

NATURAL DISASTER-INDUCED AUSTRALIAN EQUITY MARKET REACTION DISCRIMINATION ACROSS INDUSTRIES

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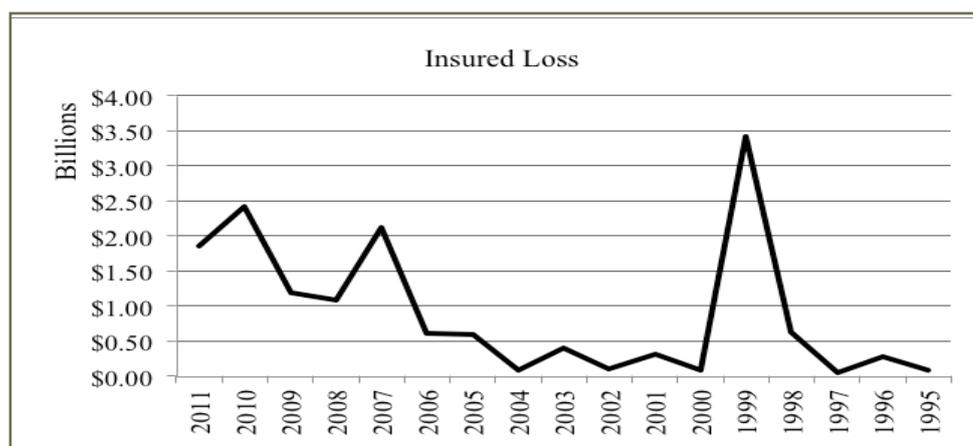
Natural disasters in Australia have caused significant damage to the local economy and businesses. This paper employs the event study methodology to examine the natural disaster-induced equity market reaction using daily equity return of 32 Australian firms within the following seven major industries in the State of Queensland: agriculture, banking, insurance, mining, construction, retailing and transportation. The result indicates that the 2005-2011 natural disasters in Queensland (severe storms, hail, cyclones and floods) have had evident negative effects on the Australian equity market, whereas the net effects across industries may be either positive or negative to different extents. Most of the effects of natural disasters on equity market returns have been statistically evident two days prior to the days of the events due to weather information disclosures, the days of the events and, with some adjustments, the days following the event, as economic and/or insured loss information is released.

INTRODUCTION

In the past decade, frequent occurrences of natural disasters in Queensland have resulted in huge economic losses to the community and local businesses. Natural disasters (including floods, storms, bushfires, hurricanes, cyclones, tsunamis and earthquakes) continue to cause severe and increasing damage to global economies and disruptions to domestic financial activities (Worthington & Valadkhani, 2005). At least part of this increase is attributed to global climate change.

In Australia, the average annual cost of natural disasters between 1967 and 1999 was A\$ 1.14 billion, including the cost of deaths and injuries (BTE, 2001). Evidence from the Australian Emergency Management (AEM) records also indicate that the number of injuries and deaths and the insured costs of disasters per year are increasing, as shown by Figure 1. These increases are partly due to better reporting, increasing populations and poor infrastructure in vulnerable areas (AEM, 2011). These increased costs that affect local industries and communities include the direct costs associated with damage to infrastructure, buildings and vehicles and the indirect costs associated with the loss of production, emergency response, relief and clean-up.

Figure 1 – Increased Insured Loss from 1995 to 2011 (Source from AEM Database)



Given the potential impact of increased catastrophic shocks caused by climate change, it is essential to analyse the Australian equity market reaction to natural disasters and to explore the market's demonstrated ability to discriminate across various industries.

If the market is rational and efficient, it would be surprising to find that exposed firms across different industries experienced a similar natural disaster-induced market reaction. If the equity returns' response to natural disasters is uniform across all firms in various industries regardless of their geographic business and risk exposure, then a type of contagion effect may have swept through all of the sample firms.

The results will indicate whether the natural disasters conveyed important new information to the market that was either reflected across all industries in the affected areas or that caused the reactions, at some level.

This article analyses the equity market reaction of 32 sample firms to 15 natural disasters that occurred in the State of Queensland, Australia, between 2005 and 2011, using the standard event study cumulative abnormal returns (CAR) method adjusted for cross-sectional dependence.

The results, as interpreted in section four, show that the natural disasters between 2005 and 2011 had a large and significantly negative impact on firms that have businesses

in the State of Queensland, with some variation across seven different industries.

This evidence is consistent with the negative effects from the pre-disaster weather forecasts and the release of relevant information and with the slow equity value increases after economic losses or post-disaster reports, which are released a few days after the occurrence of natural disasters.

Section five provides a concluding remark, and the attached appendices offer further information on disaster portfolios, the CARs of the sample firms and each of the seven industries.

LITERATURE REVIEW

In response to these concerns, a body of literature has arisen to examine the financial impact of natural events as well as corporate disasters (i.e. Knight & Pretty, 1999) on capital markets. To date, however, most of this research has focused narrowly on the property-liability insurance industry. Lamb (1995), Shelor, Anderson & Cross (1992), Angbazo and Narayanan (1996), Baginski, Corbett & Ortega (1991) and Cagle (1996) have studied the impact of natural disasters on the insurance industry as well as on the equity values of individual insurers.

Although there are two opposing effects of natural disasters on property-liability insurers, these effects are not mutually exclusive. The most commonly observed effects

are the large negative impact on insurance firms' equity value (equity prices decline at the time of the disasters) due to the large insurance claims paid to policyholders for their damages, which is only slightly offset by the subsequent premium increases. Furthermore, the events show evidence of a contagion effect on insurers with no claims exposure in the disaster-affected regions (Angbazo & Narayanan, 1996; Yamori & Kobayashi, 1999).

There is, however, another more subtle effect. That is, disasters lead to larger profits because of high post-disaster insurance rates and low perceived risk, in particular empirical evidences show that many properties were uncovered or under-covered at the time of the event. For example, in Australia, the proportion of insured losses to total losses is 35 per cent for severe storms and bushfires, 25 per cent for earthquakes, 20 per cent for tropical cyclones and as little as 10 per cent for floods (BTE, 2001). Gron (1990), Shelor, Anderson & Cross (1992), and Lamb & Kennedy (1997) argue that natural disasters increase the demand for insurance from previously uninsured consumers, thus leading to premium increases.¹ This expected higher premium and the subsequent profits increase the equity value of insurance firms at the time of the disaster (positive effect) or at least partially offset the negative effects of natural disasters.

It is clear that existing research into the financial impact of disasters suffers a number of limitations. First, the existing research concentrates on the property-liability insurance industry, although it is well known that disasters have a substantial impact on non-insured industries and sectors. Second, there has been a tendency to concentrate on single events, although valuable lessons about the different impacts of disasters are likely to be learned when several events are compared within a single study.

Shelor, Anderson, & Cross (1990) examined the effects of California's earthquake on the equity value of firms in the real estate industry. The authors argued that the earthquake conveyed important information to the market, which was reflected in significant negative equity returns among real estate firms operating near earthquake-affected areas, whereas other real estate firms were generally unaffected. Investors viewed the earthquake as a signal of unfavourable financial conditions for the real estate industry in disaster-affected areas. These studies provide part of the motivation for this study of the effects of natural disasters on the equity values of firms in various industries.

Yang, Wang & Chen's (2008) analysis indicates a significant negative correlation between the disaster loss amount and the insurance industry's equity returns and abnormal returns and a significant positive correlation with the construction industry, but no significant correlation with the real estate industry.

Worthington & Valadkhani (2004, 2005) examined the impact of natural disasters on the Australian equity

market using intervention analysis. They found that three industry sectors (consumer discretionary, financial services and materials) are the most sensitive to both natural and industrial disasters, with bushfires, cyclones and earthquakes having a major effect on market returns, and severe storms and floods having less severe effects. Although the strongest effects have occurred on the day of the event, some adjustment occurs in the days that follow.

With the exception of Worthington & Valadkhani's studies (2004, 2005), there is little evidence of the impact of ongoing natural disasters, both small and large, on the behaviour of the capital market. Furthermore, few studies have examined the influence of the many types of natural disasters positioned to have a financial impact.

Accordingly, the purpose of this paper is to model the market sector impacts of disasters in Australia. It is one of the few studies on the financial impacts of natural disasters outside the US. The paper is divided into four main areas. The second section explains the data employed in the analysis and presents some summary statistics. The third section discusses the methodology employed. The results are presented in the fourth section. The paper ends with some brief concluding remarks. The mixed results indicate the importance of disaster-effect analyses in different market settings. This research is designed to provide insight by examining the local industries' equity responses to natural disasters in Queensland, Australia.

EVENT STUDY METHODOLOGY

Schwert (1981) suggests that analyses using firms' equity price data are powerful because they incorporate all relevant information when it is available. Furthermore, these analyses facilitate the separation of firm- and industry-wide effects from market-wide movements.

Two sets of data are employed in this analysis. The first set is the daily closing prices of 32 firms and the All Ordinaries Index (All Ord) of the Australian Equity Exchange. The second set of data comprises the most significant natural disasters that occurred in Queensland, Australia between mid-2005 and November 2011, as collected from Australian Emergency Management (AEM). AEM provides a database of Australian natural disasters that is compiled using estimates from insurance industry bodies, published disaster reports and articles in newspapers and other media.

The relevant dates of the disasters were collected from the AEM database to identify the 'event date' for each natural disaster. The first trading day immediately following each disaster date, according to the records of the AEM database, was identified as the event date (Day 0) for each event in this study. In the AEM database, for each disaster recorded, the data include the disaster's occurrence date(s), period, insured loss amount, and deaths and injuries. If more than one disaster occurred on the same date, the insured loss amount and other information about these

disasters was combined to examine equity market reactions. The duration of these events varied; earthquakes and, to a lesser extent, cyclones and severe storms are confined to a single day, whereas bushfires and floods occur over several days, weeks or even months. The dates included in the analysis are when substantial loss was first deemed likely.

The final sample consisted of 15 disasters from 2005 to 2011. A summary of the characteristics of these disasters is presented in Table 1, and Table 2 shows detailed portfolios of these 15 disasters.

Table 1— Key Descriptive Statistics: Disasters in Queensland, 2005–2011

Variables	Mean	Median	SD	Skewness	Kurtosis	Min	Max	Cases
Death	2.73	0	8.95	3.84	14.82	0	35	15
Injury	2.00	0	7.75	3.87	15	0	30	15
Insured Loss								
Million (AUD)	335.01	61	631.95	2.87	8.93	15	2,400	14

Note: Insured loss has 14 cases, as a disaster does not have insured loss data available.

Table 2 — Natural Disasters Portfolio (Source from AEM Database)

Event Title	Region	Category	Start Date	End Date	Dead	Injured
Hail - Brisbane	Brisbane	Hail	19/05/2005	19/05/2005		
Flood - South East Queensland	Gold Coast, Noosa Heads	Flood	29/06/2005	30/06/2005	2	
Hail - Gold Coast	Brisbane	Hail	12/10/2005	12/10/2005		
Cyclone Larry	Cairns	Cyclone	20/03/2006	20/03/2006		30
Severe Storm - South East Queensland and Northern New South Wales	Brisbane, Bundaberg, Lismore (NSW), Roma	Severe Storm	7/10/2007	12/10/2007		
Flood - South East Queensland	Brisbane, Gold Coast, Warwick, Goodiwindi	Flood	27/12/2007	7/01/2008		
Flood - Queensland	Ayr, Birdsville, Blackall, Boulia, Cairns, Cape York, Charleville, Charters Towers, Clermont, Cooktown, Coringa Islets, Croydon, Cunnamulla (QLD), Eromanga, Longreach, Mackay, Mitchell River, Moree (QLD), Mornington Island, Mount Isa, Normanton, Osprey Reef, Richmond, Rockhampton, Roma, Taroom, Tibooburra (QLD), Townsville, Weipa, Windorah, Winton	Flood	1/01/2008	31/01/2008		
Flood - South East Queensland	Blackall, Bundaberg, Cairns, Cape York, Charters Towers, Clermont, Cooktown, Croydon, Longreach, Mackay, Mitchell River, Normanton, Rockhampton, Taroom, Tibooburra (QLD), Townsville, Weipa	Flood	10/02/2008	18/02/2008		
Flood - Mackay	Mackay	Flood	15/02/2008	17/02/2008	1	

Table 2 — Con't

Event Title	Region	Category	Start Date	End Date	Dead	Injured
Severe Storm - South East Queensland	Brisbane	Severe Storm	16/11/2008	22/11/2008	1	
Flood - North Queensland	Ayr, Mackay, Townsville	Flood	12/01/2009	14/02/2009		
Flood - North Queensland	Cairns, Townsville	Flood	31/01/2009	7/02/2009	1	
Flood - Queensland	Blackall, Brisbane, Charleville, Clermont, Eromanga, Moree (QLD), Roma, Taroom, Windorah	Flood	28/02/2010	5/03/2010		
Flood - Queensland	Brisbane	Flood	30/11/2010	17/01/2011	35	
Cyclone Yasi	Ayr, Cairns, Townsville	Cyclone	2/02/2011	3/02/2011	1	

The 40-day estimation period and 5-day event period do not overlap the estimation and event periods of other disasters in the sample. The equity price data for each natural disaster was generated from DataStream. The summary statistics of firms' share returns within the periods of the sample events are presented below.

Table 3 — Summary Statistics of All Ord and 32 Sample Firms' Daily Equity Returns

Firms	No Observ	Mean	Median	Standard Deviation	Variance	Kurtosis	Skewness	Min	Max
1	46	-0.0061	-0.0107	0.1100	0.0121	0.0852	0.5514	-0.1960	0.2743
2	46	-0.0196	-0.0138	0.1542	0.0238	2.3296	-1.0454	-0.5064	0.2549
3	46	-0.0012	-0.0363	0.3724	0.1387	35.4177	5.5778	-0.3764	2.3234
4	46	-0.0093	-0.0030	0.0965	0.0093	-0.4059	-0.3303	-0.2485	0.1680
5	46	-0.0704	0.0150	0.5539	0.3068	35.5737	-5.6697	-3.5314	0.2605
6	46	-0.0014	0.0132	0.1108	0.0123	0.8492	-0.3810	-0.3341	0.2476
7	46	-0.0061	-0.0093	0.0950	0.0090	1.5460	-0.6361	-0.3252	0.1560
8	46	0.0332	0.0074	0.2527	0.0639	0.6587	0.3458	-0.5324	0.7722
9	46	-0.0291	-0.0468	0.0865	0.0075	-0.2580	0.2078	-0.2215	0.1613
10	46	-0.0203	-0.0184	0.0981	0.0096	1.4902	0.3282	-0.2487	0.2904
11	46	-0.0317	-0.0346	0.0671	0.0045	-0.2559	0.2706	-0.1776	0.1225
12	46	0.1812	-0.0031	1.3108	1.7181	44.8366	6.6559	-0.5941	8.8259
13	46	-0.0320	-0.0185	0.1144	0.0131	7.5902	-1.7950	-0.5376	0.1893
14	46	0.0057	-0.0046	0.0861	0.0074	0.0019	-0.4267	-0.2371	0.1424
15	46	-0.0047	-0.0038	0.0971	0.0094	-0.3865	-0.1116	-0.2185	0.1860
16	46	-0.0190	0.0017	0.1486	0.0221	0.2689	-0.3733	-0.4071	0.2909
17	46	0.0010	-0.0256	0.1177	0.0139	0.4562	0.5544	-0.2821	0.2819
18	46	-0.0095	-0.0019	0.1385	0.0192	0.0737	0.0641	-0.2931	0.3604
19	46	-0.0792	-0.0639	0.1600	0.0256	0.1622	-0.3082	-0.5042	0.2489
20	46	-0.0252	-0.0200	0.1015	0.0103	0.7093	0.3325	-0.2300	0.2834
21	46	-0.0249	-0.0196	0.1147	0.0132	-0.9251	-0.0129	-0.2419	0.1912
22	46	-0.0435	-0.0543	0.1366	0.0187	-0.7226	0.1931	-0.2748	0.2346
23	46	-0.0269	-0.0305	0.0832	0.0069	-0.4076	-0.0678	-0.2309	0.1375
24	46	-0.0254	-0.0358	0.1183	0.0140	-0.3696	0.0102	-0.2739	0.2165
25	46	-0.0048	-0.0135	0.0887	0.0079	3.9527	-0.6079	-0.3296	0.2204
26	46	-0.0242	-0.0375	0.0997	0.0099	0.1622	0.0476	-0.2862	0.1826
27	46	-0.0089	-0.0086	0.0663	0.0044	0.2890	-0.0842	-0.1641	0.1397
28	46	-0.0086	-0.0145	0.0946	0.0089	-0.1389	0.3560	-0.2158	0.2104

Table 3 — Con't

29	46	-0.0119	0.0018	0.1245	0.0155	-0.7147	-0.0951	-0.2941	0.2358
30	46	-0.0320	-0.0102	0.0857	0.0073	0.5650	-0.9450	-0.2851	0.0942
31	46	-0.0353	-0.0523	0.0915	0.0084	-0.4504	0.1970	-0.2186	0.1687
32	46	-0.0124	-0.0072	0.0574	0.0033	0.1726	-0.0576	-0.1551	0.1125
AllOrd	46	-0.0132	-0.0116	0.0577	0.0033	-0.4942	0.0481	-0.1239	0.1033
Average	46	-0.0126	-0.0175	0.1698	0.0798	4.1299	0.0858	-0.4054	0.5620

This table presents the sample means, medians, variances, maximums and minimums, standard deviations, skewness and kurtosis. The lowest mean return of sample firms is for firm 19 (-0.0792 compared to -0.0132 of All Ord), and three firms have positive mean returns (firm 8, with a mean return of 0.0332; firm 17, with a mean return of 0.0010; and firm 12, with the highest mean return of 0.1812). The lowest minimum return is for firm 5, with a -3.5314 return, and the highest maximum return is for firm 12, with an 8.8259 return. The standard deviations of returns range from 0.0574 to 1.3108.²

The returns of two firms (firms 3 and 12) are significantly positively skewed (5.5778 and 6.6559, respectively), indicating a greater probability of large increases than decreases in returns, or volatility clustering in daily returns. Conversely, the returns of half of the sample firms are significantly negatively skewed (i.e., -5.6697 to -1.7950). The kurtosis, or degree of excess, in all return series is also significantly large and greater than 3 (firms 3, 5 and 12 has kurtosis greater than 35), with an average of 4.1299, indicating leptokurtic distributions. The distribution properties of the daily returns largely appear non-normal.

Because the sample firms are in different industries but have the same calendar dates for all natural disaster events, their abnormal (residual) returns are not independent; rather they are cross-sectionally correlated.

The market model is used to calculate the equity price reaction to the disasters of each sample firm. The existence of significant abnormal (excess) returns (either positive or negative) provides evidence that the disasters generated new information to the market. The sign, magnitude and statistical significance of the abnormal returns for the entire sample indicate the presence of a market response to disaster-related information. Given the evidence of a reasonable and efficient market, firms with increased exposure to the disasters are expected to sustain a larger negative response.

To isolate the effects of the disaster on equity prices, it is necessary to rule out the effects of other events that may affect equity prices simultaneously. This process involves the estimation of so-called abnormal returns for a period immediately after the disaster, followed by the alignment of these abnormal returns on the day of the disaster (day 0). The average abnormal returns are accumulated over

what is now the disaster time, resulting in a set of portfolio returns from day 0. This set of returns is known as the cumulative abnormal returns (CARs).

The expected return for securities following a bivariate normal distribution can be expressed through the market model (Brown & Warner, 1985; MacKinlay, 1997; and Corrado, 2010):

$$\hat{R}_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, \tag{1}$$

where $\hat{R}_{i,t}$ = the estimated daily equity return of firm i at day t ;

$R_{m,t}$ = the actual daily return of the market portfolio for day t (All Ordinaries Index);

α_i, β_i = the estimated market model intercept and slope parameters, respectively; and

$\varepsilon_{i,t}$ = the error term, which is assumed to be normally distributed and serially independent.

A regression of security and market returns is used to estimate the parameters α_i and β_i based on an ordinary least squares procedure over an estimation period of 40 days, ending 5 days prior to the defined event date, as above. The estimation period does not include the 5-day period (event period) immediately prior to the disaster. The abnormal return for firm i on day t is the difference between the actual return and the regressed return:

For each firm i , the abnormal return or excess return on day t ,

$$\begin{aligned} AR_{i,t} &= R_{i,t} - \hat{R}_{i,t}, \text{ or} \\ &= R_{i,t} - (\alpha_i + \beta_i R_{m,t}), \end{aligned} \tag{2}$$

where $R_{i,t}$ = the actual daily return of firm i for day t ; and

$AR_{i,t}$ = the abnormal return for firm i for day t .

The natural log of the relative price is computed for the closing prices to produce a time series of continuously compound actual daily returns: $R_{i,t} = \log(P_{t+1}/P_t)$, where P_{t+1} and P_t represent the market price at time $t+1$ and t , respectively. The use of log-transformed returns improves the normality of the return distribution and eliminates negative values. The log transformation on the market proxy improves the normality of the market return distribution.

The average abnormal return (AAR) for day t is calculated as follows:

$$AAR_t = \frac{1}{n} \sum_{j=0}^n AR_{i,t}, \quad (3)$$

where n = the number of firms in the sample.

Equation (4) presents the test for significance of AAR_t as

$$Z_t = \frac{AAR_t}{S_t}, \quad (4)$$

where

$$S_t = \sigma \sqrt{1 + \frac{1}{T} + \frac{(R_{m,t} - R_m)^2}{\sum_{-40}^{-6} (R_{m,t} - R_m)^2}}$$

and σ = the standard deviation of the AAR_t during the estimation period;

T = the number of days in the estimation period;

$R_{m,t}$ = the return on the market (All Ordinaries index) at time t ; and

R_m = the mean return on the market (All Ordinaries Index) at time t during the estimation period.

In addition to testing the individual AAR_t , the abnormal returns for each firm are accumulated over the event window as follows:

$$CAR_{(t_1,t_2)} = \sum_{t=t_1}^{t_2} AAR_t, \quad (5)$$

where $CAR_{(t_1,t_2)}$ = the CAR of sample firms on day t in the event window;

t_1 = the earliest date in the event window (-5); and

t_2 = the later date in the event window (ranges from -5 to +5).

The test statistic to measure whether the CAR is significantly different from zero is calculated as follows:

$$Z_k = \frac{\sum_{t=t_1}^{t_2} \frac{AAR_t}{S_t}}{\sqrt{K}} \quad (6)$$

where k = the number of days in the CAR period, and S_t is calculated as above.

Following Brown & Warner (1985), MacKinlay (1997) and Corrado (2010); this study tests for a relationship between natural disaster-related information and the return responses. For each sample, the statistical hypothesis is that the mean excess return of each day in the event period (day 0 to day 5) is zero.

Several tests were conducted for the actual return ($R_{i,t}$) and the abnormal return ($AR_{i,t}$) to determine the robustness of the methodology in terms of auto-correlation, heteroscedasticity, and non-normality. The Durbin-Watson test results indicate that auto-correlation is minimal for both actual and abnormal returns. Heteroscedasticity, as measured by the F-test, does not appear to be a major problem in the ARs because only 0.6 per cent have a non-constant variance. The tests for skewness and kurtosis are significant; these results are consistent with previous studies (Brown & Warner, 1985). The Kolmogorov-Smirnov results indicate that daily actual returns are non-normal, whereas the Kolmogorov-Smirnov tests of abnormal returns indicate that the results are reasonably normally distributed. The skewness and kurtosis statistics suggest that the abnormal returns are non-normal and are inconsistent with the Kolmogorov-Smirnov results.

EMPIRICAL RESULTS

The event study results are presented in Table 4. The table presents data on the sample total abnormal returns (TARs) and the cumulative abnormal returns (CARs) for the entire event period, ranging from five days before the first trading day following natural disasters, as recorded by AEM database, to five days after this trading day.

Table 4. Total Abnormal Returns and Cumulative Abnormal Return Results

Time	Total ARs	TAR Z-Statistic	TAR P-Value	CARs	CAR Z-Statistics	CAR p-value
-5	-2.9368	-0.5032	0.6148	-2.9368	-0.5032	0.6148
-4	-6.3583	-1.0894	0.2760	-9.2951	-1.1261	0.2601
-3	-16.4080	-2.8113	0.0049*	-25.7031	-2.5426	0.0110*
-2	3.0278	0.5188	0.6039	-22.6753	-1.9425	0.0521**
-1	11.7687	2.0164	0.0438*	-10.9066	-0.8357	0.4033
0	-9.3093	-1.5950	0.1107	-20.2159	-1.4141	0.1573
1	3.4369	0.5889	0.5560	-16.7790	-1.0866	0.2772
2	-10.2532	-1.7567	0.0790	-27.0321	-1.6375	0.1015
3	-6.2130	-1.0645	0.2871	-33.2451	-1.8987	0.0576**
4	18.0884	3.0992	0.0019*	-15.1567	-0.8212	0.4115
5	-19.9810	-3.4235	0.0006*	-35.1377	-1.8152	0.0695**

* is $p < 0.05$

Statistically significant negative total abnormal returns (TARs) caused by 15 natural disasters between 2005 and 2011 were identified on event days -1 and -3. Because the event date in this study is defined as the first trading day immediately following the occurrence date of the disasters, the event date -1 in the above table for most sample cases is the occurrence date of the disasters.³ The negative abnormal return on day -3 suggests that the market may have anticipated these disasters' damages, to some extent, because the media and the Bureau of Meteorology disclose weather information prior to a disaster. The negative abnormal returns observed on the event days +4 and +5 may be due to the time needed by investors and relevant authorities to assess the property damage from the disasters as well as the media's gradual release of information, such as possible economic loss, to the public. The equity market, therefore, absorbs the information within the following days. Similarly, statistically significant cumulative abnormal returns (CARs) occurred on event days -2 and -3 and on days +3 and +5. The CARs on event days -2, +3 and +5 (-22.6753, -33.2451, and -35.1377, respectively) are significant at the 10 per cent level, whereas the CAR on event day -3 (-25.7031) is significant at the 5 per cent level. These results and conclusions are consistent with the studies by Angbazo and Narayanan (1996), which indicate that the 2005–2011 Queensland natural disasters had a negative impact on the equities of the sample firms.

The sample of this study included 32 firms within seven industries that had business exposure in a disaster-affected state. The vulnerability of different industries to natural disasters is expected to be distinct. To explore the different vulnerabilities to disasters, this study examines how the natural disasters affected each of the seven industries differently. The results of this examination are presented in Table 5.

The insurance, construction, retail and transportation industries have either statistically significant TARs or CARs on event days (-5 to +5). The insurance and retail industries have significant results for both their TARs and CARs. The TAR for the insurance industry on event day +5 (-7.76) displays a larger negative reaction in the equity market, which is statistically significant at the 1 per cent level, whereas the CAR on the same event day for the insurance industry (-12.92) is significant at the 10 per cent level. This is consistent with those studies on insurance industry that were published around 1990s (i.e. Lamb, 1995; Shelor, Anderson & Cross, 1992; Angbazo & Narayanan, 1996; and Cagle, 1996). The major reason why the insurance industry has a significant TAR and CAR on day +5 rather than on event day 0 or +1 is probably due to the release of the estimates of the insured and economic losses a few days after the disaster. The equity price reactions of firms in some industries, such as the insurance industry, rely heavily on the estimates of insured losses.

The retail industry, in comparison with the insurance

industry, is affected more directly by disasters. Both the TAR and the CAR on event day 0 (-4.23 and -10.26, respectively) are significant at the 10 per cent level (as shown in column 6, table 4). The market anticipated damage to local transportation, infrastructure, and supply and demand before the disasters. The market also anticipated the post-disaster information or released reports of these damages, causing the equity market reaction of the retail industry on event days +4 and +5 in terms of TARs (6.17 on day +4 and -5.08 on day +5) and on event days -2 and +3 in terms of CARs (-7.15 on day -2 and -11.55 on day +3).

Construction and transportation have statistically significant TARs on event days; however, none of the CARs of either industry, as presented in columns 5 and 7 is significant. The CAR of the construction industry on day +4 is significant at the 5 per cent level. This result is consistent with the findings from Yang, Wang & Chen (2008). The report on estimated damages to properties that is released a few days after the disasters should contribute to abnormal returns on day +4. Similarly, media releases of damages to roads and infrastructure could be the major cause of the equity market reaction in the transportation industry to disasters, as evidenced by a significant TAR (-3.79) on day +2 at the 10 per cent level. The larger negative effect on day -3 (-4.92 at the 5 per cent level) compared to day +2 may be due to the more severe initial forecasts of the impact of extreme weather prior to the occurrence of the natural disasters.

Surprisingly, industries such as agriculture and mining, which are expected to show equity market reactions to some degree, lack the statistical evidence to support those conjectures, as shown in the table below. The banking industry, due to its wide range of businesses across regions as well as investors' anxiety in relation to the Global Financial Crisis (as the period covered includes the Global Financial Crisis), shows no significant reaction to the 2005–2011 Queensland natural disasters. Figure 2 provides a display of the CARs for all sample firms and the CARs of each industry, for further comparison across industries.

CONCLUSION

The natural disasters that occurred between 2005 and 2011 in the State of Queensland resulted in significantly negative equity price responses for firms with business exposure in the disaster-affected State. The results further indicate that sample firms across seven industries (agriculture, banking, insurance, mining, construction, retail and transportation) reacted differently (either positively or negatively) and to different extents to disasters (industries demonstrate their reaction to disasters on different event dates at different statistical confidence levels, as shown in Table 5). The insurance and retail industries showed significantly negative reactions to disasters in the equity market, whereas the construction and transportation industries were comparably less vulnerable. Surprisingly, the agriculture and mining industries demonstrated no

significant reaction to natural disasters, nor did the banking sector.

Weather forecasts by the Bureau of Meteorology and media releases of information on extreme weather, combined with post-disaster reports and news coverage on damages, contributed to the significantly negative effects on event days -3 to +5 for sample firms in general. These results indicate that the market efficiently interprets the information on extreme weather and the damages to the local economy and businesses, and it discriminates among the different industries. The industries that are shown as more vulnerable financially to extreme weather, their adaption to climate change by using relevant financial risk management instruments, such as weather derivatives, is probably one of the solutions. This study therefore is meaningful for the business decision-making in relation to environmental-related corporate governance.

Figure 2. Equity Price Reaction to 1995-2011 Natural Disasters in Queensland

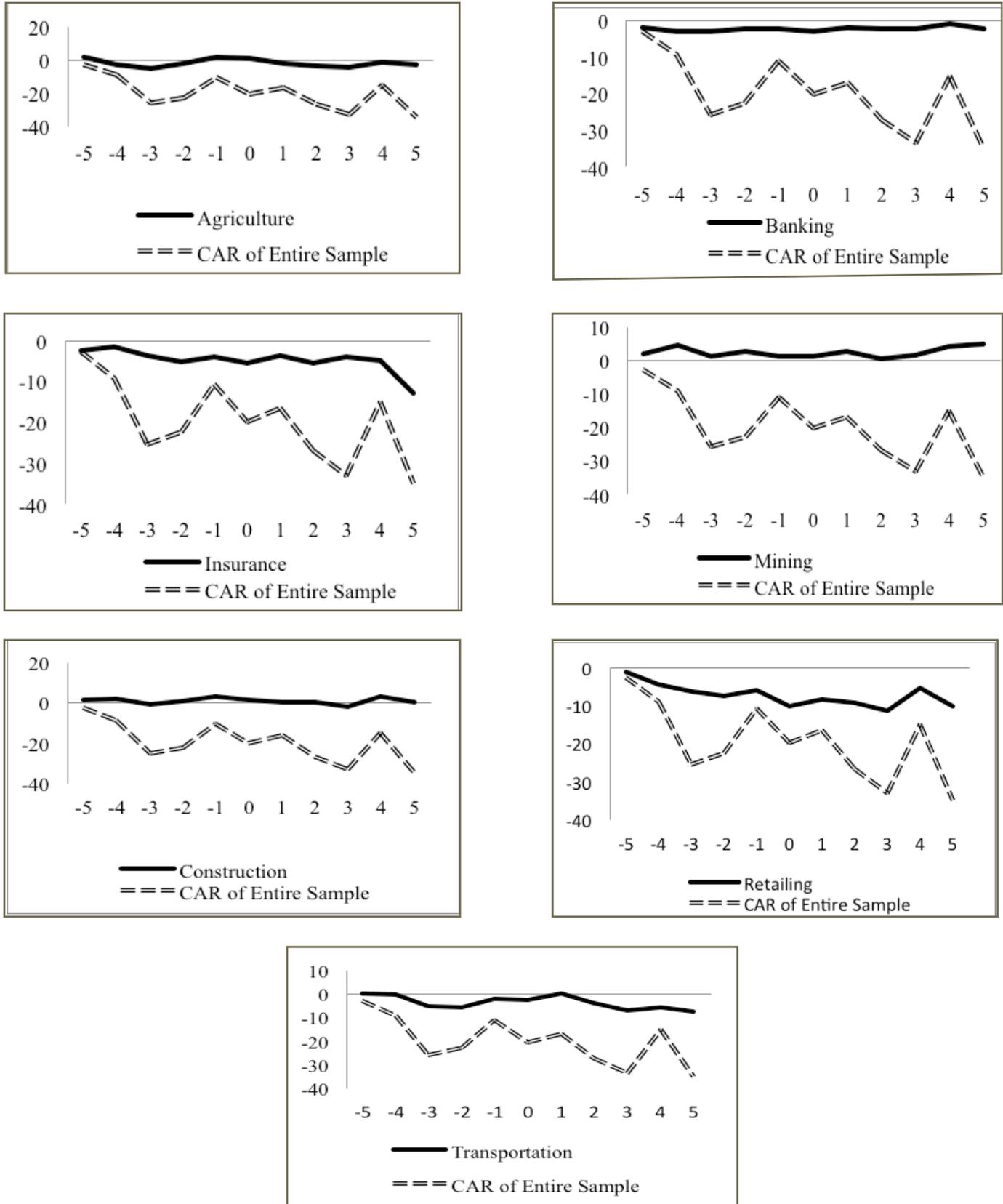


Table 5. CARs of 7 Industries

EVENT DATE	AGRICULTURE			BANKNG			INSURANCE			MINING			CONSTRUCTION			RETAILING			TRANSPORTATION		
	TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat		TOTAL ARs	TAR Z-stat	
-5	0.79	0.27	0.79	-1.80	-1.23	0.22	-2.65	-1.28	0.20	1.78	0.86	0.39	0.96	0.46	0.64	-1.31	-0.57	0.57	0.04	0.02	0.99
-4	-4.65	-1.59	0.11	-1.03	-0.71	0.48	0.96	0.47	0.64	2.70	1.31	0.19	0.74	0.36	0.72	-3.18	-1.38	0.17	-0.57	-0.25	0.81
-3	-1.88	-0.65	0.52	-0.13	-0.09	0.93	-2.09	-1.01	0.31	-3.27	-1.58	0.11	-2.86	-1.38	0.17	-1.91	-0.83	0.41	-4.92	-2.13	0.03*
-2	2.69	0.92	0.36	0.71	0.48	0.63	-1.71	-0.83	0.41	1.21	0.59	0.56	1.58	0.77	0.44	-1.11	-0.48	0.63	-0.35	-0.15	0.88
-1	4.07	1.39	0.16	0.04	0.03	0.98	1.22	0.59	0.56	-1.22	-0.59	0.55	2.49	1.21	0.23	1.48	0.64	0.52	3.53	1.53	0.13
0	-0.63	-0.22	0.83	-0.62	-0.42	0.67	-1.36	-0.66	0.51	-0.05	-0.02	0.98	-1.48	-0.72	0.47	-4.23	-1.83	0.07**	-0.40	-0.17	0.86
1	-3.45	-1.18	0.24	0.87	0.59	0.55	1.67	0.81	0.42	1.52	0.74	0.46	-1.08	-0.52	0.60	1.65	0.71	0.47	2.61	1.13	0.26
2	-1.40	-0.48	0.63	-0.35	-0.24	0.81	-1.67	-0.81	0.42	-2.32	-1.12	0.26	-0.52	-0.25	0.80	-0.92	-0.40	0.69	-3.79	-1.64	0.10**
3	-1.01	-0.35	0.73	0.20	0.13	0.89	1.59	0.77	0.44	0.98	0.47	0.64	-1.84	-0.89	0.37	-2.01	-0.87	0.38	-3.49	-1.51	0.13
4	3.55	1.22	0.22	1.27	0.87	0.38	-1.11	-0.54	0.59	2.77	1.34	0.18	4.81	2.33	0.02*	6.17	2.67	0.01*	1.59	0.69	0.49
5	-1.59	-0.54	0.59	-1.52	-1.04	0.30	-7.76	-3.76	0.00*	0.64	0.31	0.76	-2.61	-1.27	0.21	-5.08	-2.20	0.03*	-2.00	-0.87	0.38
EVENT DATE	CARs	CARs Z-Statistics	CARs p-value	CARs	CARs Z-Statistics	CARs p-value	CARs	CARs Z-Statistics	CARs p-value	CARs	CARs Z-Statistics	CARs p-value	CARs	CARs Z-Statistics	CARs p-value	CARs	CARs Z-Statistic	CARs p-value	CARs	CARs Z-Statistic	CARs p-value
-5	0.79	0.27	0.79	-1.80	-1.23	0.22	-2.65	-1.28	0.20	1.78	0.86	0.39	0.96	0.10	0.92	-1.31	-0.57	0.57	0.04	0.02	0.99
-4	-3.87	-0.94	0.35	-2.82	-1.37	0.17	-1.69	-0.58	0.56	4.48	1.54	0.12	1.69	-0.13	0.90	-4.49	-1.38	0.17	-0.53	-0.16	0.87
-3	-5.75	-1.14	0.26	-2.96	-1.17	0.24	-3.78	-1.06	0.29	1.21	0.34	0.73	-1.17	-0.72	0.47	-6.40	-1.60	0.11	-5.45	-1.36	0.17
-2	-3.07	-0.53	0.60	-2.25	-0.77	0.44	-5.49	-1.33	0.18	2.43	0.59	0.56	0.42	-0.24	0.81	-7.51	-1.63	0.10**	-5.80	-1.26	0.21
-1	1.00	0.15	0.88	-2.21	-0.68	0.50	-4.27	-0.93	0.35	1.21	0.26	0.79	2.91	0.36	0.72	-6.04	-1.17	0.24	-2.27	-0.44	0.66
0	0.37	0.05	0.96	-2.83	-0.79	0.43	-5.63	-1.11	0.27	1.16	0.23	0.82	1.43	-0.07	0.95	-10.26	-1.82	0.07**	-2.67	-0.47	0.64
1	-3.08	-0.40	0.69	-1.97	-0.51	0.61	-3.97	-0.73	0.47	2.68	0.49	0.62	0.35	-0.33	0.75	-8.62	-1.41	0.16	-0.06	-0.01	0.99
2	-4.48	-0.54	0.59	-2.32	-0.56	0.57	-5.64	-0.97	0.33	0.36	0.06	0.95	-0.17	-0.27	0.79	-9.54	-1.46	0.14	-3.84	-0.59	0.56
3	-5.49	-0.63	0.53	-2.12	-0.48	0.63	-4.04	-0.65	0.51	1.34	0.22	0.83	-2.00	-0.65	0.51	-11.55	-1.67	0.10**	-7.33	-1.06	0.29
4	-1.93	-0.21	0.83	-0.85	-0.18	0.85	-5.16	-0.79	0.43	4.11	0.63	0.53	2.80	-0.03	0.97	-5.38	-0.74	0.46	-5.74	-0.79	0.43
5	-3.52	-0.36	0.72	-2.37	-0.49	0.62	-12.92	-1.89	0.06**	4.76	0.70	0.49	0.19	-0.42	0.67	-10.46	-1.37	0.17	-7.74	-1.01	0.31

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