such information should be reflected in short-run stock price changes. These price changes then signal market views about expected changes in firm-level benefits and costs arising from climate change.

Our research uses an event analysis to study a change in market beliefs. On June 19, 2007, the non-profit organization Climate Counts released firm-level ratings of companies' plans for measuring, reporting, and reducing greenhouse gas emissions. Qualitative ratings and quantitative scores were based on twenty-two comprehensive criteria. These assessments were highly publicized and generated significant short-run media coverage.

This paper's key contribution is providing early evidence on the relationship between financial performance and *climate-related* environmental behavior.[2] This research is particularly timely as market uncertainty is likely higher for climate change than for other contemporary corporate strategic management issues. Our analysis offers several advantages over the broader empirical work linking environmental and financial performance. The quasi-experimental nature of our event study mitigates the reverse causality and omitted variable bias concerns commonly arising in the cross-sectional corporate social responsibility literature. Further, firms did not have the option to opt in or opt out of the Climate Counts rating program, nor were they able to influence their

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[1] This bill was the American Clean Energy and Security Act, commonly referred to as Waxman-Markey. The source for the cost estimates is Congressional Budget Office, "The Estimated Costs to Households from the Cap-and-Trade Provisions of H.R. 2454," June 19, 2009.

[2] We aware of only one other study explicitly exploring the link between financial performance and climate-related behavior. Kim and Lyon (2007) examine the market impact of voluntary participation in a greenhouse gas disclosure consortium.

ratings. Because Climate Counts' ratings were exogenous from the firm's perspective, concerns about the selection and self-reporting biases common in the environmental information event study literature are also minimized.

We find that the release of these climate ratings had statistically significant and large impacts on stock market returns. Investors behaved as if climate ratings were new information, at least to some market participants. Poorly rated firms' market valuations fell by between 0.6 and 1.6 percent, or somewhere between 2.7 and 7.2 billion dollars in total. These results are robust to a host of checks, including falsification tests and analyses conditioned on industry. In contrast, we find no significant benefit for firms receiving good ratings. In other words, the market penalized poor performance but did not reward good performance. We also uncover suggestive, but not definitive, evidence that the economic mechanism driving our results is not a commonly assumed direct demand effect.

2. Background

2.1 Literature

Our key finding, that climate ratings had an economically important impact on capital market returns, is consistent with an extensive theoretical literature that explores the mechanisms linking environmental and financial performance. The simplest link is that investors have "green" preferences (Portney 2008). The literature also shows that good environmental performers may: -1- attract new consumers with differentiated environmentally friendly products (Arora and Gangopadhyay 1995), -2- face decreased monitoring and enforcement oversight (Maxwell and Decker 2006), -3- preempt future regulation (Segerson and Miceli 1998, Maxwell, Lyon, and Hackett 2000), -4- experience enhanced employee loyalty (Tietenberg 1998), and/or -5- enjoy reduced costs through more efficient input use (Porter and van der Linde 1995).[3] The converse is also true; poor environmental performers may experience reduced profitability. Finally, poor performers may also suffer directly, as high compliance costs in the face of new or more stringent regulation may reduce expected profitability. Beliefs about expected profitability are then reflected in stock prices.

[3] Lyon and Maxwell (2008) survey this literature.

In contrast to clear theoretical predictions, the existing empirical evidence linking environmental and financial performance is mixed. The first strand of the related literature, which explores corporate social responsibility, is large and controversial. Recent comprehensive surveys by Margolis et al. (2007) and Reinhardt et al. (2008) find only limited support for a causal link from environmental performance to financial performance, due in part to pervasive empirical challenges including reverse causality, omitted variable bias, and sample selection bias. For example, survey authors suggest that detected correlations between social and financial performance may be driven by profitable ① firms undertaking social projects rather than vice versa, and others may be driven by omitted variables influencing both profitability and environmental performance. It has also been suggested that studies that use participation in ② voluntary programs as indicators of social responsibility may inadequately control for the sample selection bias that arises if financial outcomes for participants differ systematically from non-participants for reasons other than environmental performance.

因果关系

有限原因

The second strand of the empirical literature, consisting of environmental information event studies, is smaller but draws stronger conclusions. Most studies find evidence that stock prices declined in response to negative environmental news and increased in response to positive environmental news (Hamilton 1995, Klassen and McLaughlin 1996, Konar and Cohen 1997, Khanna et al. 1998). The event study approach used in this literature goes a long way to minimizing reverse causality and omitted variable biases, but several authors including Konar and Cohen (2001) and McWilliams et al. (2006) have noted that work in this area often faces empirical challenges. One issue that motivated this study is that many environmental data are self-reported, so firm-level data may suffer from measurement error or strategic misreporting. Uncertain event dates are another common concern.

股票的连动

In this study, we conduct an event study where the event itself was exogenous to the firm. Firms were simply rated. According to interviews with Climate Counts staff members, several assessed companies strenuously objected to be included in the ratings but were evaluated nonetheless. Further, firms did not self report their environmental information; scores and ratings were determined and reviewed by third parties. Finally, assessments were widely publicized in a short and easily identifiable two day window.

2.2 Climate Counts and Climate Scores

Climate Counts is a non-profit environmental advocacy group founded in 2007. The organization's stated goal is to pressure corporations into reducing contributions to climate change. The environmentally active dairy products company Stonyfield Farms, Inc. funds the organization, and the board of directors includes academics, staff of socially oriented advocacy groups, and strategic consultants.

Add:
(1) 旅游业
(2) 畜牧业.

In June 2007, Climate Counts rated 56 major corporations from 8 major industrial sectors including apparel/accessories, electronics, food services, internet/software, beverages, food products, household products, and media. The selection process was straightforward. Climate Counts personnel first selected eight industries that they believed had the (1) greatest contact with everyday consumers. Within these sectors, the (2) largest companies by revenue were selected. A revenue cut-off for each industry was determined by informally assessing revenues for companies in the sector; all firms above the first prominent revenue drop were rated and all firms below the first prominent revenue drop were not. Because this is not a random sample, but rather a sample of the largest and most prominent firms in consumer-centric sectors, extrapolating our results to smaller firms or other environmental ratings contexts should be done with caution.

选择这些行业的原因.

(对小公司谨慎下结论 不一定适用)

TABLE 1. Sample Climate Counts Scores and Ratings: The Apparel/Accessories Sector[a]

Firm	Score	Within-Group Ranking
Nike	73	H
Gap Inc.	39	A
Liz Claiborne	15	A
Limited Brands	5	L
VF Corp	2	L
Levi Strauss	1	L
Jones Apparel Group	0	L

[a] Scores potentially range from 0 to 100. Within-Group ratings are High (H), Average (A), and Low (L) corresponding to ratings of "Green/Striding," "Yellow/Starting," and "Red/Stuck."

Climate scores could range from 0 to 100 and were based upon 22 criteria in four categories: measurement, reduction, reporting and legislative positioning. A panel of academics and other experts developed the criteria. Data accuracy was verified by the sustainability strategy firm GreenOrder, Inc. Measurement metrics included the precision and scope of greenhouse gas emissions assessment. Reduction metrics included abatement targets, abatement resources, management support for abatement, and past records of abatement. Reporting metrics included the extent and detail of publicly disclosed emissions profiles. Finally, scores included the company's public support or opposition to mandatory climate change legislation.

In addition to numerical scores, Climate Counts assigned all 56 companies a within-sector categorical rating. If the firm performed well relative to sector peers, they were assigned a green light rating called "striding." Average firms were given a yellow light rating called "starting." Firms with below average greenhouse gas measurement, reduction, and reporting behavior were given a red light rating called "stuck." For illustration, Table 1 presents complete ratings for a sample industry, apparel and accessories. [4]

2.3 Publication and Publicity

Climate Counts coordinated the release of the climate information to maximize its impact. Select media outlets were aware that scorecard information would be released on Tuesday, June 19, but the organization embargoed information about actual company ratings until 12 noon EST on June 19, 2007. At that time, the organization posted its scores on the web at climatecounts.org and lifted the embargo on a major press release.

Media response to the press release and website was immediate and noteworthy. Articles discussing Climate Counts ratings appeared in major news outlets, including the New York Times, the Wall Street Journal, MSNBC, cnn.com, and National Public Radio. Television news networks also reported on

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[4] We analyze the financial market impacts of Climate Counts' ratings and scores. It might be interesting to separately evaluate the impact of the component metrics that determined the final ratings and scores, but June 2007 press releases and media coverage did not decompose the summary metrics. Market participants would not have been able to react to individual elements in the rankings.

the climate ratings. For example, CNN aired at least 4 stories on June 19, 3 stories on June 21, and 2 stories on June 23.

Directly measuring consumer and investor awareness of any information event is difficult. However, Google Trends reports that searches for "climate counts" were 11.9 times greater than average on June 19 and 18.1 times greater than average on June 20. This suggests the public responded to media reports by seeking more information on Climate Counts and the firm-specific ratings.

It is likely that some of the information contained in the scores and ratings was known to some market participants ahead of time. Highly motivated investors could have formed their own expectations about individual firms' climate-related liabilities and opportunities prior to June 2007. Nevertheless, at the time of the event, externally provided climate information was rare; at the time nearly all available company-specific climate information was self-reported. Investors likely updated their own priors after the Climate Counts information event. Further, ratings and scores would be novel to markets even if individual investors already were aware of much of the information. As long as investors believed that the climate information would be considered novel and consequential to some stakeholders, the information release would cause those investors to revise their expectations about profitability. For example, investors might believe that consumers or employees would respond to the highly public Climate Counts ratings. Or, investors might believe that firms' current or future relationships with regulators would be influenced by the highly public climate liability information.

3. Data

Our goal is to examine the empirical relationship between climate ratings and capital market returns. Consequently, we match climate-related performance data with financial market data at the firm level. We use historical New York Stock Exchange (NYSE) and National Association of Securities Dealers Automated Quotations (NASDAQ) daily stock and index returns data from Yahoo! Finance for market returns information. We use climate scores and within-sector performance ratings from Climate Counts for environmental information. Sensitivity analyses and further explorations use firm characteristic data from CompuStat, foreign sales data from WorldScope International, and marketcap data from ValueLine Investment Research.

Our final sample contains complete information for 47 of 56 originally rated firms. We omit two privately held corporations, six corporations traded on foreign markets without major US depository receipt listings, and one corporation associated with multiple stock tickers.[5] The vast majority of the 47 securities in our sample are US held firms. A small number of securities are depository receipt listings for NYSE or NASDAQ trades that represent equity in a foreign firm.

Daily closing prices for each security and two market indexes are directly observed. To control for scale across securities, however, we follow convention and consider daily returns as the basic unit of analysis. Security specific returns are defined as gains (losses) of the current day's close price over the previous day's close price. Returns are expressed as percentages and calculated as $(close_t - close_{t-1}) / close_{t-1}$.

Our pre-event calibration period, or estimation window, considers market returns for all trading days in 2007 prior to our event, subject to maintaining approximate day-of-week and week-of-month balance. This estimation window covers 102 trading days spanning January 21, 2007 to June 17, 2007. The subsequent event window considers market returns beginning on the date of Climate Counts' press release (June 19, 2007) and continuing for several trading days.

3.1 Summary Statistics

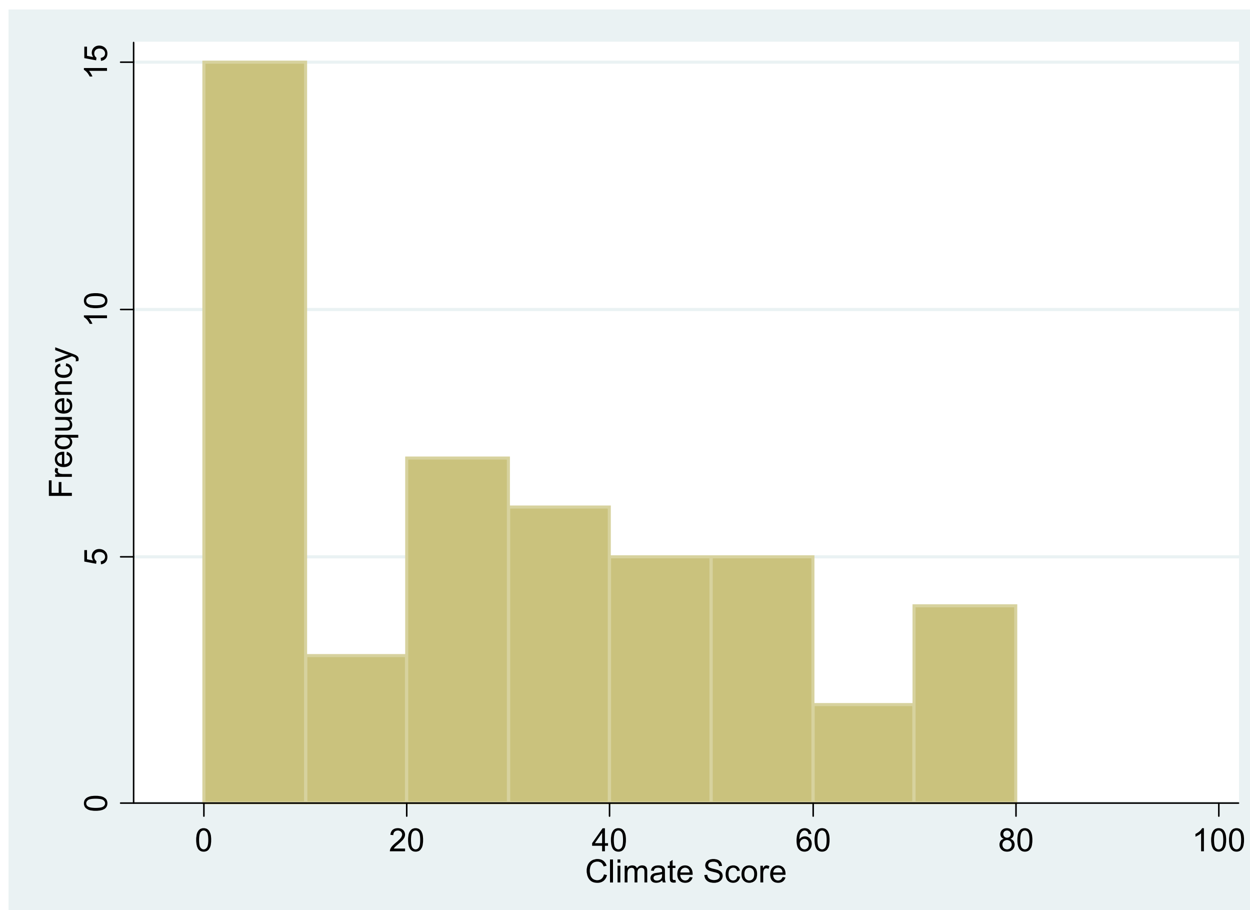
Climate Counts' scores for our sample are summarized in Figure 1. Note that scores are highly variable. While possible scores span 0 to 100, actual scores range from 0 to 77. The mean climate score was 28.8 and the median score was 29. Scores are skewed right; the modal value was 0 and more than 30 percent of scores were 6 or less.

In general, scores are considerably more variable within industries than across industries. Five of the eight sectors have mean climate scores in the twenties and thirties. By construction, the within industry ratings of 'green light/striding', 'yellow light/starting', and 'red light/stuck' are relatively balanced across sectors. Approximately 40 percent of firms are ranked below average for their industry ('stuck'), about 30 percent are ranked average for their industry

[5] Qualitative results are not sensitive to including or omitting different individual stocks associated with this corporation.

('starting'), and approximately 30 percent are ranked above average for their industry ('striding').

FIGURE 1. Distribution of Climate Scores



Market data for the pre-event estimation window are summarized in Table 2. Summary statistics suggest that US markets were relatively stable during this period.[6] The mean daily return for the S&P 500 market index was 7 one-hundredths of one percent or approximately one-tenth of one standard deviation. The mean daily return for our 47 sample firms was 8 one-hundredths of one percent, or approximately one-twentieth of one standard deviation.

Summary statistics in Table 2 also suggest some differences in average security prices across climate ratings. Highly rated firms and poorly rated firms have reasonably similar mean closing prices of 41.9 and 39.8 dollars. Firms rated near the industry average had mean closing prices of 87.0 dollars.[7] However, in contrast to closing price variation across ratings categories, all ranked firms had statistically similar and very small average *returns* for the pre-event calibration period. Mean returns were at or below one-tenth of one percent or less for firms

[6] "Bullish" trends would have generated significantly positive mean daily returns and "bearish" trends would have generated significantly negative mean daily returns.

[7] Recall that ratings reflect within-industry performance, so these differences are not driven by differences in industrial composition.

ranked high, average, and low. Once scaled, measures of financial performance are comparable across ratings.

TABLE 2. Market Data Summary Statistics: Pre-event Estimation Window[a]

	N	MEAN Daily Close	S.D. Daily Close	MIN Daily Close	MAX Daily Close	MEAN Daily Return	S.D. Daily Return	MIN Daily Return	MAX Daily Return
S&P 500	n/a	1461.2	44.17	1374.1	1539.2	0.00071	0.0072	-0.0176	0.0152
All Firms	47	52.27	65.71	14.88	518.84	0.00076	0.0138	-0.1727	0.2695
Firms Rated H	14	41.88	19.34	16.69	103.32	0.00034	0.0130	-0.1178	0.0994
Firms Rated M	15	76.99	108.4	16.32	518.84	0.00077	0.0126	-0.1727	0.0507
Firms Rated L	19	39.75	21.19	14.88	124.49	0.00107	0.0152	-0.0591	0.2695

[a] Within-Group high (H), medium (M), and low (L) ratings correspond to Climate Counts' categories "Green/Striding," "Yellow/Starting," and "Red/Stuck." For all rows, summary statistics are calculated across the 102 trading days that comprise the pre-event estimation window. Daily closes are in dollars. Returns are expressed in percent, such that 0.01 represents a one percent increase in closing prices relative to the previous day's closing prices.

4. Research Design & Graphical Analysis

Our research design follows the financial event study literature as summarized in Mackinlay (1997) and based on earlier work by Ball and Brown (1968) and Fama et al. (1969). To abstract away from general market influences, we use a market model to compute abnormal returns. Abnormal returns reflect the difference between observed returns for a given security on a given day and predicted returns for the same security on the same day. Our core analysis then examines the relationship between abnormal returns and the environmental information event.

通过异常收益
探究与环境信息事
之间的关系

4.1 The Market Model

市场模型

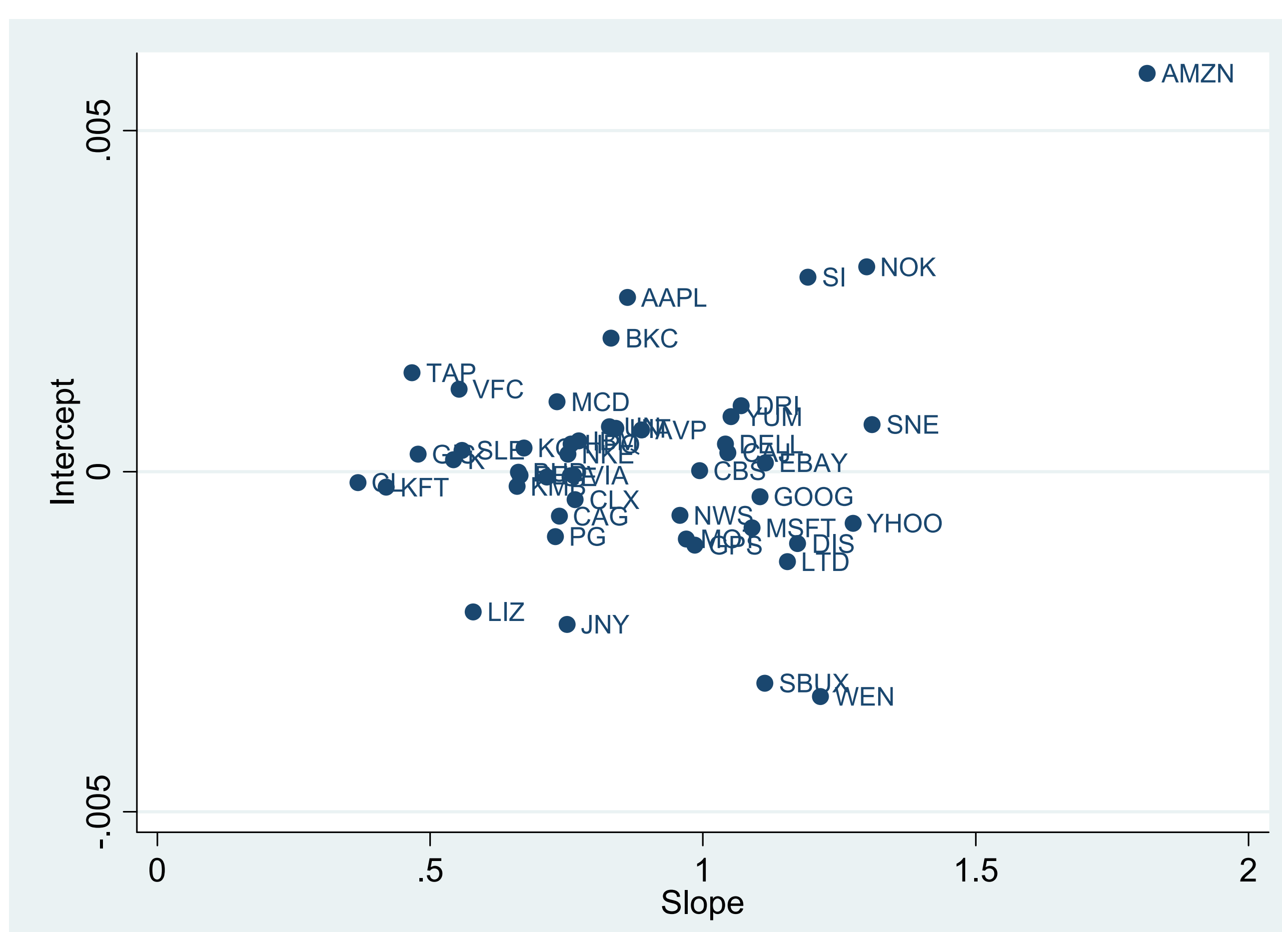
Our market model relates individual firms' returns to the market's returns. We first regress daily individual security returns on daily returns for the market as a whole. This exercise generates security-specific regression results that can be used to predict a firm's expected returns on a given day as a function of the overall market performance on that day. We run these market model regressions for the pre-event estimation window only, since we wish to identify co-movement between the stock and the market absent the impact of the event. For each rated firm i and day t of the 102 trading day pre-event estimation window τ_0, we relate return $R_{i,t}$ on day $t \in \tau_0$ to overall market return $R_{m,t}$:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t}. \tag{1}$$

$u_{i,t}$ is a mean zero, finite disturbance term, $E\left(u_{i,t}\right) = 0, \quad \text{var}(u_{i,t}) = \sigma^2_{u_{i,t}}$.

We choose the broad-based Standard & Poor's (S&P) 500 index as our market returns measure $R_{m,t}$ as this index covers large cap stocks traded on both NYSE and NASDAQ markets. Other common market indices, such as the Dow Jones Industrial average, are possible choices but mimic the industrial composition and market capitalizations of our 47 rated firms somewhat less closely than the S&P500.[8]

FIGURE 2. Market Model Results Summary



The mean R-squared from security-specific regressions of the form (1) was 0.3. Figure 2 summarizes these market model results in more detail. Points are labeled with ticker symbols. If a given stock tracked the market perfectly, its

[8] Our results are not sensitive to the choice of market index. We replicated the analysis with the DJIA as our index and found point estimates and statistical significance levels extremely similar to those presented.

intercept coefficient would be 0 and its slope coefficient would be 1. For our sample firms, the average regression intercept is 0.0001 and the average slope coefficient is 0.88. Only one estimated intercept coefficient was statistically different from zero, and all 47 estimated slope coefficients were statistically positive at a five percent level of significance. Our market model results suggest that if the market closed up (down) 1 percent on a given day, the average rated stock in our sample closed up (down) 0.89 percent that same day. The 16 stocks with slope coefficients above one had magnified movements relative to the market as a whole and the 31 stocks with slope coefficients below one had dampened movements relative to the market as a whole. Amazon.com was our greatest outlier. If the market closed up (down) 1 percent on a given day during our estimation window, on average Amazon.com closed up (down) 1.82 percent on that same day.

4.2 Abnormal Returns

The market models represented by equation (1) and summarized in Figure 2 describe the typical relationship between a given security and the market as a whole during the pre-event estimation window. Predictions from these models can be used to predict expected daily returns for a given security based upon the performance of the S&P500 index on that day.[9] For any rated firm *i* during the entire sample period τ_1, *expected* returns $E\left(R_{i,t} \mid R_{m,t}\right)$ on day $t \in \tau_1$ are:

$$E\left(R_{i,t} \mid R_{m,t}\right) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{2}$$

Given expected returns, abnormal returns are the difference between the observed return and the predicted return for that day. For any rated firm *i* during the entire sample period τ_1, *abnormal* returns $E\left(R_{i,t} \mid R_{m,t}\right)$ on day $t \in \tau_1$ are:

$$AR_{i,t} = R_{i,t} - E\left(R_{i,t} \mid R_{m,t}\right) = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t} \,. \tag{3}$$

[9] It is unlikely that our market measure R is significantly influenced by our information event, since our sample is small relative to index composition and since high and low ratings should have opposing effects. Nevertheless, if some endogeneity is present, our results are understated.

For example, suppose the S&P500 was up one percent on a given day. Our market model results suggest that we would expect Nike (stock ticker NKE) to be up 0.75 percent that same day. If Nike were actually up 0.90 percent, its abnormal return for that day is 0.15 percent (0.90 – 0.75).

4.3 Graphical Analysis

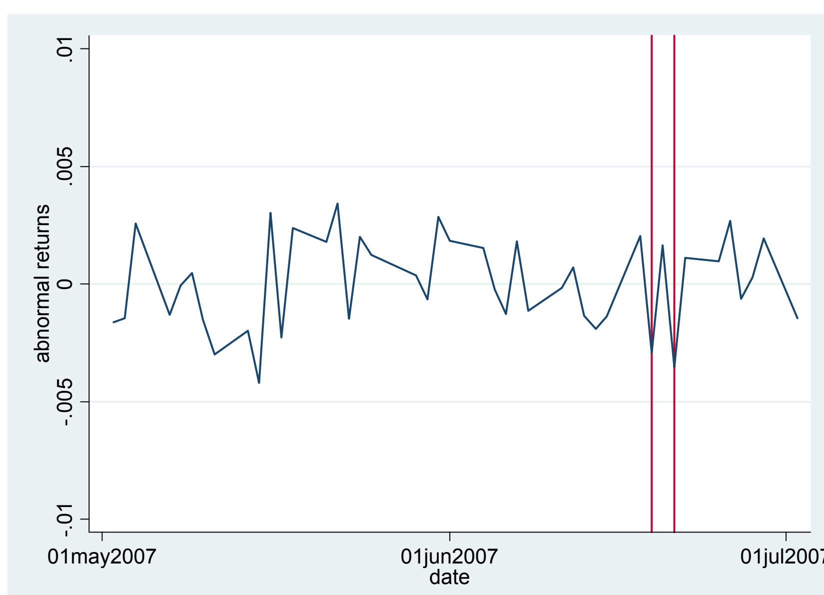
In Figure 3, we examine average abnormal returns patterns for four groups: all ranked sample firms, all sample firms rated low / “stuck” / red light, all sample firms rated average / “starting” / yellow light, and all sample firms rated high / “striding” / green light. The intent is to highlight patterns of abnormal returns during the event window. While the estimation window begins on January 21, 2007, in the interests of clarity we present a subset of dates beginning May 1.

Panel A of Figure 3 displays average daily abnormal returns for the 47 sample firms receiving any rating by Climate Counts. Vertical bands demarcate an event window beginning on the information release date of June 19, 2007 and ending on June 21, 2007, the last day of notable media coverage. Abnormal returns are somewhat negative on June 19, 2007, somewhat positive on June 20, 2007, and somewhat negative on June 21, 2007. There is no obvious pattern of abnormal returns during the highlighted three-day event window. Moreover, abnormal returns during the event period are small. For example, average returns for all rated firms on the first day of the event window are 29 one-hundredths of a percent (.0029) below expected returns. Further, the absolute values of typical abnormal returns during the pre-event estimation window are larger than the absolute values of abnormal returns during the event period. In short, Panel A of Figure 3 displays little evidence that climate ratings influenced returns across all rated firms.

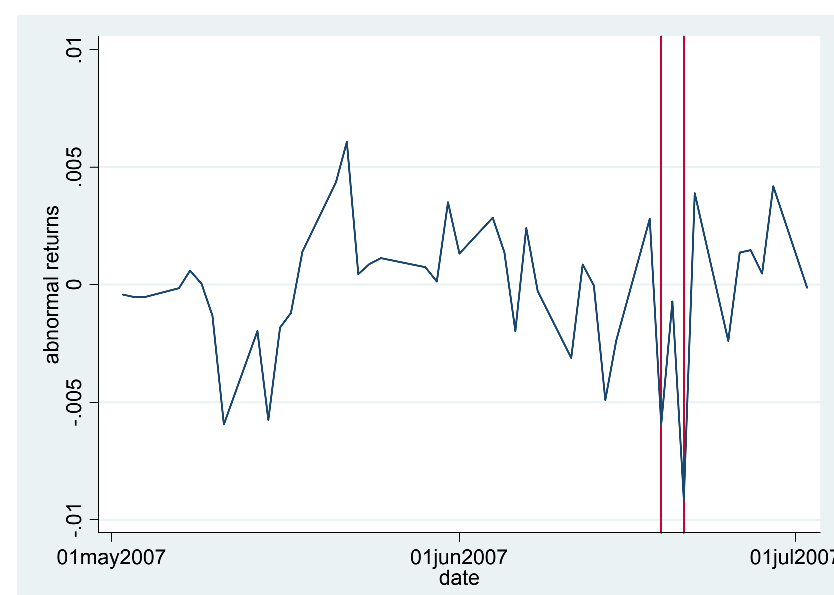
It may be unsurprising that aggregate abnormal returns for all ranked firms are small, since the analysis in Panel A simultaneously considers firms ranked high, average, and low. Panel B displays average daily abnormal returns for the 18 firm subsample receiving a low / “stuck” / red light rating by Climate Counts. As before, vertical bands demarcate a three-day event window spanning June 19, 2007 to June 21, 2007. Abnormal returns are negative on all three days of climate ratings publicity. During the event window, abnormal returns are also relatively large. For example, average returns for poorly rated firms are 60 one-hundredths of a percent below expected returns on the first day of the event and 92 one-hundredths of a percent below expected returns on the third day of the event window. The absolute values of these abnormal returns are also relatively large in relation to most abnormal returns during the pre-event estimation window. In sum, results in Panel B suggest that the market may have penalized poorly rated firms.

FIGURE 3. Abnormal Returns

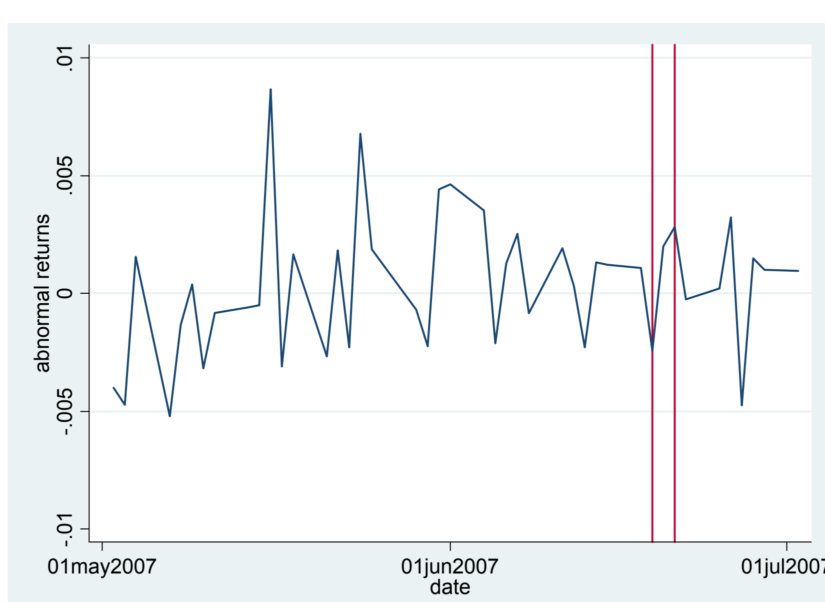
Panel A. All Firms



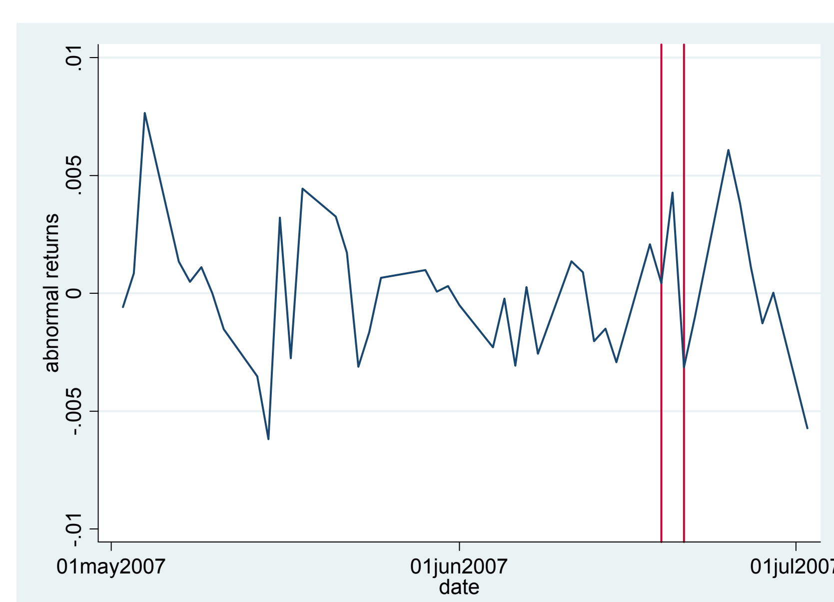
Panel B. Low / 'Stuck' / Red



Panel C. Avg / 'Starting' / Yellow



Panel D. High / 'Striding' / Green



Panel C displays the daily abnormal returns for the 15 firm subsample receiving an average / "starting" / yellow light rating by Climate Counts. Results provide little evidence that climate ratings influenced returns for these firms. Abnormal returns follow no sign clear pattern during the event window, and abnormal returns during the event window are small relative to typical abnormal returns during the estimation window. Panel D displays the average daily abnormal returns for the 14 firms receiving a high / "striding" / green light rating by Climate Counts. Results suggest the market may have weakly rewarded highly rated firms, but the evidence is not overwhelming. Abnormal returns are positive for the first and second days of the event window, but they have similar magnitudes as returns in the estimation window. Further, abnormal returns are negative on the third day of the event window.

5. Statistical Analysis

The preceding graphical analysis suggests that the market may have penalized firms receiving poor climate ratings and neither rewarded nor penalized firms receiving average or good climate ratings. We now turn to a more formal analysis in which we assess the statistical significance of these findings and perform sensitivity checks. Finally, we extend our analysis by exploring the relationships between environmental and financial performance in greater detail.

5.1 Inference with Cumulative Abnormal Returns

The standard approach to assessing statistical magnitudes in event studies aggregates abnormal returns over both securities and days to obtain *cumulative* abnormal returns. For example, cumulative abnormal returns might measure the impact of the information event for all firms ranked low / 'stuck' / red light aggregated over an event period of 3 days. For a given security, cumulative abnormal returns across days are calculated by simple summation. For day t of event window τ_1 of length d days, cumulative abnormal returns can be expressed as:

$$CAR_{i,d} = \sum_{k=t}^{t+d-1} AR_{i,k} \; . \tag{5}$$

The security-specific variance of these cumulative abnormal returns can be written:

$$\text{var}(CAR_{i,d}) = \sum_{k=t}^{t+d-1} d \times var(AR_{i,k}) \; . \tag{6}$$

Equation (5) requires security-specific variance measures and statistical independence across days. As security-specific population variances *var(*$AR_{i,k}$*)* are unknown and unknowable, we use the asymptotically equivalent sample analogs from the market model in equation (1), $\hat{\sigma}^2_{u_i}$. Temporal independence is commonly assumed in the event study literature and is relatively innocuous in the absence of major systematic shocks over the event window (MacKinlay 1997). As noted in the preceding data section, large shocks unrelated to the release of Climate Counts' scores are not apparent in the overall market data.

Given security-specific cumulative abnormal returns over days, we can aggregate across firms as well. The sample average cumulative abnormal return for a group of *n* firms, given an event window length of *d* days, can be written:

$$\overline{CAR_d} = \frac{1}{n}\sum_{i=1}^{n} CAR_{i,d}. \tag{7}$$

If we assume no cross-sectional dependence and thus zero cross-security covariances, the variance of mean cumulative abnormal returns for a group of *n* firms over an event window length of *d* days can be computed:

$$\operatorname{var}\left(\overline{CAR_d}\right) = \frac{1}{n^2}\sum_{i=1}^{n} \operatorname{var}(CAR_{i,d}). \tag{8}$$

A valid test statistic under the assumption of cross-sectional independence can then be written as:

$$\theta_d = \frac{\overline{CAR_d}}{\sqrt{\operatorname{var}\left(\overline{CAR_d}\right)}} \sim t. \tag{9}$$

We apply the test statistic in (9) to test hypotheses about cumulative abnormal returns. We test a null of no abnormal returns for the low / 'stuck' / red light group against an alternative hypothesis of negative abnormal returns. We test a null of no abnormal returns for the high / 'striding' / green light group against an alternative hypothesis of positive abnormal returns. Since the potential impact of Climate Scores on firms in the average / 'starting' / yellow light group is ambiguous a priori, we test a null of no abnormal returns for this group against an alternative hypothesis of nonzero abnormal returns.

5.2 Cross-sectional Dependence and a Portfolio Approach

The event study literature suggests that the cross-sectional independence assumption may not be innocuous. Indeed, cross-sectional independence is unlikely to hold exactly in our context, as event time and calendar time coincide for analyzed firms. The information event affects all analyzed firms on the same day and therefore some residual cross-sectional correlation is to be expected. Point estimates of average cumulative abnormal returns will remain unbiased, but the OLS-derived standard errors comprising the test statistic in (9) may be biased. Collins and Dent (1984) and Sefcik and Thompson (1986) demonstrate with analytical and simulation exercises that magnitudes of errors in inference can be large in hypothetical contexts with event date clustering.

Christie (1986), Brown and Warner (1980, 1985), and Bernard (1987), however, showed that this standard error bias is not serious in practice unless the data are characterized by heavy industrial concentration, large sample sizes, and/or long time intervals. None of these are features of our data. Our analysis categories do not exhibit industrial concentration, since ratings are defined by within-industry ratings. All ratings categories have firms from all eight evaluated industries. Our sample sizes are also relatively small. The low / "stuck" / red light group consists of 18 firms, the average / "starting" / yellow light group has 15 firms, and the high / "striding" / green light group has 14 firms. Bernard (1987) indicates that substantial inference bias arises primarily in samples of over 200 firms. Finally, our return intervals are daily rather than quarterly or annual.

Based on the above discussion, the magnitudes of errors in inference from assuming cross-sectional independence are likely to be small in our context. As a result, we use the standard test statistic in equation (9) to assess the significance of our main results. Nevertheless, to see whether cross-sectional dependence influences our findings, we supplement our main analysis with a portfolio based approach which collapses security data into a single time series for each group. Each single time series appropriately accommodates event-date clustering (Mackinlay 1997) and allays concerns when securities' cross-sectional correlations may be non-zero.[10] Mechanically, we apply an unweighted portfolio analysis to returns, abnormal returns, cumulative abnormal returns, and test statistics constructed from mean close prices for each rating and day. The cross-sectional aggregations underlying the portfolio analyses may come at the cost of reduced statistical power, but the corresponding test statistics are unbiased.

5.3 Falsification Tests

In addition to standard and portfolio event study approaches, we run falsification tests which replicate the analyses for the weeks preceding the event window. Statistically significant cumulative abnormal returns prior to the event period might suggest a flawed research design. Alternatively, significant cumulative abnormal returns during the estimation window might indicate that the market substantially anticipated the event.

6. Results

Table 4 presents our main results, with cumulative abnormal returns presented by group for varying event-window lengths. Consistent with the findings of the graphical analysis, we see significant penalties for poorly rated firms. The first row of Table 4 indicates that firms rated low / red light / 'stuck' experienced cumulative returns of 0.6 percent below expected returns on June 19, 2007, 0.7 percent below cumulative expected returns on June 20, 2007, and 1.6 percent below cumulative expected returns on June 21, 2007. All presented event window lengths generate cumulative abnormal returns with large empirical magnitudes, and two of three estimates are statistically significant at the five percent level.[11]

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[10] Alternative approaches to inferences with event-date clustering include generalized least squares (GLS), multi-index market models, and a security-by-security analysis. The assumptions required for reliable finite sample properties of GLS are often problematic in accounting and finance research (Bernard 1997). Multi-index market models do not necessarily eliminate cross-sectional dependencies. A security-by-security analysis follows in section 6.1.

[11] Results similar to those in the first row of Table 4 indicate that negative cumulative abnormal returns persist well beyond a three-day event window, and cumulative abnormal returns larger than one percent in absolute value persist well into the next trading week. However, as is common in the literature, statistical noise begins to dominate inference.

The portfolio approach yields results similar to the standard analysis. The fourth row of results in Table 4 indicates that firms rated low / red light / 'stuck' experienced cumulative returns of 0.8 percent below expected returns on June 19, 2007, 1.2 percent below cumulative expected returns on June 20, 2007, and 1.8 percent below cumulative expected returns on June 21, 2007. Estimates from all presented event window lengths have large empirical magnitudes, and all three are statistically significant at the ten percent level.

In marked contrast, falsification tests indicate no significant cumulative abnormal returns for poorly rated firms during the weeks preceding the event. Furthermore, every estimated cumulative abnormal return in rows 7, 10, and 13 of Table 4 is less than 30 percent of the magnitude of the corresponding cumulative abnormal return during the actual event period. Further, the largest test statistic is 0.47, which corresponds to a p-value greater than 0.3.

TABLE 4. Main results: Cumulative Abnormal Returns by Ratings Group

Rating	**1-day CAR**	**2-day CAR**	**3-day CAR**
Event Week - Standard Analysis			
Low Rating	-0.60% (-1.88)**	-0.67% (-1.05)	-1.58% (-1.66)**
Average Rating	-0.24% (-0.87)	-0.04% (-0.77)	+0.24% (0.28)
High Rating	+0.04% (0.15)	+0.47% (0.80)	+0.16% (0.18)
Event Week - Portfolio Analysis			
Low Rating	-0.79% (-2.04)**	-1.21% (-1.55)*	-1.78% (-1.52)*
Average Rating	-0.27% (-0.52)	+0.10% (0.10)	+0.26% (0.16)
High Rating	+0.21% (0.65)	+0.60% (0.95)	+0.36% (0.38)
Falsification Test – 1 week prior			
Low Rating	+0.09% (0.27)	+0.06% (0.09)	-0.45% (-0.47)
Average Rating	+0.04% (0.14)	-0.19% (-0.34)	-0.06% (-0.07)
High Rating	+0.10% (0.33)	-0.13% (-0.21)	-0.29% (-0.32)
Falsification Test – 2 weeks prior			
Low Rating	+0.14% (0.44)	-0.05% (-0.07)	+0.22% (0.23)
Average Rating	-0.19% (-0.68)	-0.04% (-0.08)	+0.25% (0.29)
High Rating	-0.03% (-0.09)	-0.34% (-0.56)	-0.30% (-0.33)
Falsification Test – 3 weeks prior			
Low Rating	+0.07% (0.23)	+0.08% (0.12)	+0.43% (0.44)
Average Rating	-0.06% (-0.19)	-0.28% (-0.49)	+0.18% (0.21)
High Rating	+0.08% (0.28)	+0.07% (0.11)	+0.08% (0.09)

[a] Test statistics in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent levels.

Consistent with the graphical analysis, results in rows 2, 3, 5, and 6 of Table 4 show that Climate Counts' information did not result in significant cumulative abnormal returns for firms rated medium or high. For firms rated average / 'starting' / yellow light, cumulative abnormal returns are small in absolute value and demonstrate no clear sign pattern. Companies rated high / 'striding' / green light experience cumulative returns of 0.04 percent above expected returns on June 19, 2007, 0.5 percent above cumulative expected returns on June 20, 2007, and 0.2 percent above cumulative expected returns on June 21, 2007. This sign pattern is consistently positive, but the empirical magnitudes of any rewards for highly rated firms are typically small relative to empirical magnitudes of the penalties for poorly rated firms. Finally, none of the results for highly rated firms are statistically significant at conventional levels.

6.1 Robustness

Our results are consistent across graphical and statistical analyses, but potential concerns remain. Findings may be driven by an unrelated event that is correlated with the timing of the event of interest. The event itself may have been fully anticipated. A particular concern with this study is that our sample sizes are small. We only observe information for 47 companies and these companies are further split by rating. However, we believe our results are not overly sensitive to these concerns for several reasons:

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- *We detect abnormal returns once the Climate ratings were publicized, but we do not detect abnormal returns prior to that time.* The fact that we do find cumulative abnormal returns during our event window suggests that investors believed the Climate Counts information was novel to at least some stakeholders. The fact that we do not detect cumulative abnormal returns for any of the weeks preceding the event window is reassuring.

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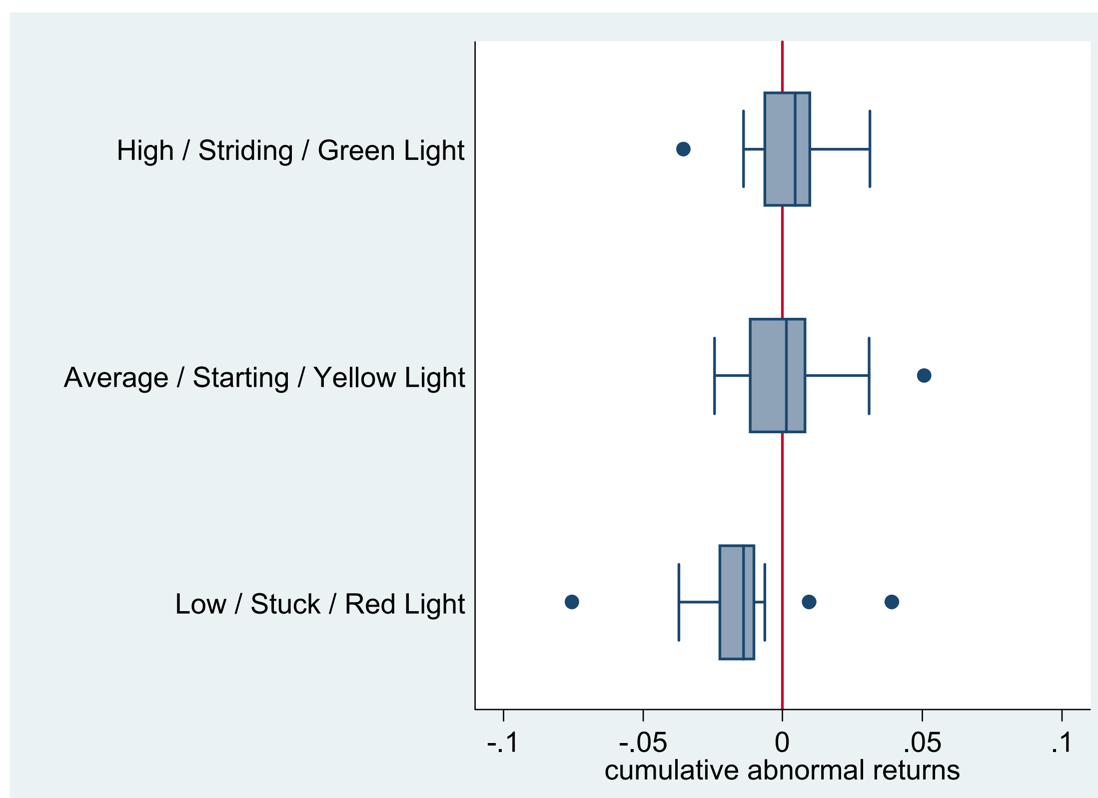
- *We find similar results when we replicate the analysis on a security-by-security basis.* Security-specific results are summarized in Figure 4. The vast majority of poorly rated firms experienced empirically large and negative cumulative abnormal returns. For returns aggregated across 3 days, 16 of 18 firms (89 percent) rated low / 'stuck' / red light had negative cumulative abnormal returns. In contrast, there is no clear pattern of results for firms rated average or high. 6 of 15 firms (40 percent) rated average / 'starting' / yellow light and 6 of 14 firms (43 percent) rated high / 'striding' / green light had negative cumulative abnormal returns.[12]

FIGURE 4. Security-by-Security Analysis Results Summary



- *We detect cumulative abnormal returns across a broad range of industries.* We find significant event study results for ratings groups consisting of firms spanning eight distinct industries. Note also that industrial composition is approximately equal across ratings categories (low, average, high), so composition effects will not drive results.

- *We are unaware of systematic confounding events for poorly rated firms.* Results are significant for poorly rated firms only, so an unrelated event might influence our results if: (a) that event's timing was highly correlated with our event, and (b) that event significantly influenced poorly rated firms but not firms rated more highly (even

[12] As perhaps expected, security-by-security analyses have low statistical power and few of the security specific cumulative abnormal returns are statistically significant.

after controlling for industry). We searched the business / financial section of the New York Times for the three days of the event window, and we found no large-scale, systematic shocks to business. We searched the New York Times business and financial section for news related to our 18 poorly rated firms during the event window. Wendy's International, a low rated company, explored a possible sale on June 19. We replicated the analysis omitting Wendy's and found similar results to those reported. Apple, another poorly rated company, was discussed due to iPhone news on June 21. We replicated the analysis omitting Apple and found similar results to those reported. Finally, we searched Google Trends for major spikes in worldwide Internet searches for our poorly rated firms during all of 2007. Major search spikes are listed in Table 5. Note that only Darden restaurants had a search spike that coincided with our event window. We replicated the analysis omitting Darden and found similar results to those reported. In short, confounding events do not appear to be driving our results.

TABLE 5. Major 2007 News Events for Poorly Rated Firms

Company	Major news events
Limited Brands	LTD to sell Express (May 16); sales decline (Nov 8)
VF Corp	VFC losses on intimates sales (Jan 23)
Jones Apparel	JNY receives offers for Barneys (July 5, Aug 6)
Apple	AAPL introduces / launches iPhone (Jan 10, June 29)
Yum! Brands	YUM rat scandal (Feb 23); high earnings (May 2, July 11)
Darden Restaurants	DAR posts earnings (March 20, June 20, Dec 19)
Burger King	BKC announces no trans-fat oils (July 6)
Wendy's Intl.	None
Anheuser-Busch	BUD and In-Bev to possibly merge (Feb 15)
Molson Coors	TAP announces operations merger with Miller (Oct 9)
Ebay	EBAY to team up with Yahoo in Japan (Dec 4)
Amazon.com	AMZN announces high profits (July 25)
ConAgra	CAG salmonella law suit (Feb 11)
Sara Lee	SLE recalls bread (July 27)
Avon	None
Clorox	CLX announces plan to buy Burt's Bees (Oct 31)
Viacom	VIA sues YouTube, Google (March 13)
CBS	CBS fires scandal-plagued Don Imus (April 12)

6.2 Further Exploration: Scores

The preceding analysis focuses on the capital market impacts of within-industry climate ratings, i.e. the low / 'stuck' / red light, average / 'starting' / yellow light, and high / 'striding' / green light assessments. We extend the analysis by exploring the effects of numerical (0-100) climate *scores* on abnormal returns as well. As raw scores may be correlated with industrial sector, in contrast to within-industry ratings, regressions include industry fixed effects. Our simplest regression specification for firm *i* in industry *j* can be written:

$$\delta_{ij} = \alpha + \theta_j + \beta SCORE_{ij} + \varepsilon_{ij}\,, \qquad (10)$$

where δ are cumulative abnormal returns, θ_j are j-1 industry fixed effects, β is the coefficient of primary interest, and ε are the usual idiosyncratic error terms.

Scores may also be correlated with firm-level characteristics other than industrial sector. We therefore also estimate extended specifications that include size as measured by market capitalization, profitability as measured by earnings per share, globalization as measured by foreign sales as a percentage of total sales, and consumer orientation as measured by advertising expenditures.[13] For covariate and parameter vectors X and Γ, the extended specifications are:

$$\delta_{ij} = \alpha + \theta_j + \beta SCORE_{ij} + X_{ij}\Gamma + \varepsilon_{ij}\,, \qquad (11)$$

For regressions of the form (10) and (11), we test null hypotheses that $\beta = 0$ against alternative hypotheses that $\beta > 0$. In other words, we test null hypotheses of no relationship between scores and cumulative abnormal returns against one-sided alternatives that cumulative abnormal returns increase in climate scores.

Finally, we supplement regressions of the form (10) and (11) with a specification that groups the score variable into three categories: (1) scores between 0 and 19, (2) scores between 20 and 49, and (3) scores greater than or equal to 50. In regressions with categorical score variables, category (3) is omitted and all coefficients are interpreted relative to the high scoring group. We test null

[13] We were unable to obtain advertising and globalization data for two firms, so relevant analyses omit these companies.

hypotheses of no difference between categories against alternative hypotheses that low or average scorers exhibit strictly lower abnormal returns than high scorers.

Table 6 presents our regression results. Test statistics, based on robust standard errors, are presented in parentheses below coefficient estimates. Before turning to our main results, we note that R-squared and F statistics suggest our independent variables explain a considerable portion of the variability in cumulative abnormal returns during the event window. We also note that most control variables are not statistically significant after controlling for industry. In other words, cumulative abnormal returns during the event window are not correlated with most firm-level characteristics. Market capitalization, however, is positively related to cumulative abnormal returns during the event window.

Linear specification results in Table 6 indicate that score coefficients are significantly positive. Cumulative abnormal returns after the information release are an increasing function of climate scores, even after conditioning on industry and other covariates. One day after the event, cumulative abnormal returns were approximately 1 one-hundredth of a percent higher for every additional climate score point. Two days after the event, cumulative abnormal returns were approximately 2 one-hundredths of a percent higher for every additional climate score point. Three days after the event, cumulative abnormal returns were approximately 3 one-hundredths of a percent higher for every additional climate score point. So, all else equal, 10 additional climate score points was associated with 0.3 percent increase in cumulative returns over the three days following the information release.

Categorical specification results in Table 6 are largely consistent with linear regression results and the earlier results in Table 4. Throughout the event window, firms receiving scores below 20 experienced cumulative abnormal returns significantly below those of firms scoring greater than or equal to 50.[14] For one and two days after the event, cumulative abnormal returns for those with low scores were a full percent lower than cumulative abnormal returns for those with higher scores. The gap between low and high scorers grew to approximately 1.4 percent as the event window lengthens to three days. In contrast, differences in cumulative abnormal returns between firms receiving roughly average scores and firms receiving high scores were substantially smaller in magnitude and typically not statistically significant.

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[14] Note that j-1 industry controls preclude interpreting the regression constant as average cumulative abnormal returns for all firms in the omitted category.

TABLE 6. Regressions of Cumulative Abnormal Returns on Climate Scores[a]

	Linear			Linear + Covariates			Categorical			Categorical + Covariates		
	1-day CAR	2-day CAR	3-day CAR	1-day CAR	2-day CAR	3-day CAR	1-day CAR	2-day CAR	3-day CAR	1-day CAR	2-day CAR	3-day CAR
Score	.015** (2.38)	.018** (1.73)	.027** (2.35)	.014** (1.87)	.017* (1.54)	.030** (2.24)	-	-	-	-	-	-
Score < 20	-	-	-	-	-	-	-.864** (-2.30)	-.985** (-1.68)	-1.38** (-2.14)	-1.05** (-1.98)	-1.07 (-1.22)	-1.54* (-1.51)
Score 20 - 49	-	-	-	-	-	-	-.349 (-1.07)	-.405 (-0.87)	-.287 (-0.42)	-.591** (-1.80)	-.651 (-0.82)	-.600 (-0.58)
Market Cap (in billion USD)	-	-	-	.005*** (2.71)	.005** (2.00)	.006*** (2.93)	-	-	-	.005*** (2.60)	.005** (1.93)	.006*** (2.65)
Advertising (in billion USD)	-	-	-	-.088 (-0.97)	-.075 (-0.46)	-.238 (-1.24)	-	-	-	-.134* (-1.47)	-.113 (-0.75)	-.257 (-1.29)
Foreign Sales as % of Sales	-	-	-	-.007 (-1.16)	-.004 (-0.19)	-.009 (-0.51)	-	-	-	-.008* (-1.34)	-.004 (-0.17)	-.006 (-0.28)
Earnings per Share	-	-	-	.033 (0.90)	-.059 (-0.63)	-.099 (-0.82)	-	-	-	0.037 (0.87)	-0.055 (-0.57)	-.086 (-0.66)
Industry Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	.360 (0.86)	.725* (1.58)	-.660 (-0.98)	.137 (0.47)	.635 (1.16)	.308 (-0.50)	1.20** (1.85)	1.71*** (2.73)	.744 (0.90)	1.17** (2.01)	1.72* (1.50)	1.19 (0.91)
Observations	47	47	47	45	45	45	47	47	47	45	45	45
F-statistic	5.28	17.17	8.47	5.01	15.32	11.63	4.77	17.90	5.71	4.35	21.66	13.89
R-squared	0.54	0.34	0.44	0.67	0.38	0.50	0.54	0.33	0.43	0.67	0.38	0.47

[a] Test statistics in parentheses. The category "Score ≥ 50" is omitted from categorical regressions. *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels.

6.3 Further Explanation: Mechanisms

The literature posits several links between environmental and financial performance. Conventional wisdom suggests that a direct consumer demand effect is the most likely mechanism. To investigate this hypothesis, we explore the interaction between cumulative abnormal returns and advertising expenditures, which might proxy for a company's sensitivity to consumer preferences.

Our implementation is necessarily straight-forward. We run regressions of the form in (11), but add an additional variable that captures the interaction between scores and advertising expenditures. An economically large and statistically significant positive coefficient on the interaction would suggest that the release of Climate Counts' scorecard had a larger influence on firms with greater consumer orientation. Table 7 presents our interaction regression results. Test statistics, based on robust standard errors, are presented in parentheses next to the coefficient estimates.

TABLE 7. Regressions with Advertising × Score Interactions

	1-day CAR	2-day CAR	3-day CAR
Score	.020** (2.11)	.026** (1.93)	.041** (2.31)
Advertising expenditures	.000 (0.87)	.000 (1.00)	.000 (0.64)
Score × Advertising	-.007 (-1.21)	-.011(-1.14)	-.129 (-0.97)
Other firm-level characteristics?	Yes	Yes	Yes
Industry Fixed Effects?	Yes	Yes	Yes
Constant	-.184 (-0.42)	.149 (0.18)	-.895 (-1.01)

Results in Table 7 provide little support for a demand-driven effect. Scores remain positive and significant, suggesting that higher (lower) climate scores were still positively (negatively) associated with cumulative abnormal returns during the event period. However, we find no statistically significant interaction effects. We find no evidence that firms with higher advertising expenditures and thus greater consumer orientation were more sensitive to climate information, ceteris paribus.

As noted in the introduction, possible mechanisms linking environmental and financial performance include consumer demand effects, employee pressure, investor preferences, regulatory preemption, input use efficiency gains, and expected future regulatory liabilities. As with other papers in this literature, we are unable to precisely determine the link that drives our results. Mechanisms are a promising area for future empirical research. However, we do explore what limited evidence is available and find no support in favor of the commonly hypothesized direct demand mechanism.

7. Discussion and Conclusion

In this paper, we find that the release of climate ratings had an immediate and statistically significant impact on capital market returns. Results are primarily driven by penalties to firms receiving poor climate performance ratings. These firms experienced expected returns that decreased by between 0.6 and 1.6 percent in response to the information. A back of the envelope calculation suggests that the aggregate impact was economically important. The total market capitalization for the 18 firms poorly rated firms in our sample was approximately $450 billion in 2007.[15] This implies that climate ratings may have reduced affected firms' total market capitalizations by as much as 2.7 to 7.2 billion dollars. While these figures are small relative to the market effects of recent economic contractions, they are large relative to most companies' environmental management budgets.

The fact that capital markets reacted to the release of climate-related ratings has several implications. First, it provides evidence that firm-specific climate liabilities and opportunities were uncertain. If the market and all stakeholders had complete information, it is unlikely that Climate Counts ratings would have influenced returns. Second, our evidence lends weight to the hypothesis that the market values environmental performance. Climate positions may remain critical corporate strategy issues for years to come. We find both implications interesting in light of the fact that Climate Counts is a small-scale nonprofit advocacy group. The organization was well funded, well researched, and quite media savvy. Ultimately, however, Climate Counts essentially consisted of three full-time staffers and a website.

We also find the asymmetric effect of good and bad ratings an intriguing area for future investigation. Our results are consistent with several explanations, but one interpretation is that information about good performers' climate strategies might have been available to the market in advance of the information

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[15] We obtain market capitalization from Value Line Financial. Results are typically similar in magnitude to market values of equity from firms' 2007 annual reports.

event. Good performers may have incentives to publicize environmental behavior; bad performers do not. Another interpretation is that media dissemination and cognitive realities imply that negative environmental information systematically generates larger market impacts than positive environmental information, even when the news is equally novel. Evidence of significant penalties for poor feedback and modest rewards for good feedback exists in other contexts such as online auctions (Standifird 2001, Reiley et al. 2007).

8. References

Arora, S., and S. Gangopadhyay, 1995, "Toward a Theoretical Model of Voluntary Overcompliance." *Journal of Economic Behavior and Organization*, 28, 289-309.

Ball, C. and P. Brown, 1968, "An Empirical Evaluation of Accounting Income Numbers," *Journal of Accounting Research* 6(2), 159-78.

Bernard, V., 1987, "Cross Sectional Dependence and Problems in Inference in Market-Based Accounting Research," *Journal of Accounting Research* 25(1), 1-48.

Brown, S. and J. Warner, 1980, "Measuring Security Price Performance," *Journal of Financial Economics* 8(3), 205-258.

Brown, S. and J. Warner, 1985, "Using Daily Stock Returns: The Case of Event Studies," *Journal of Financial Economics* 14(1), 3-31.

Christie, A., 1987, "On Cross-sectional Analysis in Accounting Research," *Journal of Accounting and Economics* 9(3), 231-258.

Collins, D. and W. Dent, 1984, "A Comparison of Alternative Testing Methodologies Used In Capital Market Research," *Journal of Accounting Research* 22(1), 48-84.

Fama, E., Fisher, L., Jensen, M. and R. Roll, 1969, "The Adjustment of Stock Prices to New Information," *International Economic Review* 10, 1-21.

Hamilton, J.T., 1995, “Pollution as news: Media and stock market reactions to the toxics release inventory data,” *Journal of Environmental Economics and Management,* 28(1), 98-113.

Khanna, M., W. Quimio, and D. Bojilova, 1998, “Toxic Release Information: a policy tool for environmental information.” *Journal of Environmental Economics and Management*, 36, 243-266.

Kim, E. and T. Lyon, 2007, “When Does Institutional Investor Activism Pay? The Carbon Disclosure Project,” Unpublished Working Paper.

Klassen, R. and C. McLaughlin, 1996, “The Impact of Environmental Management of Firm Performance,” *Management Science*, 42, 1119-1214.

Konar, S. and M. Cohen, 1996, “Information as Regulation: The Effect of Community Right to Know Laws on Toxic Emissions.” *Journal of Environmental Economics and Management*, 32, 1996, 109-124.

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

Lyon, T. and J. Maxwell, 2008, “Corporate Social Responsibility and the Environment: A Theoretical Perspective,” *Review of Environmental Economics and Policy* 2(2), 240-260.

MacKinlay, A., 1997, “Event Studies in Economics and Finance,” *Journal of Economic Literature* 35(1), 13-39.

Margolis, J., H. Elfenbein, J. Walsh, 2007, “Does it Pay to Be Good? A Meta-Analysis and Redirection of Research on the Relationship between Corporate Social Performance and Financial Performance,” *Unpublished Working Paper.*

Maxwell, J. and C. Decker, 2006, “Voluntary Environmental Investment and Regulatory Responsiveness,” *Environmental and Resource Economics* 33, 425-439.

Maxwell, J., T. Lyon and S. Hackett, 2000, "Self-Regulation and Social Welfare: The Political Economy of Corporate Environmentalism." *Journal of Law and Economics,* 43, 583-618.

McWilliams, A., D. Siegel, and P. Wright, 2006, “Corporate Social Responsibility: Strategic Implications,” *Journal of Management Studies* 43(1), 1-18.

Porter, M. and C. van der Linde, 1995, “Towards a New Conception of the Environmental Competitiveness Relationship,” *Journal of Economic Perspectives* 9, 97-118.

Portney, P., 2008, “The (Not So) New Corporate Social Responsibility: An Empirical Perspective,” *Review of Environmental Economics and Policy* 2(2), 261-275.

Reiley, D., D. Bryan, N. Prasad, and D. Reeves, 2007, “Pennies from Ebay: The Determinants of Price in Online Auctions,” *Journal of Industrial Economics* 55(2), 223-233.

Reinhardt, F., R. Stavins, R. Vietor, 2008, “Corporate Social Responsibility through an Economic Lens,” *Review of Environmental Economics and Policy* 2(2), 219-239.

Sefcik, S. and R. Thompson, 1986, “An Approach to Statistical Inference in Cross-Sectional Regression with Security Abnormal Returns as a Dependent Variable,” *Journal of Accounting Research* 24(2), 316-334.

Segerson, K. and T. Miceli, 1998, “Voluntary Environmental Agreements: Good or Bad News for Environmental Protection?” *Journal of Environmental Economics and Management*, 36(2), 109-130.

Standifird, S., 2001, "Reputation and e-commerce: eBay auctions and the asymmetrical impact of positive and negative ratings," *Journal of Management* 27(3), 279-295.

Tietenberg, T., 1998, "Disclosure Strategies for Pollution Control." *Environment and Resource Economics*, 11, 587-602.