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Environmental Incidents and Firm Value – International Evidence using a Multi-Factor Event Study Framework

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International Evidence using a Multi-Factor Event Study Framework[1]

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Abstract

Event study methodology is used to analyze whether bad news in the form of environmental (EV) incidents affect firm value negatively. An international sample of firms with EV incidents is studied. It is found that EV incidents are generally associated with loss of value. For European firms the loss is statistically significant and the magnitude of the abnormal returns should be of economic significance to corporations and investors. The results are not sensitive to multiple variations in methodology, including the use of international versions of the market model as well as of multi-factor models of the Fama-French type. Results are also robust to different parametric and non-parametric test statistics.

Keywords: multi-country-multi-factor event study, environmental incidents, abnormal returns.

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Introduction

In this study, we analyze stock price reactions to environmental (EV) incidents for a sample of international firms in the years 2003-2006. An EV incident is a company incident allegedly in violation of international norms on environmental issues. The EV incident data come from GES Investment Services (GES), and have only been used once before in academic research, in Lundgren and Olsson (2009).

In efficient capital markets, stock prices on any day fully reflect all available information about the present value of a firm's future cash flows (Fama, 1991). The empirical analysis in this paper is built on this notion. New information may cause abnormal changes in stock prices if the information deviates from expectations. We use event study methodology (see e.g. MacKinlay, 1997) to assess the effect on firm value of EV incidents. An appealing quality of event studies is that the direction of causation is quite clear. It is the release of information or the occurrence of an incident that causes stock value to change, and not vice versa. That is; good (bad) EV performance potentially induces good (bad) financial performance. This may seem obvious, but assumes significance given the fact that some studies establish a link between EV performance and financial performance, although the direction of causation is unclear (see Hay et al., 2005).

In an overview of studies on EV performance and firm performance, Hay et al. (2005)[2] however concludes that empirical evidence concerning the relation between EV and financial performance is ambiguous (for other reviews, see e.g. Orlitzky and Benjamin, 2001; Orlitzky et al., 2003; and Orlitzky and Swanson, 2008).

There are event studies that specifically consider EV news and effects on stock price (e.g. Diltz, 2002, Klassen and McLaughlin, 1996, Dasgupta et al., 2001, Gupta and Goldar, 2005, Lundgren and Olsson, 2009). These studies investigate good news (EV investments, awards, good green ratings) and/or bad news (pollution, bad green ratings, incidents) related to EV performance. Another frequent indicator of bad or good EV performance in this line of research is news about toxic releases (e.g.

[2] In the ch. by P. Portney.

Hamilton, 1995, Khanna et al., 1998 and 1999, Konar and Cohen, 2001, Khanna, 2001). As discussed in Khanna et al. (1999), these types of studies are important for the design of voluntary approaches in EV policy to stimulate corporate social responsibility. If stock markets are likely to react significantly to the release of EV information about firms, then regulators can take this into consideration when designing EV policy, as a supplement to conventional command and control policy or other economic incentives such as taxes or subsidies. Furthermore, studies of corporate EV news connected to regulation - e.g. non-compliance, lawsuits - draw similar conclusions (Lanoie and Laplante, 1994, Lanoie et al., 1998, Dasgupta et al., 2006).

Several of the above studies find a positive relation between environmental events and stock price reactions. A positive relation means that good (bad) news is associated with increased (decreased) stock price. This agrees broadly with Margolis and Walsh (2001) who review 13 EV event studies, of which 6 studies document a positive relation, 3 a negative relation, 1 both a positive and a negative relation, and 3 no relation.

The main purpose of the study is to shed light on whether the revelation of EV incidents has any effect upon firm value. This is motivated by the mixed results of previous studies on the relation between EV incidents and stock price responses.

Moreover, we extend prior research by providing evidence on EV incidents from multiple countries on different continents. Furthermore, we examine a greater number of events than many of the prior studies; Diltz (2002), Gupta and Goldar (2005), Klassen and McLaughlin (1996), each study less than 60 events, whereas we investigate 142 incidents (events). We also assess the robustness of our results to variations in methodology, because recent studies by Campbell et al. (2009) and Park (2004) indicate that multi-country event studies, such as the present one, could be sensitive to research design choices. Among other things, we use international versions of the market model as well as of multi-factor models of the Fama-French type; such multi-factor models appear not to have been used before in EV multi-country event studies. One non-parametric and three parametric test statistics of abnormal returns are employed.

The outcome of the study is of potential interest to many stakeholders. Corporations may take proactive measures to avoid EV incidents in case they are likely to be value-destructive. Investors are interested in how stock prices respond to the release of news on EV incidents and whether it is possible to trade profitably on this information. Lack of incentives (in the form of absence of stock market reactions to EV incidents) for voluntary actions of companies may encourage swift and stringent response among regulators.

The rest of the paper is organized as follows. Next, we present the conceptual framework, which discusses the mechanisms behind why bad news could lower firm value. Sections on methodological considerations, data, empirical framework and results follow. Lastly, conclusions and discussion are presented.

Conceptual framework

Several conceptual frameworks have been suggested to link environmental performance to firm value and most of them adopt some kind of expectations setting. One of the more ambitious theoretical treatments is Laplante and Lanoie (1994), which provide a relatively detailed model including expectations and behavioral assumptions for markets, regulators, and firms. The conceptual framework laid out here draws a lot on Khanna et al. (1998). They cover both how the investors react to the revelation of environmental performance, and how the firm consequently reacts to the investor’s behavior, in terms of e.g. choice of pollution level. Here we only tell the story from the investor’s side, i.e., how the market may respond to environmental incidents.

The connection between environmental performance and profitability may be justified in several ways. For example, Lundgren (2003), Kriström and Lundgren (2003) and Lundgren (2010) discuss in micro-economic, firm-level models of how "bad" social performance may have negative profitability effects due to loss of goodwill or reputational value. Other possible reasons are connected to management practices. Investors may view pollution as a waste of inputs that are not used productively or as an indicator of bad management and lack of innovativeness. Furthermore, there is research indicating that local communities and NGOs may exercise considerable leverage to pressure firms to improve their environmental performance (see e.g. Afsah et al., 1996, Blackman and Bannister, 1998, and Pargal and Wheeler, 1996). Thus, accounting only for fines and penalties and not considering the pressure that communities and markets may impose, the expected costs connected with sub-standard environmental performance may be underestimated (Dasgupta et al., 2006). On the other hand, the announcement of good environmental performance may have the opposite effect: more lax treatment by regulators, communities and the financial sector, and greater access to global markets and price premiums among the potential benefits (see e.g. Lundgren, 2010, Lanoie et al., 1998, or Konar and Cohen, 1996, for additional discussion on potential effects).

In lack of mechanisms that continuously provide information about a firm's likelihood of incidents, and thus environmental performance, the investors do not have full information to accurately predict an incident and thus environmental performance. Denote actual current environmental performance EP_{it}^{A}, where i and t are firm and time sub-indexes. Investors will formulate expectations, EP_{it}^{E}, about a firm's environmental performance based on prior information, e.g. historical incidents and pollution levels, at previous time period, EP_{it-1}^{A}. Furthermore, it is assumed that investors compare or rank firms with respect to environmental performance and likelihood of incidents, and therefore assign an expected rank R_{it}^{E} to each firm at time t. A low ranking implies relatively "bad" environmental performance. The actual EP is revealed to investors at time *t*, i.e., an incident occurs or not. The relation between actual and expected environmental performance is

$$EP_{it}^{A} = EP_{it}^{E} + u_{it} \tag{1}$$

where u_{it} is a prediction error. This implies that actual environmental performance could be larger, smaller or equal to the expected environmental performance. In the same way, the actual rank of a firm may be higher or lower than the expected rank,

$$R_{it}^{A} = R_{it}^{E} + e_{it} \tag{2}$$

Define the actual market value of a firm at time *t*, V_{it}^{A}, as a function of a vector of indicators of financial health, $\mathbf{H}_{it}$, a variable representing environmental performance, EP_{it}^{A}, and its relative rank R_{it}^{A},

$$V_{it}^{A} = V^{A}\left(\mathbf{H}_{it}, EP_{it}^{A}, R_{it}^{A}\right) \tag{3}$$

Investors are assumed to have full information about financial health, but incomplete information on environmental performance and rank. The ascribed or expected market value of a firm can then be written,

$$V_{it}^{E} = V^{E}\left(\mathbf{H}_{it}, EP_{it}^{E}, R_{it}^{E}\right). \tag{4}$$

When the true environmental performance is revealed to the investors, e.g. here in case of an incident, it is likely that actual market value, V_{it}^{A}, diverge from the expected value, V_{it}^{E}. The change in the market value in each time period is then given by the difference between actual outcome and expected outcome,

$$V^{A}\left(\mathbf{H}_{it}, EP_{it}^{A}, R_{it}^{A}\right) - V^{E}\left(\mathbf{H}_{it}, EP_{it}^{E}, R_{it}^{E}\right) = \Delta V(\mathbf{H}_{it}, EP_{it}^{A}, EP_{it}^{E}, R_{it}^{A}, R_{it}^{E}). \tag{5}$$

This implies that if an environmental incident is “out of expectation”, the market reacts and thus lower the value of the firm.

Methodological considerations

When it comes to method, most event studies are performed by first estimating a model to assess normal returns, and then using these estimates to investigate whether there are abnormal returns in an event window. In conducting an event study, there are several research design choices to be made, including what model to use for (ab)normal returns and what event-study test statistics to use to determine whether the abnormal returns are significant or not. That these choices can affect results and thus are important, in particular for multi-country event studies are pointed out by, e.g., McWilliams et al. (1999), Park (2004) and Campbell et al. (2009).

Compared to Lundgren and Olsson (2009), who analyze the same EV incidents, the present study incorporates many recent and important advances in theory, data, models, tests statistics and overall methodology. This study includes new comprehensive index and factor data, non-parametric test statistics, additional and more elaborate normal return models including ortogonalized exchange rate factors and Fama-French factors, extensive estimation period results, and a battery of robustness tests encompassing, among other things, a greater variety of event windows.

As to the model for normal returns in multi-country event studies, Park (2004) recommends using a multi-factor model with a world stock market index, a local stock market index and foreign currency exchange factors. Already Fama and French (1993) suggest augmenting the simple market model with the so-called Fama-French size (SMB) and book-to-market (HML) factors. This seems natural, given the fact that many studies have demonstrated the ability of these two factors to explain variations in stock returns in conjunction with the market factor (see, e.g., Davis et al., 2000). For event studies, Campbell et al. (2009), however, find in simulations and empirical tests that models of normal returns using a local market index as a single factor work well, that is, are able to detect abnormal performance when such is present and yield reasonable results overall. Moreover, none of the 18 recent multi-country event studies reviewed by Campbell et al. (2009) use multi-factor models for normal returns. [3]

In view of the foregoing, we examine in a multi-country setting the performance of a number of single and multi-factor models in estimation and event periods to find out whether results are sensitive to the choice of normal return model, and whether the simpler market model is sufficient as the results of Campbell et al. (2009) indicate. To our knowledge, no EV multi-country event studies use the Fama-French factors. A probable reason is lack of readily available data on the book-to-market and size factors for markets outside the US. Creating these factors from scratch is often impractical, since it "involves difficulties surrounding the nature and construction of the size (SMB) and book-to-market (HML) factors..." and "...particularly so in smaller markets where extensive and reliable data over sufficiently long time-series are prohibitively expensive to compile or often simply do not exist. " (Faff, 2001, p. 2) Instead, we use a recently released family of indexes, the MSCI Global Investable Market Indices, which permit us to create proxies of the Fama-French SMB and HML factors for countries other than the US. We do not attempt to use industry factors. This is based on Thompson (1988) who empirically compares industry, market-industry and market models, and find that they produce very similar event study results.

[3] An exception to the use of single factor models is Tawil (1999), who applies a non-standard multi-factor model to US data to investigate the effects of solid waste management. Also, see Dam and Scholtens (2007) for a multi-factor event study regarding CSR in banking.

As suggested by Park (2004), we also include in the normal return model foreign currency exchange rate factors. Prior research, however, suggests that such factors are expected to have limited marginal explanatory power in a multi-factor model which include a broad market index (see, e.g., Verschoor and Muller, 2006). Several alternative currency factors are possible to use, including the exchange rate of the currency of the single most important trading country, multiple exchange rates of a set of the most important trading partners, or single aggregate measures reflecting the average currency exchange rates of a set of the largest trading countries. Following Park (2004) and others, we choose to use the last kind of exchange rate measure.

The world index is generally highly correlated with the country indices. When the world index and a country index are used as regressors in the same equation, there is a potential multicollinearity problem. To mitigate the problem, we choose to orthogonalize the country index following Asgarian and Hansson (2002).

Campbell et al. (2009) conclude that the choice of "event-study test statistic is crucial for correct inference in multiple-country samples", in particular in studies with multi-day event windows, which are used here. The reason is that the statistical properties of multi-day multiple-country stock returns are such that common parametric event-study test statistics, which rely on the normal distribution, and work well on fairly normally distributed US data, tend to be miss-specified and of low statistical power. In response, we examine several widely used test statistics, both parametric and non-parametric, including the generalized sign (GS) test which is the best performing statistic in the multi-country setting analyzed by Campbell et al. (2009). Compared to the sample in Campbell et al. (2009), the sample used in this study contains larger firms and includes US firms. We therefore expect stock return distributions to be closer to the normal distribution than in Campbell et al. (2009). Consequently, the different test statistics are anticipated to perform more similar here than in Campbell et al. (2009).

Other research design considerations include the return form, the length of the estimation period, and the treatment confounding events. Rate of returns may be calculated as simple returns or continuously compounded returns (see, e.g., Thompson, 1988). Brown and Warner (1985) and Thompson (1988) find that either type of return leads to similar results in event studies. We use simple returns.

Increasing the length of the estimation period increases the number of observations to base the estimations on, but a longer estimation period probably also increases the likelihood of structural changes in model parameters. In addition, longer estimation periods increase data requirements in general and can result in fewer observations. Corrado and Zivney (1988) compare an estimation period of 239 days to one as short as 89 days and find that the test statistics are "virtually unaffected". We employ an estimation period of 88 trading days (around 4 months), since a longer estimation period would result in loss of valuable observations.

Another concern is confounding or extraneous events in the event period, that is, other potentially price changing events than the event under examination. One would however expect the net impact on stock price from diverse events to be zero in repeated measurements. Thompson (1988) investigates the impact of extraneous events and concludes that they have little impact on event study results. Based on the preceding, we do not make any adjustments for extraneous events. In addition to presenting results for the full sample, researchers sometimes present results for a reduced sample excluding the extraneous events they have been able to identify. Armitage (1995) points out that adjustment of this kind may be partial, because it is difficult to identify all the many extraneous events there are.

Data

The empirical analysis use EV incident data and stock and market index returns. These data are described in turn below.

Incidents

The incident data were supplied by GES, which describes the data as follows:

"*Since 2003, GES Alert Service provides clients with weekly news briefings on recently reported company incidents allegedly in violation of international norms on Environmental ... issues. The news are forwarded to the client within a week after obtained through GES' screening. By this systemized process, GES Alert Service singles out news of special investor concern which often take long before being* *highlighted in mainstream media or disappear in the torrent of news.* [...] *The GES Alert Service covers major world indexes*."[4]

The GES data contain firm identification codes and incident reporting dates, that is, the dates the incidents were reported to the clients of GES. The actual incident date may differ from the reporting date. This means that for a given reporting date, there is some uncertainty about when the incident actually occurred. We deal with this by using windows of different lengths around the event. The incidents we analyze are from 2003-2006.

Table 1 shows the distribution of incidents and firms across sectors. The frequency of EV incidents per sector is highest for the sectors Oil & Gas, Basic Materials, and Industrials, known to be environmentally challenging.

Table 1. Distribution of incidents and firms across sectors

Sector	**Incidents**	**Firms**	**Frequency**
Oil & Gas	21	7	3
Basic Materials	64	28	2.3
Industrials	22	11	2
Consumer Goods	17	12	1.4
Consumer Services	5	4	1.2
Utilities	5	4	1.2
Healthcare	3	3	1
Financials	2	2	1
Technology	2	2	1
Telecommunications	1	1	1
Totals	142	74	

Table 2 shows the number of firms with a particular number of incidents. 42 firms have just 1 incident. 15 firms have 2 incidents. One firm has a many as 11 incidents.

[4]www.ges-invest.com, Oct. 3, 2007.

Table 2. Distribution of incidents across firms

Incident/firm	Firms
1	42
2	15
3	10
4	4
6	1
7	1
11	1
Totals	74

According to Table 3, the majority of incidents in our sample happens to US firms. According to relative frequency, the UK has most incidents per firm.

Table 3. Distribution of incidents across countries

Country	Incidents	Firms	Frequency
Australia	5	3	1.7
Germany	7	5	1.4
Canada	12	7	1.7
Danmark	2	2	1.0
Finland	4	2	2.0
Japan	2	2	1.0
Netherlands	1	1	1.0
Switzerland	6	5	1.2
UK	16	5	3.2
US	87	42	2.1
Totals	142	74	

Financial data

Data for calculating individual daily simple stock returns, adjusted for corporate actions and dividends net of tax, were retrieved from Thomson Datastream for 1260 firms monitored by GES in 2003-2006, as were sector classifications according to Industry Classification Benchmark (ICB) and country classifications according to Thomson Datastream. The 1260 firms are, with few exceptions, the largest stocks in terms of market value in the MSCI World Index during 2003-2006.

The stock market indexes used in this study are part of the relatively new MSCI All Country World Investable Market Index (ACWI IMI) which include stocks in 23 developed and 22 emerging countries (but not so-called frontier markets), and cover some 99% of the total “investable” equity market value in each country. The ACWI IMI is segmented, without gaps or overlaps, by region/country, size (large, mid and small cap), and value/growth styles.[5] This exacting segmentation is what allows the construction of reasonable proxies of the SMB and HML factors (Fama and French, 1993).

Specifically, the indices used in the study are the ACWI IMI Core (ACWI) and country IMI Core indices for the ten countries listed in Table 3. For the ACWI core and each of the ten countries, the corresponding Large Growth (lg), Small Growth (sg), Large Value (lv), and Small Value (sv) indices are retrieved. All this data were sourced from Thomson Datastream.

In a similar manner as Faff (2001), we calculate the SMB and HML factors at time *t* as

$$SMB_t = \frac{sg_t + sv_t}{2} - \frac{lg_t + lv_t}{2} \text{ , and} \tag{6}$$

$$HML_t = \frac{lv_t + sv_t}{2} - \frac{\lg_t + sg_t}{2} \text{ ,} \tag{7}$$

where

$sg_t =$ small cap growth index return at time t
$sv_t =$ small cap value index return at t
$lg_t =$ large cap growth index return at t
$lv_t =$ large cap value index return at t.

Foreign currency exchange rate

Park (2004) suggests including in the model of normal return a factor related to the movements in foreign currency exchange rate a stock is exposed to. As a proxy for this factor, we use daily returns of JP Morgan’s broad nominal trade-weighted exchange rate indices. This kind of index is a weighted average of a basket of foreign

[5] For a description of these indices including their construction see MSCI Global Investable Market Indices Methodology (August 2009) http://www.mscibarra.com/eqb/methodology/meth_docs/MSCI_Aug09_GIMIMethod.pdf

currencies, where the weights reflect the foreign currencies share in the export and import of the domestic country.[6] For three countries (Finland, Germany and Netherlands) with Euro, the weights are based on the international trade of the whole Euro-zone, and are thus probably less representative for each one of these countries. The exchange rate indices were downloaded from Thomson Datastream.

Empirical framework

The effects of the incidents on firm value are analyzed as follows.[7] (*i*) During an estimation period prior to an incident, we estimate normal return with a *K*-factor model. (*ii*) In an event window, separated from and subsequent to the estimation period, we estimate abnormal returns surrounding an incident. (*iii*) The abnormal returns are calculated for each period in the event window, i.e., the actual return minus normal return. (*iv*) Cumulative abnormal returns for each event and event window are calculated, and these are then averaged across events. (*v*) Test if cumulative abnormal returns are significantly different from zero.

Normal returns are estimated in the estimation period prior to each incident according to:

$$r_{i\tau} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{k\tau} + e_{i\tau}, \tag{8}$$

where

$i = 1...N$ incidents

$F_{k\tau} =$ the return on the *k*th factor in period τ

$K =$ number of factors,

$\tau = 1...T,$ days in estimation period.

OLS regressions are performed using realizations of $r_{i\tau}$ and $F_{k\tau}$ to obtain estimates of α_i and the factor sensitivities β_{ik}. The residual $e_{i\tau}$ is assumed to have white noise properties. The estimate of the variance of the observed residuals is given by,

[6] According to JP Morgan, “a substantially similar methodology” is used by the Federal Reserve Board (FRB). Indeed, the correlation between the daily return of FRB’s “Trade Weighted Exchange Index: Broad” and the return of the US currency index used here is 0.99 for 1 Jan 2003 to 29 Dec. 2006).

[7] For details see, e.g., MacKinlay (1997).

$$\sigma_i^2 = \frac{1}{T}\sum_{\tau=1}^{T} e_{i\tau}^2 . \tag{9}$$

As mentioned, when the world index $r_{W\tau}$ and a country index $r_{C\tau}$ are regressors in the same regression, we orthogonalize the country index by first regressing it on the world index:

$$r_{C\tau} = a_C + b_C r_{W\tau} + e_{Ct} .$$

Then we compute the ortogonalized country index $r_{C\tau}^o$ as

$$r_{C\tau}^o = a_C + e_{C\tau} ,$$

where $r_{W\tau}$ and $r_{C\tau}^o$ are uncorrelated.

The estimated market model is used to predict returns in the event window. The prediction errors are the abnormal returns. Abnormal returns are defined as the difference between actual and predicted (normal) returns,

$$\begin{aligned} ar_{it} &= r_{it} - NormalReturn_{it} \\ &= r_{it} - \left(\alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} \right) \end{aligned} \tag{10}$$

where $t = t_b ... t_0 ... t_e$. t_0 denotes the event day, t_b and t_e is beginning and ending day, respectively, and L is the length of the event window. If the OLS assumptions hold also in the event window, then the expected abnormal return is zero, and there is no serial correlation or covariance with factor returns. That is,

$$\begin{aligned} &E\left[ar_{it}\right] = 0, \\ &\operatorname{cov}\left[ar_{it}, ar_{is}\right] = \left\{ \begin{matrix} 0 \text{ for } t \neq s \\ c_{it}\sigma_i^2 \text{ for } t = s \end{matrix} \right\}, \\ &\operatorname{cov}\left[ar_{it}, F_{kt}\right] = 0, \\ &s, t = t_b ... t_0 ... t_e, \text{ and} \\ &i = 1...N, \; k = 1...K \end{aligned} \tag{11}$$

Further, we also make the following assumption,

$$\operatorname{cov}\left[ar_{it}, ar_{jt}\right] = \left\{ \begin{matrix} 0 \text{ for } i \neq j \\ c_{it}\sigma_i^2 \text{ for } i = j \end{matrix} \right\}. \tag{12}$$

This implies no cross-sectional dependence of abnormal returns in event window.[8] The parameter c_{it} corrects event window variance to account for possible increase in variation outside the estimation period (see Patell, 1976). The multi-factor, Patell-type of variance correction $\mathbf{c}_{iL}$ is computed as,

$$\begin{aligned}
\mathbf{c}_{iL} &= \left[c_{it_b} \ldots c_{it_e} \right] = L \times 1 \text{ vector} = diag\left[\mathbf{X}_L \left(\mathbf{X}^{'}\mathbf{X} \right)^{-1} \mathbf{X}_L^{'} + 1 \right], \\
\mathbf{X}_L &= L \times K \text{ matrix giving event window observations on} \\
& \quad K-1 \text{ factors (with a first column of 1's),} \\
\mathbf{X} &= T \times K \text{ matrix giving estimation period observations on} \\
& \quad K-1 \text{ factors (with a first column of 1's).}
\end{aligned} \tag{13}$$

With only one factor, $\mathbf{c}_{iL}$ collapses to the variance correction term C_{it} in equation (6a) in Patell (1976).

Using sigma from the estimation period, equation (9), abnormal returns, and the Patell variance correction, we can define the standardized abnormal return as,

$$sar_{it} = \frac{ar_{it}}{\sqrt{c_{it}\sigma_i^2}}, \tag{14}$$

which is approximately unit normal. Define the normalized sum (over L) of cumulative standardized abnormal returns of event i as,

$$scar_{iL} = \sum_{t=1}^{L} \frac{ar_{it}}{\sqrt{Lc_{it}\sigma_i^2}} = \frac{1}{\sqrt{L}} \sum_{t=1}^{L} sar_{it}. \tag{15}$$

The main reason for using standardized abnormal returns is that it prevents securities with large variances from dominating the test.[9] The multiplication of the denominator by $\sqrt{L}$ scales the daily standard deviation to an L-day standard deviation corresponding to the event window length. Finally, form the normalized sum (over N) to obtain the following test statistic,

$$P = scar_{NL} = \frac{\sum_{i=1}^{N} scar_{iL}}{\sqrt{N}}. \tag{16}$$

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[8]This assumption may seem superfluous since the market model implicitly assumes that all cross-sectional dependence is captured by the market. We include this assumption explicitly only because we relax it later.

[9]Standardizing means each observation is weighted in inverse proportion to the standard deviation. Brown and Warner (1980, 1985) conclude that in principle standardized abnormal returns is superior to unstandardized, but in very short-horizon event studies, it makes little difference what measure is used.

P is a t-statistic, used in, e.g., Patell (1976), which can be used to test whether incidents have any significant effect on returns during the specified event window.

A risk when forming $\sum_{i=1}^{N} scar_{iL}$ is that possible event induced variance is ignored. Boehmer et al. (1991) suggest an augmented test statistic which they call the standardized cross-sectional method.[10] This test statistic is found by dividing the P-test statistic by a cross-sectional standard error,

$$\Omega_N = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(scar_{iL} - \sum_{i=1}^{N}\frac{scar_{iL}}{N}\right)^2}\ . \tag{17}$$

The appropriate t-distributed test statistic is then,

$$BMP = \frac{P}{\Omega_N} \tag{18}$$

When $\Omega_N = 1$, then $P = BMP$.

A third, simpler test statistic can be derived from unstandardized abnormal returns. Cumulative abnormal returns in an event window is,

$$car_{iL} = \sum_{t=1}^{L} ar_{it} \tag{19}$$

so that average cumulative abnormal returns over all events can be written,

$$acar_{NL} = \frac{\sum_{i=1}^{N} car_i}{N}\ . \tag{20}$$

A (simple) t-test statistic of abnormal returns is then specified as,

$$T_0 = \frac{acar_{NL}}{\sqrt{\frac{1}{N^2}\sum_{i=1}^{N} L\sigma_i^2}} = \frac{acar_{NL}}{\frac{\sqrt{L}}{N}\sqrt{\sigma_i^2}} = \frac{acar_{NL}}{\sqrt{L}\ \bar{\sigma}_i}\ . \tag{21}$$

Note that this test will not be sensitive to changes in variance due to out-of-estimation-period forecasting or event induced variance.

Finally, the non-parametric GS test (Cowan, 1992; Campbell et al., 2009) is applied. The null hypothesis of the GS test is that the fraction of CARs having a particular sign

[10] In an extensive review of the event study literature, Khotari and Warner (2006) concludes that specification bias arising due to cross-correlation in returns can be a serious problem, especially for long-horizon tests of price performance.

is equal to the fraction of estimation-period abnormal returns with that sign. We test the null of a non-negative sign. The one-sided alternative hypothesis is that the number of stocks with *negative* CAR in the event window exceeds the number expected in the absence of abnormal performance. The number expected is based on $\hat{p}$, the fraction of negative abnormal returns in the estimation period

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{\tau=1}^{T} S_{i\tau} \ , \qquad (22)$$

$$\text{where } S_{i\tau} = \begin{cases} 1 & \text{if } e_{it} < 0 \\ 0 & \text{otherwise} \end{cases} .$$

The GS-test statistic is

$$GS = \frac{w - N\hat{p}}{\sqrt{N\hat{p}(1-\hat{p})}} \ , \qquad (23)$$

where w is the number of stocks for which the measure of abnormal return (CAR or BHAR, see below) in the event period is negative.

The four statistics T_0, P, BMP and GS are used to test whether abnormal returns associated with environmental incidents are negative.

The tests are carried out for alternative windows, symmetric and asymmetric, surrounding the event day. The motivation for this is to account for uncertainty about the actual incident date. Using longer event windows increases to likelihood of including the event when its date is uncertain, but it also increases the risk that other events confound, thereby potentially decreasing the statistical power of the event study method (Brown and Warner, 1980; MacKinlay, 1997). Moreover, the number of incidents possible to analyze decreases with longer event windows, because there is an increased tendency for desired estimation and event windows to extend outside the date range of available data. In selecting the event window-lengths to analyze, we attempt to balance these considerations.

We also conduct some sensitivity analyses based on factor model buy-and-hold abnormal return (BHAR), which over the period t_b to t_e is defined as

$$BHAR_i(t_b, t_e) = \prod_{t=t_b}^{t_e}(1 + r_{it}) - 1 - \left[\prod_{t=t_b}^{t_e}(1 + NormalReturn_{it}) - 1\right]. \qquad (24)$$

Results

We estimate the following 10 variations of the normal return model, equation (8) (we do not write out subscripts on country and currency factors linking these to a given firm):

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + e_{i\tau}, \qquad \text{Model 1}$$

$$r_{i\tau} = \alpha_i + b_{Ci} r_{C\tau} + e_{i\tau}, \qquad \text{Model 2}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + e_{i\tau}, \qquad \text{Model 3}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b_{Xi} r_{X\tau} + e_{i\tau}, \qquad \text{Model 4}$$

$$r_{i\tau} = \alpha_i + b^o_{Ci} r^o_{C\tau} + b_{Xi} r_{X\tau} + e_{i\tau}, \qquad \text{Model 5}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + b_{Xi} r_{X\tau} + e_{i\tau}, \qquad \text{Model 6}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + s_{Wi} SMB_{W\tau} + h_{Wi} HML_{W\tau} + b_{Xi} r_{X\tau} + e_{i\tau}, \qquad \text{Model 7}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + s_{Wi} SMB_{W\tau} + h_{Wi} HML_{W\tau} + e_{i\tau}, \qquad \text{Model 8}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + s_{Ci} SMB_{C\tau} + h_{Ci} HML_{C\tau} + b_{Xi} r_{X\tau} + e_{i\tau}, \qquad \text{Model 9}$$

$$r_{i\tau} = \alpha_i + b_{Wi} r_{W\tau} + b^o_{Ci} r^o_{C\tau} + s_{Ci} SMB_{C\tau} + h_{Ci} HML_{C\tau} + e_{i\tau}, \qquad \text{Model 10}$$

where

$r_{W\tau}$ = world market index return

$r_{C\tau}$ = country specific market index return of the country of a given stock

$r^o_{C\tau}$ = country specific market index return orthogonal to the world market index return

$SMB_{W\tau}$ = world SMB return,

$HML_{W\tau}$ = world HML return

$SMB_{C\tau}$ = country SMB return for the country of a given stock,

$HML_{C\tau}$ = country HML return for the country of a given stock,

$r_{X\tau}$ = currency index return for the country of a given stock

For every incident, all Models 1 to 10 are estimated in the estimation period, beginning 88 trading days before the start of each event window, for all 1260 stocks in the sample, subject to data availability. With totally 142 incidents, this results in a considerable number of regressions being run; for example, for Model 1, the number is 174614. The shorthand notation (-*Pre*, *Post*) denotes an event window having *Pre* pre-event days and *Post* post-event days.Estimation period results are displayed only for the estimation periods corresponding to the (-20, 20) event windows (estimation period results corresponding to other event windows are virtually identical).

We present results from the estimation period, because we think it is important to provide evidence on the goodness of fit of the different normal models with daily returns and whether simpler models perform differently than more elaborate ones. In addition, to our knowledge there appear to be no recent results on the issue. Jain (1986), for instance, presents somewhat detailed estimation period results for the market model, but later studies seem to omit results from the estimation periods. It seems interesting to include the specifications with the Fama-French factors as these factors originate from a later date. Moreover, implementing the world index single factor model (Model 1) requires considerably less data than Model 9, the most complex one. In the latter case, with 10 countries and 7 currencies, 57 indices[11] are needed compared to one world index series. Of course, compared to the total amount of data used in a study such as this one, the additional number of data series this generates may appear immaterial. But if certain data are expensive or difficult to obtain, e.g., the Fama-French factors, it seems desirable to be able to exclude such data based on empirical evidence.

[11] That is, 10 country indices, 40 country style indices (10 sv, 10 lv, 10 sg, 10 lg used to create 10 SMB and HML country factors) and 7 currency factors.

Table 4. Estimation period results.

Model		α	b_W	b_C	b_C^o	b_X	s_W	h_W	s_C	h_C	$Adj.R^2$	no. obs
1	mean	0.000	1.021								0.17	174614**
	prop sign*	0.030	0.876									
2	mean	0.000		1.021							0.31	149899
	prop sign	0.032		0.965								
3	mean	0.000	1.028		0.982						0.32	149899
	prop sign	0.031	0.894		0.814							
4	mean	0.000	1.067			0.808					0.22	149899
	prop sign	0.031	0.846			0.452						
5	mean	0.000		1.019		-0.019					0.32	149899
	prop sign	0.032		0.958		0.135						
6	mean	0.000	1.026		0.980	0.013					0.33	149899
	prop sign	0.031	0.854		0.746	0.126						
7	mean	0.000	1.012		0.982	0.021	0.217	0.006			0.37	149899
	prop sign	0.028	0.826		0.740	0.116	0.142	0.178				
8	mean	0.000	1.013		0.987		0.217	0.007			0.35	149899
	prop sign	0.028	0.872		0.815		0.145	0.182				
9	mean	0.000	0.995		0.990	-0.018			0.181	-0.003	0.38	149899
	prop sign	0.029	0.818		0.740	0.109			0.247	0.294		
10	mean	0.000	0.997		0.982				0.181	-0.002	0.37	149899
	prop sign	0.028	0.862		0.804				0.249	0.305		

* t-test of coefficients: Proportion of coefficients significant at 5% (|t|>1.96) level or better.

** There are more observations for Model 1, because the world index is available for all countries, whereas the ACW local market indices and factors are only available for 10 countries.

In the following, we focus the discussion on regression model performance in terms of explanatory power and the proportion of significant coefficients.

Comparing Adj.R^2 (coefficient of determination adjusted for degrees of freedom) of Model 1 and 2 reveals that country indices on average explain 14% more of the variation in stock returns than do the world index. Explanatory power is increased substantially by using country indices instead of the world index. The country index (world index) betas are significant at the 5% level in 96% (88%) of the regressions.

Using both the world index and an ortogonalized country index, as in Model 3, only increases average Adj.R^2 by 1% compared to Model 2.

Including the return on a foreign currency exchange index lead to marginal increases in explanatory power, except for Model 4 where Adj.R^2 goes up by 5% compared to Model 1. In Model 4, the fraction of significant coefficients on the currency factor is 45%; otherwise, it is below 0.135.

In Model 10, which is Model 3 with country SMB and HML factors added, mean Adj.R^2 is 5% greater than in Model 3. The fractions of significant coefficients on country SMB and HML factors are 0.249 and 0.305, respectively. Adding world SMB and HML factors to Model 3, results in Model 8; the increment in average Adj.R^2 is 3%, and the fractions of significant HML and SML coefficients are lower than for Model 10.

Summing up, we can extract the following main results. For Model 2, which uses only single country indices, average Adj.R^2 is 31% and 96.5% of the slopes are statistically significant. In Model 9, the one with the highest average explanatory power, four additional factors are included relative to Model 2, and this effort increases average Adj.R^2 by 7% to 38%. Augmenting the local market model (Model 2) with exchange rate factors or a world index or the SMB and HML factors hence only lead to marginal or moderate increases in explanatory ability.

Event period

We test for abnormal returns of EV incidents for all firms regardless of geographical location, and separately for US, non-US and European firms. We use all 10 different normal return models. We explore event windows of different length, by varying the numbers of pre-event and post-event daysSpecifically, we use *Pre*=0, 5, 10, 20, 30, 40, 50, *Post*=0, 5, 10, 20, 30, 40, 50. The shortest resulting event window is 1 day (0+1+0), and the longest 101 days (50+1+50). In total, we examine 1960 (4*10*49) combinations of firm nationality, normal return models, and event windows.

Although average CARs are negative (barring a handful exceptions) across these 1960 combinations, it is only for European firms with EV incidents that we find abnormal returns that are statistically significant. We therefore report results only for the European sample. Moreover, to conserve space, we confine the presentation of results to Model 2, which is parsimonious and performs quite well in the estimation window, and to Model 9, the most elaborate model with the highest explanatory power in Table 4. (Results for the other normal return models are similar.) In addition, examining Model 2 is interesting, since Campbell et al. (2009) find Model 2 to be "sufficient" in multi-country event studies.

Table 5 presents the event study results according to Model 2 and 9. Panels 2A and 9A display average CAR, *acar*, for different event windows surrounding the event date, the EV incident publication date. These panels suggest that there is a statistically and economically significant negative stock price reaction to EV incident reports. According to both Model 2 and 9, *acar* is significantly negative at the 5% level or better for the (-40, 40), (-30, 30), (-30, 20) and (-20, 20) windows according to 14 test statistics out of 16. Moreover, the (-30, 20) window in both Panel 2A and 9A displays the most negative *acar* per day indicating that the negative effect mainly takes place within this window; Figure 1 illustrates by showing *acar* for Model 9 in the (-50, 50) window and the (-30, 20) window. The statistically significant *acar*s in Panels 2A and 9A appear to be of economic significance as well. For example, the negative *acar* per day of –0.073% in the (-30, 20) window of Model 9 corresponds to -18% per year assuming 250 trading days in a year.

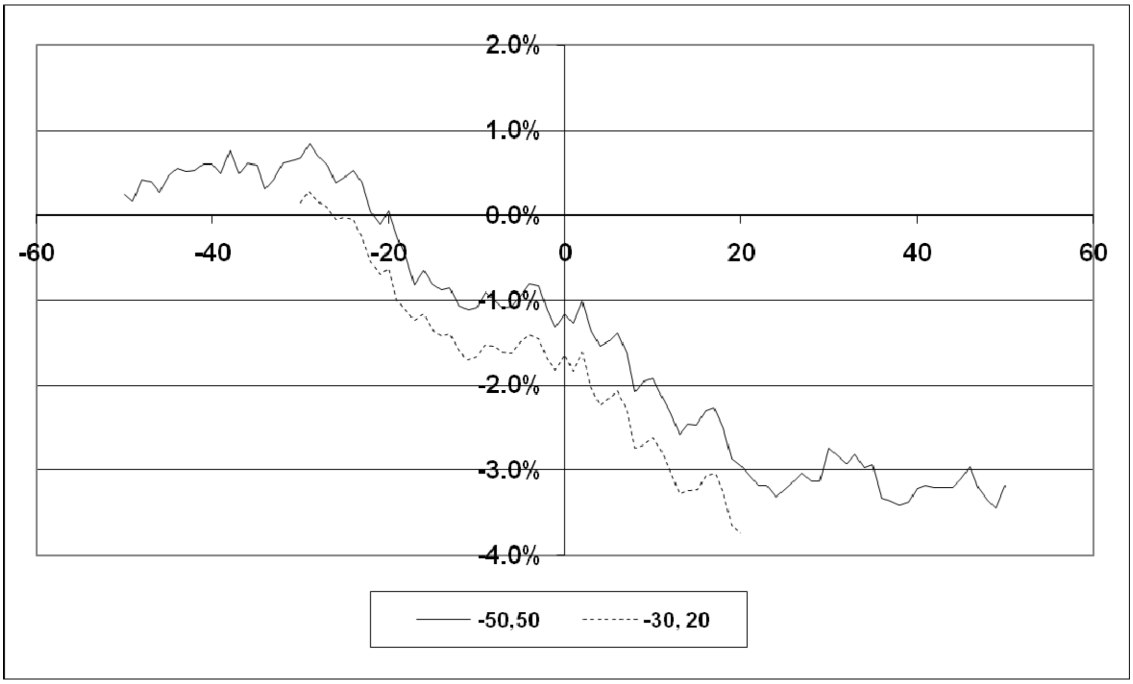
Table 5. Event period results for European firms.

	Pre	*Post*	N	*acar* /day	*acar*	T_0	*P*	*BMP*	*GS*
Model 2	Panel 2A								
	50	50	32	-0.037%	-3.78%	-2.12 *	-2.04 *	-1.40	-1.96 *
	40	40	33	-0.066%	-5.38%	-3.38 **	-3.03 **	-2.51 **	-2.13 *
	30	30	34	-0.073%	-4.47%	-3.17 **	-2.90 **	-2.39 **	-1.93 *
	30	20	34	-0.089%	-4.54%	-3.52 **	-3.35 **	-3.00 **	-2.61 **
	20	20	34	-0.079%	-3.25%	-2.81 **	-2.28 *	-2.28 *	-1.55
	10	10	35	-0.055%	-1.16%	-1.42	-0.98	-1.03	-0.34
	5	5	36	-0.067%	-0.74%	-1.26	-0.69	-0.78	0.81
	0	0	36	0.051%	0.05%	0.29	0.52	0.42	-0.19
	Panel 2B								
	40	0	34	-0.050%	-2.06%	-1.86 *	-1.59	-1.70 *	-1.91 *
	30	0	35	-0.066%	-2.06%	-2.09 *	-1.98 *	-2.05 *	-2.05 *
	20	0	35	-0.049%	-1.02%	-1.27	-0.85	-1.03	-2.02 *
	10	0	35	-0.007%	-0.07%	-0.12	0.11	0.15	0.68
	5	0	36	0.000%	0.00%	-0.01	0.27	0.29	0.81
	Panel 2C								
	0	40	35	-0.066%	-2.70%	-2.34 **	-1.54	-1.35	-1.06
	0	30	35	-0.059%	-1.83%	-1.82 *	-1.06	-0.93	-1.39
	0	20	35	-0.099%	-2.08%	-2.52 **	-2.00 *	-2.15 *	-0.72
	0	10	36	-0.095%	-1.04%	-1.78 *	-1.23	-1.44	-1.53
	0	5	36	-0.115%	-0.69%	-1.59	-0.92	-1.07	-1.53
Model 9	Panel 9A								
	50	50	32	-0.031%	-3.17%	-1.93 *	-1.47	-1.19	-0.21
	40	40	33	-0.059%	-4.77%	-3.26 **	-2.50 **	-2.06 *	-0.71
	30	30	34	-0.058%	-3.52%	-2.75 **	-2.25 *	-1.85 *	-1.89 *
	30	20	34	-0.073%	-3.74%	-3.19 **	-2.71 **	-2.47 **	-1.89 *
	20	20	34	-0.062%	-2.53%	-2.42 **	-1.80 *	-2.14 *	-1.65 *
	10	10	35	-0.013%	-0.26%	-0.36	0.20	0.23	0.32
	5	5	36	-0.032%	-0.36%	-0.67	0.06	0.06	0.17
	0	0	36	0.139%	0.14%	0.88	1.33	1.02	-0.26
	Panel 9B								
	40	0	34	-0.048%	-1.95%	-1.92 *	-1.40	-1.24	-1.90 *
	30	0	35	-0.051%	-1.57%	-1.76 *	-1.46	-1.49	-0.66
	20	0	35	-0.033%	-0.69%	-0.93	-0.47	-0.57	-1.44
	10	0	35	0.038%	0.41%	0.78	1.08	1.64	0.99
	5	0	36	0.020%	0.12%	0.30	0.80	0.89	0.17
	Panel 9C								
	0	40	35	-0.052%	-2.14%	-2.06 *	-1.09	-0.94	-1.46
	0	30	35	-0.050%	-1.55%	-1.72 *	-0.98	-0.76	-2.47 **
	0	20	35	-0.091%	-1.91%	-2.58 **	-1.94 *	-1.86 *	-2.13 *
	0	10	36	-0.059%	-0.65%	-1.23	-0.51	-0.52	-0.59
	0	5	36	-0.055%	-0.33%	-0.85	-0.08	-0.07	-0.92

Estimation period is 88 days (4 months). *Pre* = days in window before event date, *Post* = days after event date. Event window-length = *Pre*+1+*Post*. One-sided alternative hypothesis (lower-tail) for tests of abnormal returns, where * and ** denote statistical significance at 5% and 1% level, respectively.

Results for event windows with zero post-event days and zero pre-event days are displayed in Panels 2B and 9B and Panels 9C and 9C, respectively. *acar* in these subwindows represents a breakdown of *acar* in the corresponding windows in Panel 2A and 9A, except that day 0 is included in both subwindows and that the number of events are different due to data availability. For instance, *acar* in the (-30, 20) window *acar* is roughly the sum of *acar* in the (-30, 0) and the (0, 20) subwindows. There is some evidence of a significant negative stock price effect in the longer event windows with zero post-event days according to Panel 2B and 9B. That there would be an effect in thesewindows is expected, since the EV incidents occur - and are known - before they are reported by GES.

Figure 1. *acar* for Model 9 in (-50, 50) and (-30,20) window



Panels 2C and 9C, which present *acar* in event windows with zero pre-event days, should be of interest to investors. These windows include the event day, which according to both Model 2 and 9 has a (statistically insignificant) positive *acar*. This makes the tests more conservative (more difficult to observe negative *acar*) than if the event day had been excluded from the windows. There is strong evidence that *acar* is significantly negative in the (0, 20) window according to both Model 2 and 9; an *acar* of around -2% in the (0, 20) window, a period of 21 (trading) days, corresponds to almost –24% per year.

Based on simulations, Campbell et al. (2009) find normal return models including just a single local market factor to be sufficient compared to models involving more factors. The results obtained here agree with theirs in that tests based on Model 2 with a single local market factor do not lead to different conclusions than tests based on the more elaborate Model 9. Figure 2 portrays the behavior of *acar* for Model 2 and 9 in the (-30, 20) window.

Figure 2. acar for Model 2 and Model 3 in (-30,20) window

Campbell et al. (2009) find evidence of both parametric and GS test statistics being misspecified. They observe that return distributions in their multi-country sample are asymmetric and fat-tailed. For instance, Campbell et al. (2009) find that the statistic T_0 tends to reject the null too frequently.[12] As expected, (untabulated results indicate that) the return distributions of the 1260 stocks used in this study exhibit less skewness and kurtosis than those of the stocks in Campbell et al. (2009). Also, for the European sample, we cannot reject that *car* of Model 2 and 9 in the (-30, 20) window is normally distributed.. [13] Although T_0 rejects the null the strongest and most often, the test statistics used here perform quite similar.

[12] In a successful attempt to eliminate the accumulated impact of consecutive outlier returns as a source of misspecification in the GS test, Campbell et al. (2009, p. 24) use BHARs. We also employed BHARs in conjunction with Model 2, only to get very similar results as with CAR.
[13] Based on the skewness and kurtosis test for normality (sktest) of the statistics software Stata 9.

Conclusion and discussion

This paper investigates by event study methodology if environmental (EV) incidents affect firm value negatively. We use a global data set on incidents from GES Investment Services, which contain 142 EV incidents for some of the largest corporations in the world covering the years 2003-2006.

The main result is that the EV incidents are generally associated with loss of firm value, but which are not statistically significant, except for firms in Europe. In addition to being statistically significant, the observed abnormal returns should also be of economic significance to corporations and investors. We subjected the results to a battery of robustness tests. We used international versions of the market model as well as multi-factor models of the Fama-French type, including foreign currency exchange factors. We employed different parametric and non-parametric test statistics. Overall, the results were rather insensitive to these variations in methodology. The findings of this study thus support the conclusion of Campbell et al. (2009) that normal return models with a single local market factor are sufficient - compared to models involving more factors - in multi-country event studies. Despite differences in method, models and data, the results and conclusions of the present study agree in general with those of Lundgren and Olsson (2009).

There is also evidence pointing to US firm values being insensitive to EV incidents, implying that investors have different views on EV incidents in Europe and the US. A likely explanation for this difference relates to differences in the regulatory environment. Konar and Cohen (2001) propose that the occurrence of EV incidents might lead to more severe regulatory actions, which could have negative impact on firms' profitability. This effect is probable more pronounced in Europe than in the US, because the regulatory environment is less stringent and developed in Europe. In other studies on US firms it is often found that environmental news have an impact on firm value through stock price change, e.g. Hamilton (1995) Khanna et al. (1998, 1999), and Konar and Cohen (2001). Our results would contradict their findings. However, the present study setting is somewhat different, since we are looking at a different period, and we only study bad news, i.e., EV incidents. Other studies have often focused on good news or a mix of bad and good news, e.g. the toxic release information studies by Hamilton (1995) and Khanna et al. (1998, 1999).

The findings in this paper suggests that a firm's voluntary effort to avoid EV incidents may be more pronounced in Europe than in the US, since "punishment" from stakeholders is more likely (here in the form of loss in firm value). This means that policy directed towards designing e.g. public disclosure programs of EV performance,[14] which increase transparency with respect to EV issues, have the potential to be successful when it comes to motivating firms to voluntary internalize externalities from production.[15] Furthermore, Rauscher (2006), in a study of voluntary emission reductions, suggest that if there is a social reward (punishment) for corporate social responsibility (irresponsibility), then traditional EV policy, e.g. taxes and subsidies, may hamper the private provision of voluntary over-compliance. That is, social rewards (punishments) may be crowded out by EV regulation in the shape of a tax or regulation.

References

Afsah, S., B. Laplante, D. Wheeler (1996). Controlling industrial pollution: a new paradigm. *Policy Research Working Paper*, vol. 1672. The World Bank.

Asgharian, H, B. Hansson (2003). The explanatory role of factor portfolios for industries exposed to foreign competition: evidence from the Swedish stock market. *Int. Fin. Markets, Inst. and Money* 13, 325- 353.

Boehmer, E., J. Musumeci, A. B. Poulsen (1991). Event-study methodology under conditions of event-induced variance. *Journal of Financial Economics* 30, 253-72.

Blackman, A., G.J. Bannister (1998). Community pressure and clean technology in the informal sector: an econometric analysis of the adoption of propane by traditional Mexican brick makers. *Journal of Environmental Economics and Management* 35, 1 --21.

[14]For example, the Toxic Release Inventory published by the US Environmental Protection Agency.

[15]Note that if effects of bad and good news are symmetrical, then social rewards should increase firm value in case of good news according to the findings in the present paper. If such symmetry exists has to be further analyzed.

Armitage, S. (1995). Event study methods and evidence on their performance. *Journal of Economic Surveys* 8(4): 25-52.

Brown, S., J. Warner (1980). Measuring security price performance. *Journal of Financial Economics* 8, 205-58.

Brown, S., J. Warner (1985). Using daily stock returns: the case of event studies. *Journal of Financial Economics* 14, 3-32.

Campbell, C. J., V. Salotti, A. R. Cowan (2009). Multi-Country Event Study Methods (June 29, 2009). Working paper, available at SSRN: http://ssrn.com/abstract=1359798

Corrado, C. J., T. L. Zivney (1992). The Specification and Power of the Sign Test in Event Study Hypothesis Tests Using Daily Stock Returns. *Journal Of Financial and Quantitative Analysis* 27(3), 465-478.

Cowan, A. R. (1992), Nonparametric event study tests. *Review of Quantitative Finance and Accounting*, 1(4), 343–358.

Dam, L., B. Scholtens (2007) Banking on the Equator. Are banks that Adopted the Equator Principles Different from non-Adopters? *World Development* 35(8), 1307–1328.

Dasgupta, S., B. Laplante, and M. Nlandu (2001). Pollution and Capital Markets in Developing Countries. *Journal of Environmental Economics and Management* 42, 310-335.

Dasgupta, S., J.H. Hong, B. Laplante, N. Mamingi (2006). Disclosure of environmental violations and stock market in the Republic of Korea. *Ecological Economics* 58, 759-777.

Diltz, J.D. (2002). US Equity Markets and Environmental Policy: The Case of electric Utility Investor Behaviour During the Passage of the Clean Air Act Amendments of 1990. *Environmental and Resource Economics* 23, 379-401.

Davis, J. L., E. F. Fama, K. R. French (2000). Characteristics, Covariances, and Average Returns: 1929 to 1997. *Journal of Finance* 55, 389-406.

Faff, R. (2001). An Examination of the Fama and French Three-Factor Model Using Commercially Available Factors. *Australian Journal of Management* 26(1), 1-18.

Fama, E. F. (1991), Efficient Capital Markets, *Journal of Finance* 40, 1575-1617.

Fama, E. F., K. R. French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3–56.

Gupta, S., B. Goldar (2005). Do Stock Markets Penalise Environment-Unfriendly Behaviour? Evidence from India. Ecological *Economics* 52, 81-95.

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, 98-113.

Hay, B. L., R. N. Stavins, R. H. K. Vietor (eds) (2005). *Environmental protection and the social responsibilities of firms - perspectives from law, economics, and business*. Resources for the Future, Washington, DC, USA.

Hassel, L., H. Nilsson, N. Semenova (2009). The Value Relevance of Environmental and Social Performance in SIX 300 Companies. *Accounting and Taxation*, forthcoming.

Hassel, L., N. Semenova (2008). Financial Outcomes of Environmental Risk and Opportunity for U.S. Companies. *Sustainable Development* 16(3), 195–212.

Jain, P. C. (1986). Analyses of the distribution of security market model prediction errors for daily returns data. *Journal of Accounting Research* 24(1), 76-96.

Khanna, M., W. R. H. Quimio, D. Bojilova (1998). Toxics release information: a policy tool for environmental protection. *Journal of Environmental Economics and Management* 36, 243-266.

Khanna, M. and L.A. Damon (1999). EPA's Voluntary 33/50 Program: Impact on Toxic Releases and Economic Performance of Firms. *Journal of Environmental Economics and Management* 37, 1-25.

Khotari, S. P., J. B. Warner (2006). "*Econometrics of Event Studies*". Handbook of Corporate Finance: Empirical Corporate Finance, Volume A (*Handbooks in Finance Series*), Elsevier/North-Holland, Ch. 1.

Klassen, R. D. and C. P. McLaughlin (1996). The Impact of Environmental Management on Firm Performance. *Management Science* 42, 1199-1214.

Konar, S., M.A. Cohen (2001). Does market value environmental performance. *Review of Economics and Statistics* 83, 281-289.

Kriström, B., T. Lundgren (2003). Abatement investment and green goodwill. *Applied Economics* 35(18), 1915-21.

Lanoie, P., B. Laplante (1994). The market response to environmental incidents in Canada: a theoretical and empirical analysis. *Southern Economic Journal* 60, 657-672.

Lanoie, P., B. Laplante, M. Roy (1998). Can capital markets create incentives for pollution control? *Ecological Economics* 26, 31- 41.

Lundgren, T. (2003). A real options approach to abatement investment and green goodwill. *Environmental and Resource Economics* 25, 17-31.

Lundgren, T. (2010). A microeconomic model of corporate social responsibility. Forthcoming *Metroeconomica*.

Lundgren, T., R. Olsson (2009). How bad is bad news? Assessing the effects of environmental incidents on firm value. *American Journal of Finance and Accounting* 1(4), 376-92

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature* Vol. XXXV, 13-39.

Margolis, J., J. Walsh (2001). *People and profits?* Mahwah, NJ: Lawrence Erlbaum associates.

McWilliams, A., D. Siegel, S. H. Teoh (1999). Issues in the Use of the Event Study Methodology: A Critical Analysis of Corporate Social Responsibility Studies. *Organizational Research Methods* 2(4), 340-65.

MSCI Global Investable Market Indices. Methodology (August 2009) www.mscibarra.com/eqb/methodology/meth_docs/MSCI_Aug09_GIMIMethod.pdf

Pargal, S., D. Wheeler (1996). Informal regulation of industrial pollution in developing countries: evidence from Indonesia. *Journal of Political Economy* 104, 1314-1327.

Patell, J. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical tests. *Journal of Accounting Research*, 246-76.

Paton, D., D. Siegel, eds, (2005). The economics of corporate social responsibility. *Structural Change and Economic Dynamics* 16, 309-431.

Paul, C. M., D. Siegel, eds, (2006). Special issue on corporate social responsibility (CSR) and economic performance. *Journal of Productivity Analysis* 26(3), 207-87.

Rauscher, M. (2006). Voluntary emission reductions, social rewards, and environmental policy. *CESifo Working Paper* No. 1838.

Thompson, J.E. (1988). More Methods That Make Little Difference In Event Studies. *Journal of Business Finance & Accounting* 15(1), 77-86.