Human rights abuse and corporate stock performance - an event study analysis*

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Abstract

The effect of sustainable economic behavior on stock performance is often assessed by employing event study methodology. In this paper we extend the notion of sustainability to human rights by using a unique sample of publicly known discrimination cases. We analyze the short term effect of these announcements on corporate stock performance. Our results show that human rights abuse is associated with negative stock performance for US and UK firms. In contrast, the German and Swiss companies in our sample provide weak evidence of a positive effect of discrimination cases on corporate stock performance.

Keywords: CSR, Human rights abuse, Event study, GARCH models

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1 Introduction

On 10 December 1948, the General Assembly of the United Nations adopted and proclaimed the Universal Declaration of Human Rights, which claims that all human beings are born free and equal in dignity and rights. According to Art. 2

> "Everyone is entitled to all rights and freedoms set forth in this Declaration, without distinction of any kind, such as race, colour, sex, language, religion, political or other opinion, national or social origin, property, birth or status. [...]"[1]

However, everyday life shows that human rights are being violated – by individuals, corporate and even governmental entities. Newspaper articles report that companies repeatedly discriminate against individuals because of their sex, race, religious or other beliefs. Furthermore, mostly multinational companies have increasingly been accused of child labor use and in this regard the violation of human rights. The consequences of such activities in legal terms typically include legal complaints and possibly subsequent fines. In addition to this, corporate "unsocial" behavior can have detrimental effects in terms of reputation loss and a significant drop of a company's real value, i.e. bad stock performance. In the last few years social behavior issues such as general management and leadership as well as environmental and social awareness have received increasing attention by the broad public. The growing use of catchwords like "sustainable management" and "corporate social responsibility" by companies as well as the emergence of several stock market indexes of environmental and social responsibility reveal that the behavior of firms is a current and hot issue. At the same time, the scientific community has put forth a substantial body of literature on Corporate Social Responsibility (CSR) and its effects on corporate financial performance. However, the findings of the literature are anything but clear-cut. Current theory on the effects of CSR on corporate financial performance makes ambiguous predictions. The idea of a *negative* relationship between social and financial performance is based on Friedman's view that corporate social behavior raises costs which are not or not fully compensated by the arising benefits. Accordingly firms that "act responsibly" face competitive disadvantages. Supporters of

[1] See United Nations General Assembly (1948).

a *positive* relationship claim that firms which try to minimize their (implicit) costs (e.g. environmental costs) and thus behave socially irresponsible will, as a consequence, be hit by higher (explicit) costs (e.g. payments to bondholders), finally resulting in competitive disadvantages. Last, there is also the view that there is simply no systematic relation between social and financial performance.[2] Even the empirical literature provides no coherent results about the direction of CSR effects on financial performance. Originally applied in finance and accounting, event studies have increasingly been used to analyze the effect of environmental and social events on corporate financial performance. A large literature deals with the question of how environmental news, e.g. the disclosure of positive or negative corporate environmental performance (see for example Klassen and McLaughlin (1996), Dasgupta, Laplante, and Mamingi (2001), Gupta and Goldar (2005), Capelle-Blancard and Laguna (2006), as well as Hamilton (1995), Konar and Cohen (1997), Khanna, Quimio, and Bojilova (1998)) affect companies' stock performance.[3] Some authors report results which predict a significantly positive impact of CSR on stock performance. Other studies however show opposing findings or do not even find any significant results at all. A fundamental problem in assessing the potential impact of CSR on financial performance empirically is the difficulty of measuring corporate social behavior appropriately. According to the literature, CSR comprises "social as well as environmental issues". Based on this vague definition, there is a full range of different CSR measures. These measurement problems can explain at least to some extent the ambiguous results of previous studies.[4] While there is a wide literature on the effect of environmental events on corporate financial performance, there are only few studies who deal with the impact of social events. Becchetti, Ciciretti, and Hasan (2007) analyze the effect of corporate entry (exit) into (from) the Domini 400 Social Index between 1990 and 2004.[5] They find a significant negative effect on abnormal returns after exit announcements, by analyzing a sample consisting of 327 cases. Posnikoff (1997) examines the effect of disinvestment from South Africa on American firms between 1980 and 1991 on a sample of 40 US firms. Disinvestment is thereby interpreted as a posi-

[2] See Waddock and Graves (1997).

[3] See Oberndorfer and Ziegler (2006).

[4] See Waddock and Graves (1997)).

[5] Note that one of the eight screening categories of the Domini 400 Social Index are human rights (See Becchetti, Ciciretti, and Hasan (2007, p. 12)).

tive action regarding human rights since disinvesting firms abandon their engagement in a country where human rights are obviously violated. The results show a positive and significant increase in returns in the period surrounding the announcement of disinvestment. Dag, Eije, and Pennink (1998) address the human rights issue in a similar way. They analyze the consequences of Amnesty International press releases on the returns of multinational firms. Dag, Eije, and Pennink (1998) searched for "a country which in recent times violated human rights according to Amnesty International", and selected Indonesia.[6] Using a sample of 48 cases in 1996, they found no significant influence of press releases on stock returns of multinational companies. Wright, Ferris, Hiller, and Kroll (1995) analyze a sample of 35 US companies between 1988 and 1992 regarding settlements of discrimination cases. They detect significant negative effects at the event date.[7] Contrary to the other studies the motivation for their study is to analyze human resources effects rather than human rights abuse cases.

Having in mind the ambiguous results of previous studies regarding the effect of CSR on stock performance, we investigate the impacts of negative corporate social responsibility. Using event study methodology, we analyze the effects of human rights abuses on corporate stock performance. The goal of this study is twofold. Other than many previous studies, we use international data (US market vs. Germany, Switzerland, UK and Ireland) to examine whether there are any significant country specific differences. Beside the simple Capital Asset Pricing Model (CAPM) we also include GARCH effects to determine corporate abnormal returns. Last but not least, to the best of our knowledge this is the first study that investigates the effects of specific human rights abuses on the firm level within the framework of an event study.

The remainder of the paper is organized as follows: Section 2 briefly reviews the methodology of event studies based on the well known CAPM and then explains our approach of modeling GARCH effects in the context of event studies in more detail. Section 3 describes the sample selection procedure. Section 4 presents the results, and section 5 concludes.

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[6] See Dag, Eije, and Pennink (1998, p. 4).

[7] Note that McWilliams and Siegel (1997) replicate this study but do not find any significant negative abnormal returns at the event date.

2 Methodology

2.1 The classical Event Study Approach

From asking the question whether a certain event affects the value of one or more corporation(s) the field of Event Study Analysis arose. The foundation of contemporary Event Study Analysis was set by the articles of Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969). Since the early seventies the number of published event studies has steadily increased until the early nineties to a (roughly) steady level from then on.[8] The fundamental idea can be summarized as follows: use the return as a measure of the change in the company value and examine if there are "unusual" high or low or both high and low returns – depending on the specific question - surrounding the event date. "Unusual" in this context means that we first employ an empirical asset pricing model and then test the assumption if the error terms (in the event study literature they are called "abnormal returns", and we will henceforth use this term) are drawn from the same distribution as the abnormal returns before some particular event. Short horizon event studies typically utilize the Market Model or the CAPM. Since we use daily data, we follow this practice.[9]The assumptions for obtaining valid results are twofold: first we must assume that our asset pricing model is well specified (this concerns the functional form, the inclusion of all relevant factors and assumptions about the distribution of pricing errors).[10] Second: new information is expected to be incorporated "fast" into asset prices (where "fast" means within one or at least a few days).

[8]See the survey by Kothari and Warner (2004, Table 1).

[9]Some articles use multifactor models like the Fama-French three factor model (e.g. Oberndorfer and Ziegler (2006)). Contrary to this practice Campbell, Lo, and MacKinlay (1997, p. 156) argue, that the marginal explanatory power of additional factors is usually small and the improvement of the variance-estimate of the abnormal return is therefore also small.

[10]For the validity of small sample results we have to assume that the pricing errors are normally distributed, but the asymptotic results are valid without the normality assumption (the other assumptions of the Simple Linear Regression Model should still hold (no autocorrelation, no heteroskedasticity)).

The CAPM employed for the estimation can be written as follows:[11]

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}$$
$$\mathrm{E}[\varepsilon_{it}] = 0 \qquad \mathrm{Var}[\varepsilon_{it}] = \sigma^2_{\varepsilon_i} \tag{1}$$

where R_{it} and R_{mt} are the period-t returns on security i and the market portfolio, R_{ft} is the period-t rate for riskless borrowing and ε_{it} is the period-t zero mean disturbance term. α_i, β_i and $\sigma^2_{\varepsilon_i}$ are the parameters of the CAPM for each security i. Parameter estimates are calculated by using data prior to the event date (the so called estimation window). The OLS estimates are denoted by $\hat{\alpha}_i$, $\hat{\beta}_i$ and $\hat{\sigma}^2_{\varepsilon_i}$.Turning to the observations surrounding the event (these observations constitute the so called event window) we define the estimated abnormal return $\hat{\varepsilon}^\star_{i\tau}$ of stock i as the observed deviation of the observed excess return of stock i from its expectation which is formed by using the CAPM, given the parameter estimates from the estimation window:

$$\hat{\varepsilon}^\star_{i\tau} = (R^\star_{i\tau} - R^\star_{f\tau}) - \hat{\alpha}_i - \hat{\beta}_i(R^\star_{m\tau} - R^\star_{f\tau}) \tag{2}$$

where * indicates that the data stem from the event window and therefore $\tau = T_1, T_1 + 1, \ldots, T_2$ with the event window starting at T_1 and ending at T_2. Next we define the observed cumulative abnormal return and the observed standardized cumulative abnormal return of security i from time τ_1 to time τ_2:[12]

$$\widehat{CAR}_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{\tau_2} \hat{\varepsilon}^\star_{it} \qquad \widehat{SCAR}_i(\tau_1, \tau_2) = \frac{\widehat{CAR}_i(\tau_1, \tau_2)}{\hat{\sigma}_i(\tau_1, \tau_2)} \tag{3}$$

where $\hat{\sigma}^2_i(\tau_1, \tau_2)$ denotes an estimate of the cumulative abnormal return variance of security i. To widen our inference to the whole sample, the cumulative abnormal returns and the standardized cumulative abnormal returns are further aggregated by averaging

[11] Note that in a strict sense this model does not represent the CAPM, it is only based on the CAPM. In a pure CAPM specification the α_i coefficient would be restricted to zero. Furthermore, the CAPM is a one-period model and for the generalization to an n-period model one needs to impose further assumptions. In particular: preferences and future opportunity sets have to be state independent. For a detailed treatment see Merton (1973). To keep things simple we use subsequent the term CAPM for this model.

[12] It is common in the event study literature to use event time notation. This means time $t = 0$ is associated with the date of the specific event, time $t = 1$ ($t = -1$) is associated with the day after (before) the specific event and so on.

the cumulative abnormal returns and the standardized cumulative abnormal returns, defined in equation (3), across the individual securities. We define the cumulative average abnormal return and the standardized cumulative average abnormal return each of N securities from τ_1 to τ_2 as:

$$\overline{CAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N}\widehat{CAR}_i(\tau_1,\tau_2) \qquad \overline{SCAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N}\widehat{SCAR}_i(\tau_1,\tau_2) \tag{4}$$

We test the hypothesis H_0 that *the given event has no impact on the mean or variance of the returns* across all N different securities.[13] It is thereby assumed that the N event windows of the different securities do not overlap. We use two test statistics, J_1 in case of the cumulative abnormal returns and J_2 in case of the standardized cumulative abnormal returns as defined in equation (3):

$$J_1 = \frac{\overline{CAR}(\tau_1,\tau_2)}{[\hat{\overline{\sigma}}^2(\tau_1,\tau_2)]^{1/2}} \overset{a}{\sim} \mathcal{N}(0,1) \qquad J_2 = \left(\frac{N(L_1-4)}{L_1-2}\right)^{1/2}\overline{SCAR}(\tau_1,\tau_2) \overset{a}{\sim} \mathcal{N}(0,1) \tag{5}$$

where $\hat{\overline{\sigma}}^2(\tau_1,\tau_2)$ denotes an estimate of the cumulative average abnormal return variance $\overline{\sigma}^2(\tau_1,\tau_2)$.

Which one of these two test statistics is more powerful depends on the alternative hypothesis. J_1 is more powerful if the true abnormal return is larger for securities with higher variance and J_2 is more powerful if the true abnormal return is constant across securities.[14] For a detailed derivation of these statistics see the textbook of Campbell, Lo, and MacKinlay (1997, Ch. 4). We essentially employ the same formulas as in Campbell, Lo, and MacKinlay (1997) with the exception that we use excess returns instead of returns.

2.2 Event Study Methodology and GARCH effects

The approach outlined in section 2.1 is often criticized because of its restrictive assumptions. An important shortcoming of this approach is addressed by Boehmer, Musumeci, and Poulsen (1991). They note that in the presence of event induced variance, which means that the return variance increases jointly with the absolute value of the abnormal

[13]See Campbell, Lo, and MacKinlay (1997, p. 160).

[14]See Campbell, Lo, and MacKinlay (1997, p. 162).

return or increases prior to the event, because of uncertainty, it is often undesirable to test the joint hypothesis that the event has no impact on the mean *and* the variance of the return because one is only interested in testing the hypothesis concerning the mean return. To circumvent the problem of event-induced variance we use a different method than Boehmer, Musumeci, and Poulsen (1991)[15], namely we employ GARCH models to allow for a varying conditional variance of stock returns. Since the seminal paper of Bollerslev (1986) GARCH models are widely used to describe asset returns, as they do a reasonably good job in describing daily asset returns.[16] Some studies treat the subject of event studies and GARCH effects including the articles of Brockett, Chen, and Garven (1999) and and Frame and Lastrapes (1998). The modeling of GARCH effects within event studies is also present in the CSR literature.[17] and Frame and Lastrapes (1998) formulate a multivariate GARCH(1,1) model with a time-varying slope coefficient for the market factor. Brockett, Chen, and Garven (1999) use a univariate GARCH(1,1) model together with a time varying coefficient regression model for the market factor. Since the models of Frame and Lastrapes (1998) and Brockett, Chen, and Garven (1999) are approaches on their own and not in line with standard event study methodology we do not follow these suggestions and incorporate instead GARCH effects into the standard event study methodology as outlined in section 2.1.

We modify equation (1) to allow the conditional variance to vary according to a GARCH(1,1) process:

$$\mathrm{Var}[\varepsilon_{it}|\varepsilon_{i,(t-1)}, R_{m,(t-1)}, R_{f,(t-1)}, \ldots] = h_{it} = c_i + a_i \varepsilon^2_{i,(t-1)} + b_i h_{i,(t-1)}$$

Furthermore, we assume that the error terms conditional on the data known until time $t-1$ are normally distributed:

$$\varepsilon_{it}|\varepsilon_{i,(t-1)}, R_{m,(t-1)}, R_{f,(t-1)}, \ldots \sim \mathcal{N}(0, h_{it})$$

[15] In this paper a method is suggested in which the standardized abnormal returns (standardized by using the estimated variance of the estimation window) from the event window of the individual securities are used to obtain cross-sectional variance estimates. In contrast to the GARCH approach this method "assumes that the event-induced increase in variance is proportional for each firm" (Binder (1998, p. 115)).

[16] For instance see the article of Akgiray (1989).

[17] See for instance Becchetti, Ciciretti, and Hasan (2007).

The normality assumption is necessary since we estimate the parameters by Maximum Likelihood (ML).[18] We jointly estimate five parameters: $\tilde{\alpha}_i$ and $\tilde{\beta}_i$ are the estimates of the CAPM-coefficients and $\tilde{c}_i$, $\tilde{a}_i$ and $\tilde{b}_i$ are the estimated parameters of the conditional variance.[19]

An estimate of the covariance matrix of the abnormal returns can be constructed by substituting the variance and covariance terms by their ML estimates. As an estimate of the conditional variance $h_{i\tau}$ we use its estimated value, given the parameter estimated from the estimation window and conditioned upon its most recent forecast error and conditional variance:

$$\tilde{h}^{\star}_{iT_1} = \tilde{c}_i + \tilde{a}_i \cdot \tilde{\varepsilon}^2_{i,(T_1-1)} + \tilde{b}_i \cdot \tilde{h}_{i,(T_1-1)}$$

and for $\tau > T_1$:

$$\tilde{h}^{\star}_{i\tau} = \tilde{c}_i + \tilde{a}_i \cdot \tilde{\varepsilon}^2_{i,(\tau-1)} + \tilde{b}_i \cdot \tilde{h}_{i,(\tau-1)}$$

Using these formulas we calculate the cumulative abnormal returns and the standardized cumulative abnormal returns in the same fashion as in section 2.1. The test statistics J_1 and J_2 are constructed analogously to equation (5) in section 2.1.

3 Data

3.1 Event data

The identification and selection of events is based on the use of LexisNexis, an international database of newspapers and scientific publications.[20] Our search is conducted in three steps. In *step one*, we define keywords to identify newspaper articles on firms violating human rights. The keywords can be divided in three categories. The first category contains keywords describing the particular kind of human rights abuse, such as “child labor”, “race (racial) discrimination”, “sex (gender) discrimination”, “religious discrimination”. The second category covers keywords which help to detect the events in

[18] For an excellent treatment on ML estimation see chapter 5 of Hamilton (1994).

[19] The ˜ symbol indicates that parameters are estimated by ML.

[20] LexisNexis covers Denmark, France, Italy, Netherlands, Switzerland, Spain, UK, US, and Asia/Pacific, as well as all major newspapers in English and German.

general, such as “scandal”, “affair”, “abuse”, “violation”, “sweatshop”, “sexual harassment”, “disclosure”, “reveal”, “discover”, “uncover”, “fine”, “settlement”. Furthermore, we use “company”, “business”, “corporate”, “enterprise”, “factory”, “manufacture” as additional keywords.[21] A first search identifies 438 possible cases for the period 1983-2008, where several firms appear more than once, implying that they were involved in more than one case of human rights abuse. Most events are covered by different media sources on different dates. From the resulting newspaper articles we select the earliest article and define the date of this article as the particular event date. Despite this procedure, with a certain probability there might be an earlier article omitted by our search in the first step due to the particular choice of keywords. In *step two* we therefore search for the identified events again, adding the third keyword category, the firm names. In 97 cases we find earlier articles and thus identify earlier event dates. In *step three* we finally collect the necessary financial data, using Thomson Financial Datastream (TDS). From the original sample 264 events are removed due to two major reasons: either the firms are not publicly traded companies, or there are no data available for the particular time span. We remove 15 firms containing 16 events because they could not be assigned to a country sample. The final sample contains 92 firms and 153 events in total.

3.2 Financial data

The mapping of the identified event firms with the stock data available in TDS is arranged in two steps. First we search for the firm names quoted in the newspaper articles (or some parts of it). This search reveals that some firms are acquired by other corporations prior to the event or they turn out to be subsidiaries of available corporations. In this case we use the parent company as the event firm in our sample (examples are “Cub Foods”/“SuperValu”, “Dresdner Bank”/“Allianz” or “Hollister”/“Abercrombie & Fitch”).

Data on returns are collected from TDS. We exclude firms which are delisted[22], rarely traded[23] and firms for which no stock market data are available regarding the considered

[21] Note that we use the same set of keywords in German to screen German-language newspapers.

[22] In some cases TDS reports the last valid price/return index years after the stock had been delisted (see also Ince and Porter (2006, p. 465)).

[23] We exclude firms for which we observe no changes of the return index on more then 35% of the days in the estimation window.

period. We also exclude stocks which happen to have too few observations to estimate the parameters[24] or could not be assigned to a country sample.

Furthermore, we apply two strategies to subdivide our sample. The first strategy subdivides our sample into four parts and the second strategy subdivides our sample into two parts. Our first sample is, in both strategies, composed of 74 firms from the United States and 122 events, which we identify for these firms. The strategy for the remaining samples is twofold: first we look at German firms (5 firms, 13 events), firms from Switzerland (6 firms, 10 events) and firms from the United Kingdom (7 firms, 8 events) separately. Second we aggregate the results from these countries and add one Irish firm ("Ryanair"). The arrangements of the specific country samples are based on the country location of the stock exchange on which the particular securities are listed.[25]

For the US stocks we use the value weighted index from Fama and French (1993)[26] as the market return and a three month treasury bill (from TDS) as the risk free rate for calculating excess returns. The chosen market indices for the other samples are the German Composite DAX (CDAX), the Swiss Performance Index (SPI), the British Financial Times Stock Exchange All-Share Index (FTSE All-Share) and the Irish Stock Exchange Quotient Overall Index (ISEQ). The chosen riskfree rates are daily records of the German, Swiss, British and Irish three month interbank (offered) rate.

4 Results

This section presents the estimation results for the five different samples. The estimation window consists of $n = 200$ observations and ends ten business days before the event date. Departing from the notation in section 2 we observe N different events (instead of N different securities) and since some firms have more than one observed event, the number of securities is less than the number of events. The average cumulative abnormal returns and the average standardized abnormal returns are reported for the event date (window [0]), one day after the event (window [1]), cumulated one and two days

[24]The sample size of the estimation window is $n = 200$, so there must be at least 210 observations prior to the event.

[25]Thus we include ADRs if the newspaper articles are related to US subsidiaries.

[26]The value weighted market index calculated from NYSE, NASDAQ and AMEX stocks can be downloaded from Kenneth Frenchs website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`).

after the event (window [1,2]), cumulated one to five days after the event (window [1,5]), cumulated one day before the event to one day after the event (window [-1,1]), cumulated five days before the event to one day after the event (window [-5,1]) and cumulated five days before the event to five days after the event (window [-5,5]). Besides the abnormal returns we report the J_1 and J_2 statistics (see section 2) for the CAPM and the GARCH-adjusted CAPM, as well as the corresponding p-values. We also report the t-Statistic as proposed by Boehmer, Musumeci, and Poulsen (1991). Additionally, we visualize the one period aggregated abnormal returns in Figures 1-5. In each Figure the upper row displays the average cumulated abnormal returns and the average standardized abnormal returns as estimated by the CAPM (see section 2.1). The lower row displays the average cumulated abnormal returns and the average standardized abnormal returns as estimated by the GARCH-adjusted CAPM (see section 2.2).

For the sake of brevity we mainly discuss the results from the average standardized abnormal returns.

To quantify the economic impact of the discrimination cases we additionally report statistics about the estimated dollar change of the company market value based on the excess returns over the event period in tables 6-9.[27] Because the mean values are highly sensitive to outliers, we also report the median values besides standard deviations, minima and maxima.

4.1 United States

First, take a look at the graph of the one period averaged standardized abnormal returns regarding the CAPM (upper right panel of Figure 1). The one period averaged standardized abnormal returns three and four days before the event and one day after the event are negative and significant.[28] If we aggregate the one period averaged standardized abnormal returns across the time dimension we observe significant aggregated abnormal

[27]We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1+\hat{\varepsilon}^\star_{it}) - 1 \right)$, where $\hat{\varepsilon}^\star_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

[28]Here and thereafter "significant" means: "significant different from zero at the 5 % level".

returns for the windows [-5,5], [-5,1], [1] and [1,5] (see Table 1). For the GARCH-adjusted CAPM we observe a similar pattern, the negative abnormal return two days before the event is even more pronounced than in the CAPM case (see Figure 1, lower right panel).

[Insert Figure 1 around here]

[Insert Table 1 around here]

In summary we observe significant *negative* abnormal returns for the eleven days period surrounding the event and for three of the reported sub-periods.We observe an average decrease in the market value by 892.33 million US-Dollars and a mean decrease by 47.31 million US-Dollars observed for the median firms, for the eleven days period surrounding the event, respectively (see Table 6). This result suggests that US corporations are (on average) punished with negative returns by investors if human rights violations become public knowledge. Our results suggest that the relevant information is incorporated three to four days before and one day after the reported event date.

[Insert Table 6 around here]

4.2 Germany

Figure 2 displays the one period aggregated abnormal returns for the German sample. The one period average standardized residuals for the CAPM as well as for the GARCH-adjusted CAPM are in any case insignificant. Although it is noticeable that we report mostly positive abnormal returns (see Table 2) for the reported cumulation periods.

[Insert Figure 2 around here]

[Insert Table 2 around here]

The results suggest that there is no apparent relation between discrimination cases and stock returns for the German sample. By taking a look at the market value changes in Table 7 we observe that the mean values are positive whereas the median values are negative (with one exception).

[Insert Table 7 around here]

4.3 Switzerland

Figure 3 shows the one period aggregated abnormal returns for the Swiss sample. In case of the average standardized abnormal returns (upper right panel), we observe that the abnormal return at the event date is positive and marginally significant. Furthermore, we observe a significant positive aggregated abnormal return for window [-1,1] (see Table 3). The results from the GARCH-adjusted CAPM are essentially the same as the CAPM findings.

[Insert Figure 3 around here]

[Insert Table 3 around here]

In summary we observe significant *positive* abnormal returns over the period one day before until one day after the event. Interestingly, this finding can be interpreted as evidence for companies being rewarded by investors for committing human rights violations. Yet we observe a slight different picture if we use the average cumulated abnormal returns for the statistical tests. In this case the findings above are only supported if we use a 10 % significance level.[29] Nevertheless, we detect positive abnormal returns. The significant abnormal returns show up immediately at the event date. The changes in the market value, reported in Table 8, show exclusively positive mean and median values. The median values are considerably smaller than the mean values, indicating some outliers to the right of the distribution concerning the changes in the market value.

[Insert Table 8 around here]

4.4 United Kingdom

In the upper right panel of Figure 4 the one period average standardized abnormal returns for the UK sample are displayed. We observe significant *negative* average standardized abnormal returns for the event day and the day before the event. Five days before the event we observe a significant positive average standardized abnormal return.

[29] We rely on the findings of the average standardized returns, since we do not observe a sound relation between abnormal returns and variances, in which case the statistic J_1 would be more powerful. So we believe that the statistic J_2 is at least as powerful or even more powerful as J_1.

However, if we cumulate the average standardized abnormal returns over the period beginning five days before the event to one day after the event (window [-5,1]) we detect significant negative abnormal returns (see Table 4).[30] For the cumulated standardized abnormal returns of window [-1,1] we observe a significant negative abnormal return.

[Insert Figure 4 around here]

[Insert Table 4 around here]

Summarizing the findings of the UK sample, we can state that UK firms face lower abnormal returns when being associated with discriminating behavior. The information considering the discrimination event seems to be recognized by investors one day prior to the reported event date or immediately at the event date. The mean and median values of the changes in the market value (see Table 9) are mostly negative. In case of window [-1,1] we exclusively observe decreasing market values.

[Insert Table 9 around here]

4.5 Germany, Switzerland, United Kingdom and Ireland

Finally, we subsume all events of the German, Swiss and UK samples into one sample and add one Irish observation ("Ryanair"). We use individual market indices and risk free rates for each country as described in section 3.2.

Figure 5 shows the one period average standardized abnormal returns. Only in the case of the GARCH-adjusted CAPM estimation we observe one significant positive abnormal return (at time $t = -2$). For all other cases the abnormal returns are insignificant. For the reported cumulation periods (see Table 5) none of the abnormal returns are significant.

[Insert Figure 5 around here]

[Insert Table 5 around here]

[30] Contrary to the findings of the CAPM and the GARCH-adjusted CAPM, the t-statistic proposed by Boehmer, Musumeci, and Poulsen (1991) does not reject the null hypothesis of no abnormal mean returns on all conventional significance levels.

The results for the German, Swiss, UK and Irish sample imply that the disclosure of discrimination cases has no effect on the firms of the composite country sample. Having in mind the results of the separate country samples, we must be cautious about drawing conclusions. The positive abnormal returns of the Swiss and German samples seem to be offset by the negative abnormal returns of the UK sample.

[Insert Table 10 around here]

5 Conclusions

To resolve the relation between company value and sustainable corporate behavior (or CSR) we focus on one particular factor, namely the abuse of human rights. The cases we consider include age discrimination, child labor, gender discrimination, intimidation, racial discrimination, religious discrimination and other discrimination cases. To assess directly the effect of a public announcement of such cases we collect newspaper articles and use event study methodology. Beyond conventional event study methods we model GARCH effects in the return series to account for a possible misspecification due to ignoring such effects. GARCH effects are detected for approximately 50% - 70% of all events, depending on the significance level.[31]

Our results show that US and UK firms experience significant negative abnormal returns when human rights abuses become publicly known. Hence, these results suggest that corporate unsocial behavior is immediately punished by investors. However, the same results do not hold for German and Swiss firms. The findings of the individual-country samples provide weak evidence for positive abnormal returns. Whether this rather counterintuitive result occurs due to country peculiarities which have not been considered so far or as a consequence of too small country samples, will be the subject of future research.

[31] The results are not reported but are available from the authors upon request.

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Table 1: Estimation results for the US sample

Window	[-5,5]	[-5,1]	[-1,1]	[0]	[1]	[1,2]	[1,5]
CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	-2.01	-1.37	-0.19	0.21	-0.32	-0.40	-0.95
J_1	-2.84	-2.46	-0.51	1.01	-1.53	-1.35	-2.03
p-value	(0.00)	(0.01)	(0.61)	(0.31)	(0.13)	(0.18)	(0.04)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	-0.25	-0.23	-0.05	0.12	-0.19	-0.14	-0.18
J_2	-2.70	-2.53	-0.57	1.28	-2.09	-1.54	-2.02
p-value	(0.01)	(0.01)	(0.57)	(0.20)	(0.04)	(0.12)	(0.04)
Boehmer, Musumeci, and Poulsen (1991) Method							
t	-2.30	-2.62	-0.54	1.02	-1.95	-1.60	-1.60
p-value	(0.02)	(0.01)	(0.59)	(0.31)	(0.05)	(0.11)	(0.11)
GARCH-adjusted CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	-2.95	-1.99	-0.44	0.12	-0.40	-0.58	-1.36
J_1	-3.73	-3.17	-1.16	0.54	-1.93	-1.90	-2.64
p-value	(0.00)	(0.00)	(0.24)	(0.59)	(0.05)	(0.06)	(0.01)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	-0.30	-0.28	-0.08	0.11	-0.20	-0.15	-0.22
J_2	-3.29	-3.09	-0.92	1.22	-2.19	-1.63	-2.39
p-value	(0.00)	(0.00)	(0.36)	(0.22)	(0.03)	(0.10)	(0.02)

Note: The Table shows estimation results for average cumulated abnormal returns ($\overline{CAR}$), reported in percent (%), and average standardized abnormal returns ($\overline{SCAR}$), reported in standard deviations (sd), for the CAPM and the GARCH-adjusted CAPM.
The J_1 and J_2 rows report the statistics depicted in sections 2.1 (CAPM) and 2.2 (GARCH-adjusted CAPM). p-value reports the probability of observing a J value in the row above, given the validity of the corresponding null hypothesis. The t row reports the t statistic proposed by Boehmer, Musumeci, and Poulsen (1991).

The sample consists of 74 firms/securities and 122 events.

Table 2: Estimation results for the German sample

Window	[-5,5]	[-5,1]	[-1,1]	[0]	[1]	[1,2]	[1,5]
CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	1.51	0.97	0.64	0.36	0.27	0.16	0.81
J_1	1.28	1.04	1.06	1.04	0.76	0.31	1.03
p-value	(0.20)	(0.30)	(0.29)	(0.30)	(0.44)	(0.75)	(0.30)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.33	0.26	0.09	0.31	-0.07	-0.05	0.17
J_2	1.20	0.92	0.32	1.10	-0.26	-0.19	0.63
p-value	(0.23)	(0.36)	(0.75)	(0.27)	(0.79)	(0.85)	(0.53)
Boehmer, Musumeci, and Poulsen (1991) Method							
t	1.07	0.73	0.23	1.02	-0.12	-0.12	0.48
p-value	(0.29)	(0.47)	(0.82)	(0.31)	(0.90)	(0.90)	(0.63)
GARCH-adjusted CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	1.60	1.06	0.72	0.40	0.28	0.21	0.82
J_1	1.19	0.99	1.03	1.00	0.70	0.37	0.93
p-value	(0.23)	(0.32)	(0.30)	(0.32)	(0.48)	(0.71)	(0.35)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.38	0.31	0.08	0.35	-0.14	-0.13	0.16
J_2	1.36	1.11	0.30	1.26	-0.50	-0.46	0.58
p-value	(0.17)	(0.27)	(0.76)	(0.21)	(0.62)	(0.65)	(0.56)

Note: The Table shows estimation results for average cumulated abnormal returns ($\overline{CAR}$), reported in percent (%), and average standardized abnormal returns ($\overline{SCAR}$), reported in standard deviations (sd), for the CAPM and the GARCH-adjusted CAPM.
The J_1 and J_2 rows report the statistics depicted in sections 2.1 (CAPM) and 2.2 (GARCH-adjusted CAPM). p-value reports the probability of observing a J value in the row above, given the validity of the corresponding null hypothesis. The t row reports the t statistic proposed by Boehmer, Musumeci, and Poulsen (1991).

The sample consists of 5 firms/securities and 13 events.

Table 3: Estimation results for the Swiss sample

Window	[-5,5]	[-5,1]	[-1,1]	[0]	[1]	[1,2]	[1,5]
CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	1.97	1.21	1.56	0.83	0.41	1.36	1.18
J_1	1.18	0.92	1.83	1.69	0.84	1.96	1.06
p-value	(0.24)	(0.36)	(0.07)	(0.09)	(0.40)	(0.05)	(0.29)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.47	0.37	0.68	0.63	0.27	0.57	0.39
J_2	1.49	1.17	2.13	1.99	0.85	1.80	1.23
p-value	(0.14)	(0.24)	(0.03)	(0.05)	(0.40)	(0.07)	(0.22)
Boehmer, Musumeci, and Poulsen (1991) Method							
t	2.26	1.40	2.05	2.05	1.46	1.85	2.00
p-value	(0.02)	(0.16)	(0.04)	(0.04)	(0.14)	(0.06)	(0.05)
GARCH-adjusted CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	2.06	1.27	1.59	0.85	0.35	1.28	1.15
J_1	1.36	1.04	2.01	1.92	0.80	2.02	1.15
p-value	(0.18)	(0.30)	(0.04)	(0.06)	(0.43)	(0.04)	(0.25)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.50	0.37	0.65	0.76	0.28	0.54	0.46
J_2	1.58	1.15	2.05	2.39	0.88	1.71	1.43
p-value	(0.11)	(0.25)	(0.04)	(0.02)	(0.38)	(0.09)	(0.15)

Note: The Table shows estimation results for average cumulated abnormal returns ($\overline{CAR}$), reported in percent (%), and average standardized abnormal returns ($\overline{SCAR}$), reported in standard deviations (sd), for the CAPM and the GARCH-adjusted CAPM.
The J_1 and J_2 rows report the statistics depicted in sections 2.1 (CAPM) and 2.2 (GARCH-adjusted CAPM). p-value reports the probability of observing a J value in the row above, given the validity of the corresponding null hypothesis. The t row reports the t statistic proposed by Boehmer, Musumeci, and Poulsen (1991).

The sample consists of 6 firms/securities and 10 events.

Table 4: Estimation results for the UK sample

Window	[-5,5]	[-5,1]	[-1,1]	[0]	[1]	[1,2]	[1,5]
CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	-1.96	-2.45	-3.51	-0.90	-0.02	0.03	0.57
J_1	-1.24	-1.96	-4.33	-2.13	-0.04	0.04	0.60
p-value	(0.22)	(0.05)	(0.00)	(0.03)	(0.97)	(0.97)	(0.55)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	-0.52	-0.71	-1.66	-0.89	-0.06	-0.09	0.12
J_2	-1.47	-2.00	-4.67	-2.66	-0.18	-0.26	0.37
p-value	(0.14)	(0.05)	(0.00)	(0.01)	(0.86)	(0.80)	(0.71)
Boehmer, Musumeci, and Poulsen (1991) Method							
t	-1.33	-1.14	-4.24	-2.97	-0.19	-0.24	0.35
p-value	(0.18)	(0.25)	(0.00)	(0.00)	(0.85)	(0.81)	(0.72)
GARCH-adjusted CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	-2.03	-2.47	-3.52	-0.98	-0.08	-0.11	0.36
J_1	-1.23	-1.92	-4.12	-2.06	-0.17	-0.17	0.32
p-value	(0.22)	(0.06)	(0.00)	(0.04)	(0.86)	(0.86)	(0.75)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	-0.51	-0.72	-1.65	-1.00	-0.17	-0.25	-0.02
J_2	-1.43	-2.01	-4.64	-2.81	-0.48	-0.70	-0.05
p-value	(0.15)	(0.04)	(0.00)	(0.00)	(0.63)	(0.48)	(0.96)

Note: The Table shows estimation results for average cumulated abnormal returns ($\overline{CAR}$), reported in percent (%), and average standardized abnormal returns ($\overline{SCAR}$), reported in standard deviations (sd), for the CAPM and the GARCH-adjusted CAPM.
The J_1 and J_2 rows report the statistics depicted in sections 2.1 (CAPM) and 2.2 (GARCH-adjusted CAPM). p-value reports the probability of observing a J value in the row above, given the validity of the corresponding null hypothesis. The t row reports the t statistic proposed by Boehmer, Musumeci, and Poulsen (1991).

The sample consists of 7 firms/securities and 8 events.

Table 5: Estimation results for the German, Swiss, UK and Irish sample

Window	[-5,5]	[-5,1]	[-1,1]	[0]	[1]	[1,2]	[1,5]
CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	0.77	0.17	-0.13	0.17	0.22	0.48	0.83
J_1	0.92	0.25	-0.30	0.69	0.91	1.37	1.48
p-value	(0.36)	(0.80)	(0.76)	(0.49)	(0.36)	(0.17)	(0.14)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.16	0.04	-0.17	0.09	0.02	0.11	0.20
J_2	0.88	0.25	-0.95	0.49	0.10	0.59	1.11
p-value	(0.38)	(0.80)	(0.34)	(0.62)	(0.92)	(0.56)	(0.27)
Boehmer, Musumeci, and Poulsen (1991) Method							
t	0.82	0.18	-0.63	0.41	0.06	0.45	1.04
p-value	(0.41)	(0.86)	(0.53)	(0.68)	(0.95)	(0.65)	(0.30)
GARCH-adjusted CAPM							
Average Cumulated Abnormal Return							
$\overline{CAR}$ (in %)	0.81	0.21	-0.10	0.19	0.21	0.47	0.81
J_1	0.95	0.31	-0.22	0.75	0.83	1.32	1.42
p-value	(0.34)	(0.75)	(0.83)	(0.45)	(0.41)	(0.19)	(0.16)
Average Standardized Abnormal Return							
$\overline{SCAR}$ (in sd)	0.19	0.06	-0.18	0.13	-0.01	0.06	0.21
J_2	1.05	0.35	-1.00	0.74	-0.07	0.32	1.16
p-value	(0.30)	(0.72)	(0.32)	(0.46)	(0.95)	(0.75)	(0.24)

Note: The Table shows estimation results for average cumulated abnormal returns ($\overline{CAR}$), reported in percent (%), and average standardized abnormal returns ($\overline{SCAR}$), reported in standard deviations (sd), for the CAPM and the GARCH-adjusted CAPM.
The J_1 and J_2 rows report the statistics depicted in sections 2.1 (CAPM) and 2.2 (GARCH-adjusted CAPM). p-value reports the probability of observing a J value in the row above, given the validity of the corresponding null hypothesis. The t row reports the t statistic proposed by Boehmer, Musumeci, and Poulsen (1991).

The sample consists of 18 firms/securities and 31 events.

Table 6: Estimated change in the market value - US sample

Window	Mean	Median	Standard deviation	Minimum	Maximum
CAPM					
$[-5,5]$	-892.33	-47.31	5295.74	-38787.31	47770.60
$[-5,1]$	-732.68	-34.82	2836.36	-26583.43	8283.07
$[-1,1]$	-10.78	6.56	2537.32	-17169.03	20828.81
$[0]$	78.03	1.86	1385.77	-6550.18	12261.30
$[1]$	-80.18	-32.00	1236.61	-6996.48	10759.09
$[1,2]$	-183.01	-10.68	2098.39	-16133.28	18368.36
$[1,5]$	-255.08	-31.98	4344.61	-20084.69	50713.45
GARCH-adjusted CAPM					
$[-5,5]$	-1109.64	-92.50	5682.47	-42569.32	51049.84
$[-5,1]$	-899.55	-67.06	3062.60	-29573.22	9164.39
$[-1,1]$	-92.02	1.17	2652.67	-19171.28	21667.93
$[0]$	55.73	1.06	1436.47	-7126.81	13039.76
$[1]$	-117.35	-32.48	1242.77	-7809.33	10301.96
$[1,2]$	-245.62	-6.39	2145.22	-16420.30	18375.48
$[1,5]$	-363.37	-34.07	4516.07	-22180.27	52165.31

Note: The Table shows the estimated change in the market value in million US-Dollars. The window column shows the beginning and the end of the event window in event time.
These figures are real quantities, inflation adjusted on a monthly basis with November 2008 as the base month.

We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1 + \hat{\varepsilon}^\star_{it}) - 1 \right)$, where $\hat{\varepsilon}^\star_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

Table 7: Estimated change in the market value - German sample

Window	Mean	Median	Standard deviation	Minimum	Maximum
CAPM					
$[-5,5]$	368.42	-183.28	307.84	-673.28	3074.18
$[-5,1]$	202.71	-135.80	212.45	-903.40	1758.32
$[-1,1]$	157.32	-220.20	323.84	-818.87	4312.62
$[0]$	79.36	84.04	77.46	-474.12	457.07
$[1]$	138.39	-125.04	335.72	-998.77	4538.08
$[1,2]$	128.17	-130.51	335.77	-1004.81	4472.89
$[1,5]$	309.37	-91.29	473.65	-1590.10	6441.48
GARCH-adjusted CAPM					
$[-5,5]$	420.62	-164.41	329.13	-611.38	3462.38
$[-5,1]$	240.50	-137.26	224.27	-918.95	1761.06
$[-1,1]$	182.55	-222.11	337.63	-772.71	4530.77
$[0]$	87.95	97.69	78.77	-457.22	510.89
$[1]$	150.83	-130.81	344.57	-972.41	4676.92
$[1,2]$	145.29	-130.05	344.71	-976.09	4617.90
$[1,5]$	335.60	-50.16	486.62	-1590.72	6642.14

Note: The Table shows the estimated change in the market value in million US-Dollars. The window column shows the beginning and the end of the event window in event time.
These figures are real quantities, inflation adjusted on a monthly basis with November 2008 as the base month.

We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1+\hat{\varepsilon}^\star_{it}) - 1 \right)$, where $\hat{\varepsilon}^\star_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

Table 8: Estimated change in the market value - Swiss sample

Window	Mean	Median	Standard deviation	Minimum	Maximum
CAPM					
$[-5,5]$	2535.72	353.98	1163.78	-1099.92	12948.73
$[-5,1]$	1454.14	712.04	943.35	-5074.68	10574.13
$[-1,1]$	1486.88	364.62	667.86	-1980.34	6519.42
$[0]$	873.82	429.67	397.84	-1909.76	3694.81
$[1]$	405.94	117.63	227.37	-785.44	2210.91
$[1,2]$	1182.26	423.44	590.81	-1449.53	5952.40
$[1,5]$	1462.63	470.88	642.69	-1578.80	6722.05
GARCH-adjusted CAPM					
$[-5,5]$	2732.27	259.95	1181.14	-1159.21	13077.47
$[-5,1]$	1558.81	753.57	953.25	-5029.61	10634.06
$[-1,1]$	1538.48	483.98	676.59	-1948.95	6687.75
$[0]$	908.56	383.98	403.14	-1901.86	3702.83
$[1]$	390.80	73.06	225.74	-785.46	2217.53
$[1,2]$	1181.06	406.08	587.07	-1330.81	5968.04
$[1,5]$	1539.84	345.07	649.27	-1286.54	6721.98

Note: The Table shows the estimated change in the market value in million US-Dollars. The window column shows the beginning and the end of the event window in event time.
These figures are real quantities, inflation adjusted on a monthly basis with November 2008 as the base month.

We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1+\hat{\varepsilon}^{\star}_{it}) - 1\right)$, where $\hat{\varepsilon}^{\star}_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

Table 9: Estimated change in the market value - UK sample

Window	Mean	Median	Standard deviation	Minimum	Maximum
CAPM					
$[-5, 5]$	-201.98	-218.69	133.53	-1154.21	1153.00
$[-5, 1]$	-173.56	-218.25	121.29	-1046.31	1018.21
$[-1, 1]$	-318.50	-216.72	89.67	-1033.24	-25.85
$[0]$	-85.93	-30.31	26.77	-306.62	3.90
$[1]$	21.49	-3.30	24.65	-176.30	230.46
$[1, 2]$	16.38	8.22	26.22	-192.40	223.79
$[1, 5]$	-9.35	-19.29	44.73	-296.80	445.06
GARCH-adjusted CAPM					
$[-5, 5]$	-215.88	-230.57	137.28	-1248.36	1153.00
$[-5, 1]$	-179.69	-223.88	122.13	-1028.66	1018.20
$[-1, 1]$	-322.25	-217.79	90.15	-1026.22	-25.63
$[0]$	-87.68	-28.96	27.21	-306.99	3.90
$[1]$	20.98	-4.30	24.52	-178.39	232.59
$[1, 2]$	14.43	8.10	26.60	-196.50	228.68
$[1, 5]$	-18.23	-19.05	47.23	-341.65	458.39

Note: The Table shows the estimated change in the market value in million US-Dollars. The window column shows the beginning and the end of the event window in event time.
These figures are real quantities, inflation adjusted on a monthly basis with November 2008 as the base month.

We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1 + \hat{\varepsilon}^{\star}_{it}) - 1 \right)$, where $\hat{\varepsilon}^{\star}_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

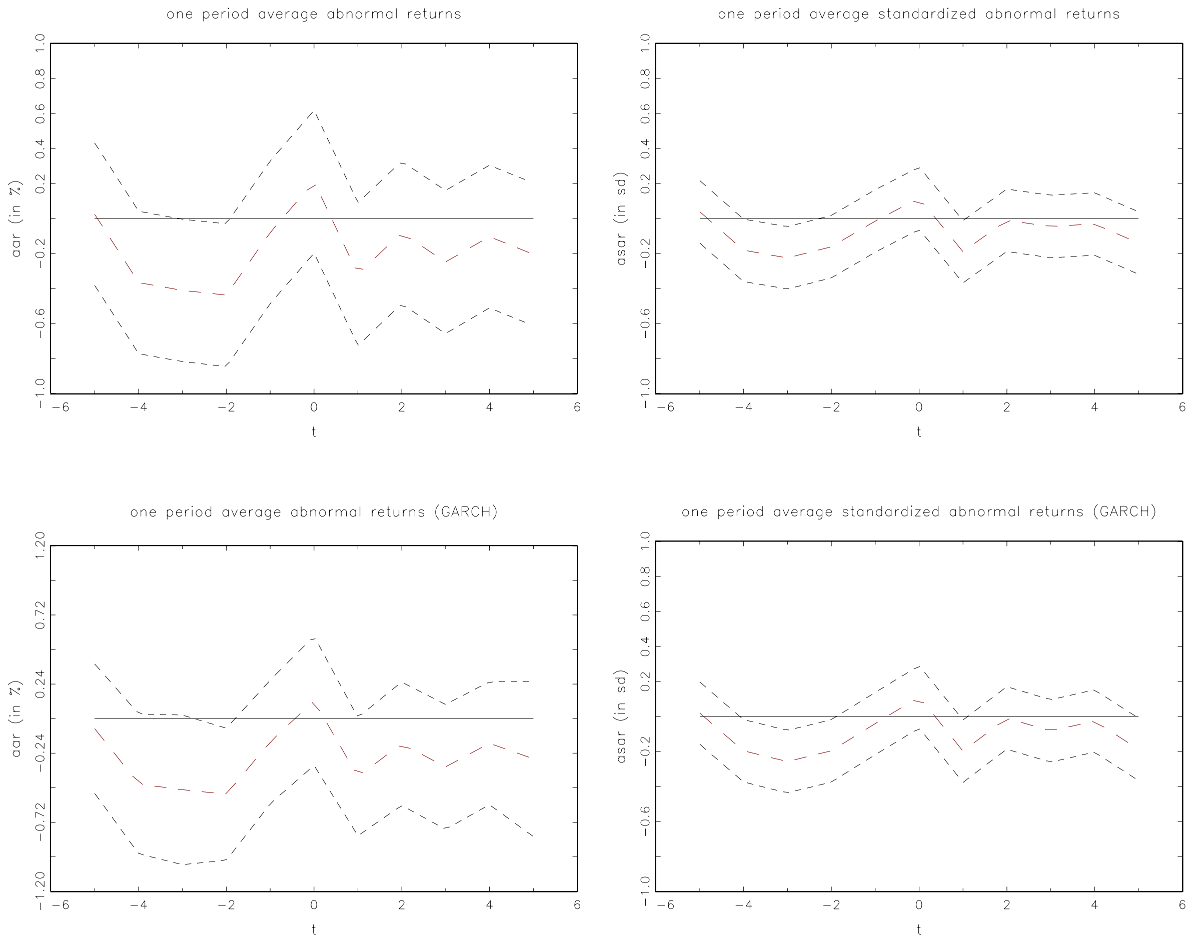
Table 10: Estimated change in the market value - German, Swiss, UK and Irish sample

Window	Mean	Median	Standard deviation	Minimum	Maximum
CAPM					
$[-5, 5]$	921.35	-25.98	1210.21	-1153.31	12945.83
$[-5, 1]$	509.93	141.30	974.11	-5070.66	10572.39
$[-1, 1]$	463.69	-61.45	748.02	-1978.72	6519.47
$[0]$	293.07	12.19	406.05	-1909.20	3694.58
$[1]$	194.63	-34.02	405.73	-998.89	4538.27
$[1, 2]$	439.53	15.88	679.31	-1449.70	5951.90
$[1, 5]$	599.58	41.15	798.20	-1590.29	6730.27
GARCH-adjusted CAPM					
$[-5, 5]$	1357.43	4.73	1625.57	-1680.41	17266.18
$[-5, 1]$	741.47	32.38	1288.70	-7440.74	14040.16
$[-1, 1]$	708.88	-23.30	945.31	-2758.52	8689.39
$[0]$	395.26	3.54	539.51	-2683.27	4807.75
$[1]$	261.13	-28.68	457.30	-1138.23	4603.29
$[1, 2]$	646.31	5.64	866.93	-1498.54	7793.06
$[1, 5]$	859.35	5.96	1018.05	-1654.62	9741.05

Note: The Table shows the estimated change in the market value in million US-Dollars. The window column shows the beginning and the end of the event window in event time.
These figures are real quantities, inflation adjusted on a monthly basis with November 2008 as the base month.

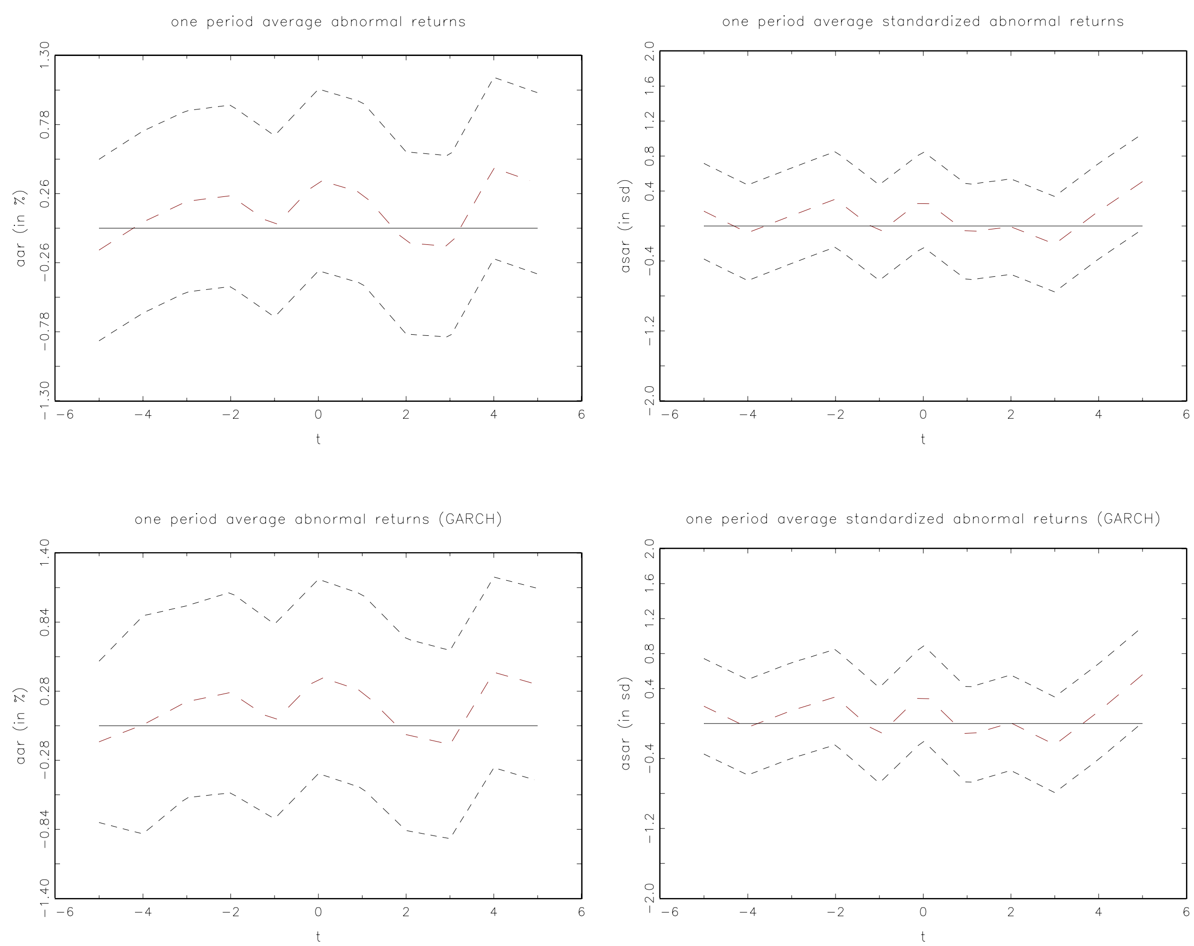
We calculate these figures by assuming a domestic investor who holds the local currency. For comparing purposes we convert the proceeds each day into US-Dollars. We calculate the estimated Dollar Change in the Market Value as: $\Delta MV^i_{t_1,t_2} = MV^i_{t_1-1} \cdot \left(\prod_{t=t_1}^{t_2} (1 + \hat{\varepsilon}^\star_{it}) - 1 \right)$, where $\hat{\varepsilon}^\star_{it}$ denotes the abnormal return of security i at time t, $MV^i_{t_1-1}$ denotes the market value of security i one day before the event window, $\Delta MV^i_{t_1,t_2}$ denotes the change in the market value over the considered event window, t_1 and t_2 denote the beginning and the end of the event window, respectively.

Figure 1: One period average abnormal and standardized average abnormal returns - US sample.



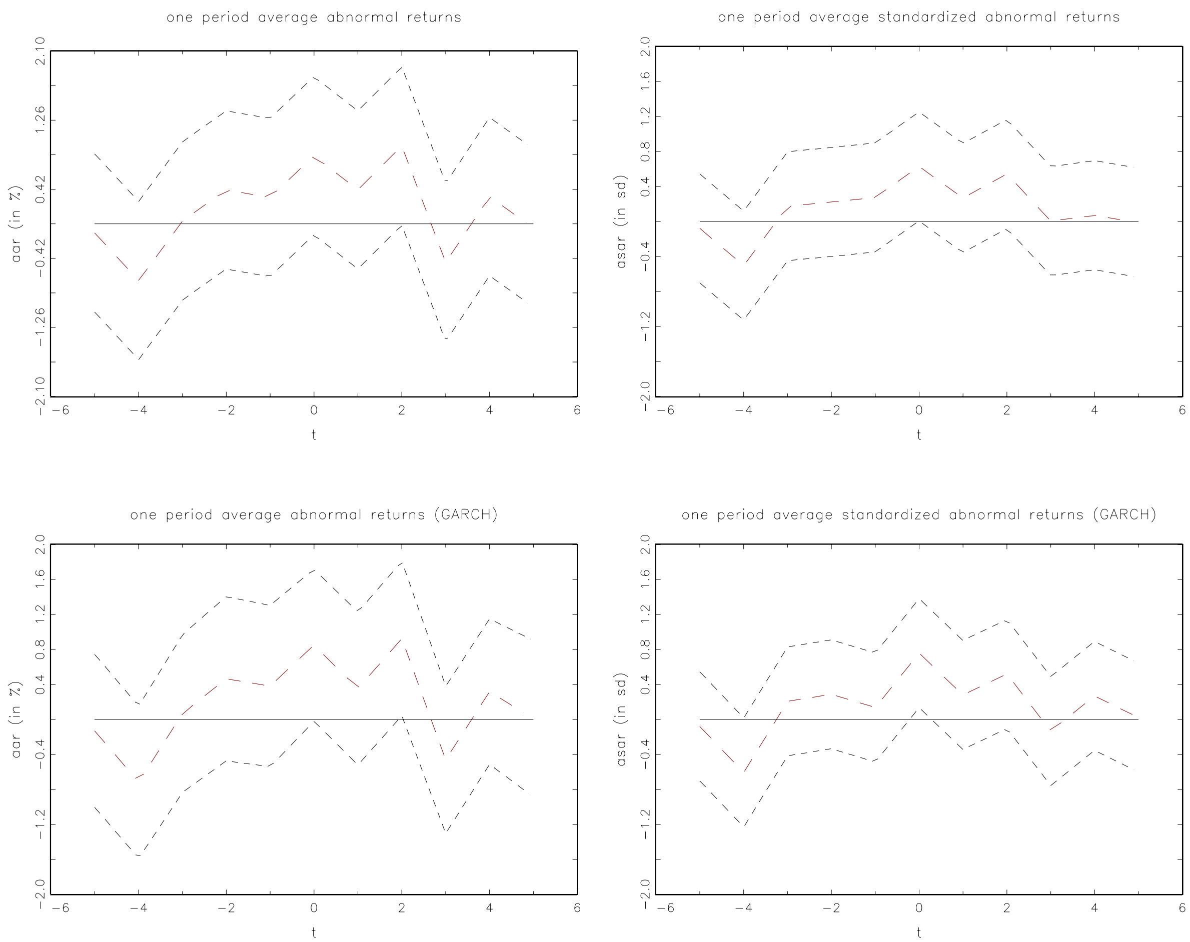
Note: The Figure shows in the upper two graphs the one period abnormal returns of the CAPM estimation and in the lower two graphs the one period abnormal returns of the GARCH-adjusted CAPM estimation. The middle dashed line represent the one period abnormal return. The other dashed lines represent upper and lower bounds of a 95% confidence interval around the respective abnormal return.

Figure 2: One period average abnormal and standardized average abnormal returns - German sample.



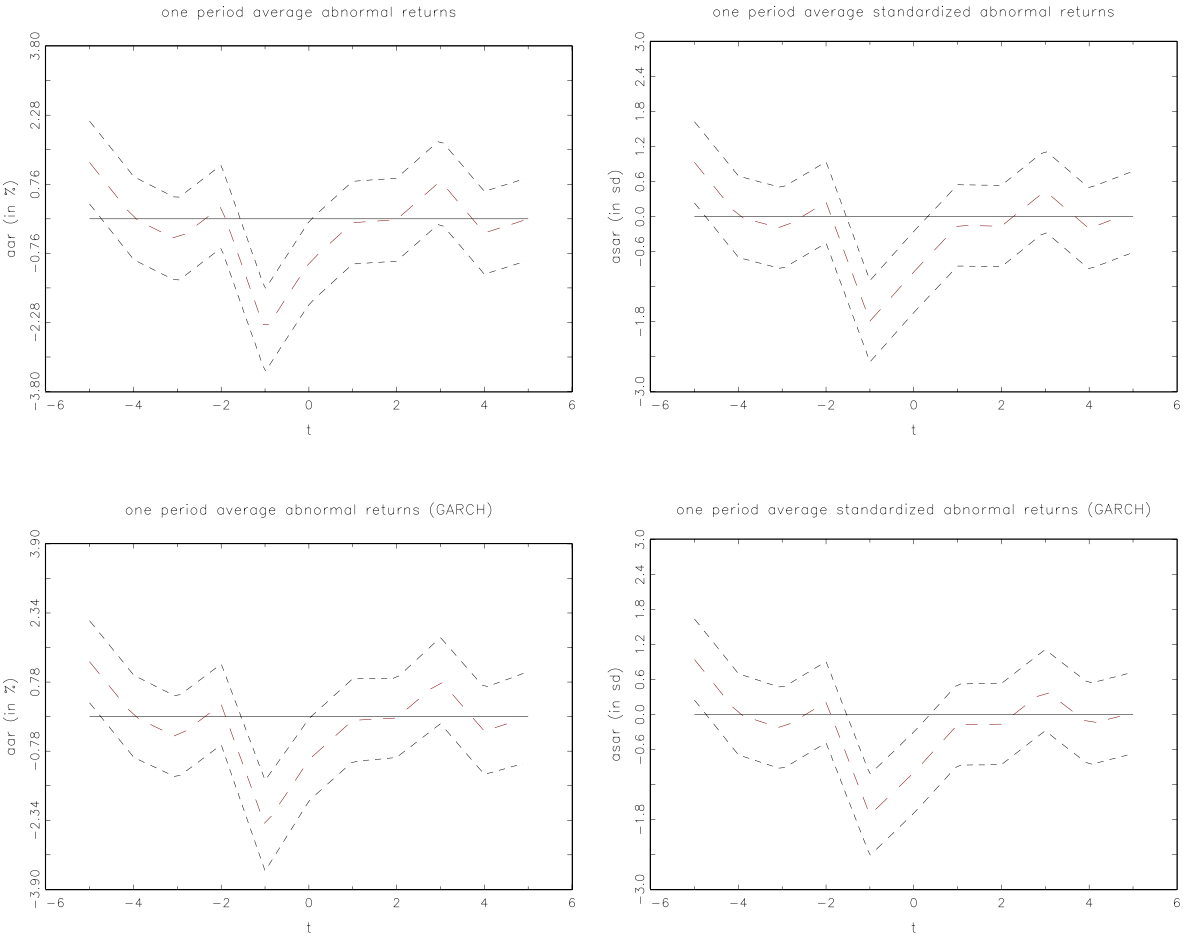
Note: The Figure shows in the upper two graphs the one period abnormal returns of the CAPM estimation and in the lower two graphs the one period abnormal returns of the GARCH-adjusted CAPM estimation. The middle dashed line represent the one period abnormal return. The other dashed lines represent upper and lower bounds of a 95% confidence interval around the respective abnormal return.

Figure 3: One period average abnormal and standardized average abnormal returns - Swiss sample.



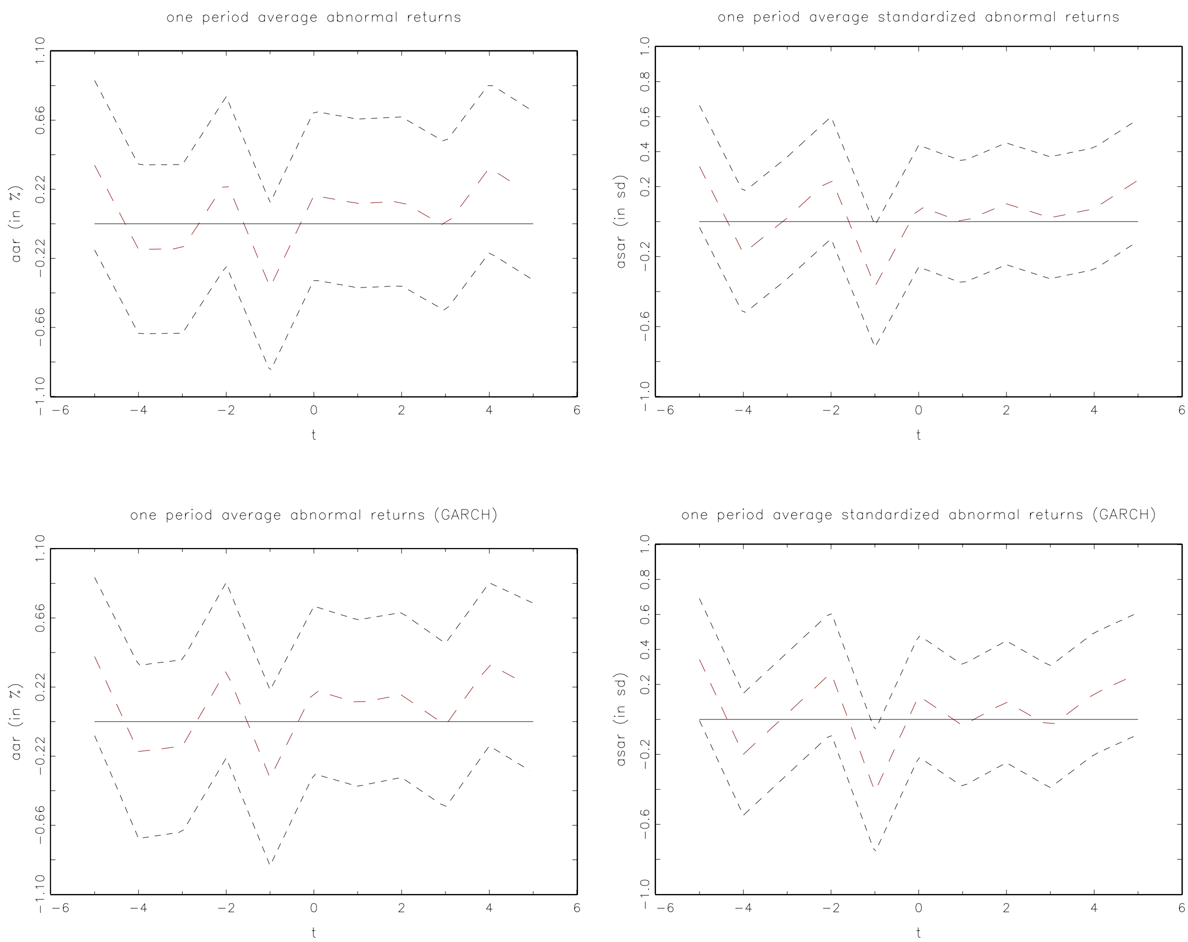
Note: The Figure shows in the upper two graphs the one period abnormal returns of the CAPM estimation and in the lower two graphs the one period abnormal returns of the GARCH-adjusted CAPM estimation. The middle dashed line represent the one period abnormal return. The other dashed lines represent upper and lower bounds of a 95% confidence interval around the respective abnormal return.

Figure 4: One period average abnormal and standardized average abnormal returns - UK sample.



Note: The Figure shows in the upper two graphs the one period abnormal returns of the CAPM estimation and in the lower two graphs the one period abnormal returns of the GARCH-adjusted CAPM estimation. The middle dashed line represent the one period abnormal return. The other dashed lines represent upper and lower bounds of a 95% confidence interval around the respective abnormal return.

Figure 5: One period average abnormal and standardized average abnormal returns - German, Swiss, UK and Irish sample.



Note: The Figure shows in the upper two graphs the one period abnormal returns of the CAPM estimation and in the lower two graphs the one period abnormal returns of the GARCH-adjusted CAPM estimation. The middle dashed line represent the one period abnormal return. The other dashed lines represent upper and lower bounds of a 95% confidence interval around the respective abnormal return.