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Catastrophic Shocks in the Property-Liability Insurance Industry: Evidence on Regulatory and Contagion Effects

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ABSTRACT

Natural disasters are conjectured to have two opposing effects on insurance firm values: a negative effect due to payments on policyholders' claims and a positive effect due to expectations of higher premiums. We test for the presence and relative strengths of these two effects by examining the impact of Hurricane Andrew and a subsequent change in the regulatory environment on the stock prices of 48 publicly-traded property-liability insurers. We find that Andrew had a large negative effect on insurance stocks that was ameliorated to some extent by a smaller positive effect. This suggests that the market expected insurers to recoup some of their losses from Andrew with subsequent premium increases. We also find that Andrew and the regulatory event had industry-wide *contagion* effects since they significantly affected most insurers, regardless of whether these firms had any claims exposure in the hurricane-affected states.

INTRODUCTION

In the past few years, natural disasters in the United States have resulted in huge losses, much of which were recovered from insurers.[1] Given the magnitude of these losses and the burdensome regulations in the industry, it is essential to analyze the financial and regulatory impact of such catastrophes on the insurance industry. We take a step in this direction by examining the effects of Hurricane An-

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[1] For example, insured losses were estimated at $16.5 billion for Hurricane Andrew, $4.2 billion for Hurricane Hugo, and $2.5 billion for the California (Loma Prieta) earthquake.

drew and its regulatory aftermath on the stock prices of property-liability insurance firms. As Schwert (1981) suggests, tests with stock price data are more powerful than other measures because stock prices are more accurate and they incorporate all relevant information as soon as they become available; also, the existence of well-specified models of expected return allow us to isolate firm- and industry-specific effects from marketwide movements.

Insurance experts have suggested two opposing, but not mutually exclusive, effects of major natural disasters on insurance firms. The first and obvious effect is that they cause losses to insurers due to the large reimbursements paid to policyholders for their damages. The expectation of these losses should cause insurance stocks to decline at the time of the disaster (the negative effect). But there is another more subtle effect that such disasters are hypothesized to have on insurance firms: they lead to larger profits because of increases in future premiums. Different theories have been proposed to explain such premium increases. Cagle and Harrington (1995), Cummins and Danzon (1996), Gron (1989, 1990), and Winter (1992) analyze models where the supply of insurance is an increasing function of the insurer's capital. Natural disasters reduce the capital of insurance firms, thus reducing their short-run supply of insurance and causing premiums to increase. Another explanation for higher premiums is that there is an easing of regulatory pressures on insurance firms following these disasters. This allows firms to raise premiums without incurring significant opposition from the regulators. For example, *Forbes* magazine (January 8, 1990, p. 184) wrote in the wake of Hurricane Hugo and the California earthquake that "Insurers are expected to use the two disasters as an excuse to boost rates modestly in 1990—and few people will fight the increases." Finally, Gron (1990) and Shelor, Anderson, and Cross (1992) argue that natural disasters increase the demand for insurance from previously uninsured consumers, leading to premium increases. The expectation of higher premiums and profits will cause insurance stock prices to increase at the time of the disaster (the positive effect) or at the very least to partially offset the negative effect. Therefore, the net effect of a natural disaster on insurance stocks would be positive, negative, or zero depending on the relative strengths of these two effects. A corollary to the hypothesis about higher premiums is that, if there is an unexpected tightening of the regulatory environment following the disaster, insurance stocks should fall since the premium increases expected at the time of the disaster are now less likely to occur.

This article tests for the presence and relative strengths of these two effects by examining the impact of Hurricane Andrew on the stock prices of 48 publicly-traded property-liability insurance firms. We chose Hurricane Andrew because it is the costliest natural disaster ever to occur in the United States, making it relatively easy to detect the two hypothesized effects (if they are present). We use two techniques to measure Andrew's impact on insurance stocks: a generalized least squares (GLS) estimation technique based on Zellner's (1962) seemingly unrelated regression model and the standard event study cumulative abnormal returns (CAR) tests adjusted for cross-sectional dependence. The results from both techniques indicate that Andrew had a large and significantly negative impact on insurance stocks with a three-day CAR = −1.97 percent.

This evidence is consistent with either Andrew having both positive and negative effects with the latter dominating or with Andrew having only a negative effect. We are able to indirectly identify the former explanation as the correct one by examining the effect of a subsequent announcement. On September 5, 1992, twelve days after Andrew first came ashore, a story carried by most major newspapers alleged that, while Hurricane Andrew was ravaging South Florida, executives at the insurance giant American International Group (AIG) were passing around an internal memo to senior managers that the storm would present an opportunity to obtain rate increases.[2] The resulting furor caused the Florida insurance commissioner to freeze AIG's premiums on September 9, 1992, and to issue a warning that regulators would not permit any unjustified rate increases sought in the wake of Hurricane Andrew.[3] We believe that this unexpected event changed the regulatory environment and made it more difficult for insurance firms to increase premiums.[4] If a partially offsetting positive stock price effect did occur at the time of the hurricane due to the *expected* premium increases, then the change in the regulatory environment should have a negative impact on the prices of insurance stocks. Our analysis reveals that there was a significant decline in stock prices during this regulatory change period (three-day CAR = −1.55 percent). This indirect evidence is consistent with the presence of a positive stock price effect during Hurricane Andrew (due to expected premium increases) which was dominated by a larger negative effect.

Finally, we attempt to explain the cross-sectional variation of Andrew's impact in our sample of insurance stocks. We find that Andrew negatively affected a majority of firms in our sample, and this effect was unrelated to the firms' exposure levels in the affected states (Florida and Louisiana). This seems to imply that Andrew had a contagion effect on the entire insurance industry and was not restricted only to firms that had large claims exposures to the hurricane. We also find that the commissioner's warning had a similar contagion effect. Regression analysis reveals that Andrew's stock price effect was less negative for firms with large loss reserves, suggesting that the market expects such firms to be better able to weather the hurricane. But the relationship between the stock price effect and loss reserves is statistically weak and it seems to be restricted mostly to the unexposed firms in our sample. Similarly, we do not find any statistically significant relationship between the hurricane's impact on a firm and its extent of reinsurance protection.

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[2] See the September 5, 1992, issues of the *Washington Post* (p. A1) and the *Los Angeles Times* (p. D1).

[3] See the *New York Times*, September 10, 1992, p. D1.

[4] Our belief is confirmed to some extent by a *Wall Street Journal* article on February 22, 1993 (p. A3), six months after Andrew, which says that insurance rates have held steady in the wake of Hurricane Andrew and they will stay that way for another year.

The literature on the market impact of natural disasters is fairly recent but growing. Cagle (1996), Gron (1990), and Lamb, Speltz, and Lemire (1993) find no market reaction for insurance firms as a whole to Hurricane Hugo. But Cagle (1996) and Lamb (1995) find a significant negative reaction for those firms which are most vulnerable to damage claims and not for other firms in their studies of Hugo and Andrew, respectively. Gron (1990) and Shelor, Anderson, and Cross (1992) find a positive reaction to the California earthquake, which they attribute to the expected increase in the demand for earthquake insurance after the earthquake.

DATA AND METHODOLOGY

We collect our sample of publicly-traded property-liability insurance firms by first identifying all firms in the Center for Research in Securities Prices (CRSP) file that have primary SIC codes of 6311 (life insurance) and 6331 (fire, marine, and casualty insurance). This gives us an initial sample of 170 firms with SIC code 6311 and 49 firms with SIC code 6331. We select from this initial sample only those firms that are listed in the 1992 edition of *Best's Insurance Reports—Property/Casualty* in order to drop the life insurance firms and focus only on the property-liability firms. This leaves a total of 60 firms, 18 with SIC code 6311 and 42 with SIC code 6331. Finally, we exclude those firms that do not have daily returns data on the CRSP file for all of 1992 (the event year). The final sample of 48 firms are listed in the Appendix.

The data for our study are obtained from different sources. Daily stock returns data are obtained from the CRSP tape. The data on each firm's loss reserves and amount of reinsurance protection for the pre-hurricane year (1991) are obtained from the 1992 edition of *Best's Insurance Reports—Property/Casualty.* The data on each firm's exposure in Florida and Louisiana at the end of 1991 are obtained from *National Underwriter Profiles.* The firm-specific data are used in the cross-sectional analysis.

We use two methodologies to measure the stock price impact of Hurricane Andrew and the subsequent regulatory environment change events: a modified event study methodology (proposed by Brown and Warner, 1985) and a generalized least squares (GLS) methodology (proposed by Schipper and Thompson, 1983). Because our sample stocks are all in the same industry and have the same calendar date for both events, their abnormal (residual) returns will not be independent but will instead be cross-sectionally correlated. The event study approach takes this into account by modifying the test statistic used in standard event studies (which assume independent abnormal returns). The GLS approach is econometrically more satisfying because it explicitly incorporates this heteroscedasticity in the estimation process. It also makes more efficient use of the available data and is particularly suitable for small samples. Another advantage of this approach over the event study methodology is that it allows testing of joint hypotheses as well as tests about average and cumulative excess returns. Not surprisingly, this approach is often used in studies that measure the stock price impact of new regulations where cross-sectional dependence is often a problem due to event-date clustering.[5] We briefly describe these two methodologies and the cross-sectional analysis technique below.

Modified Event Study Approach

We assume that the unconditional return-generating process is described by a stationary market model. We then calculate the abnormal returns for each firm and for the entire sample around the two events. The sign, magnitude, and statistical significance of the sample excess returns indicate the stock price impact of the events. The market model is given by

$$\tilde{R}_{it} = \beta_{i0} + \beta_{im}\tilde{R}_{mt} + \tilde{\varepsilon}_{it}, \tag{1}$$

where $\tilde{R}_{it}$ = rate of return for firm i on day t ($i = 1, 2, \ldots, N$),
$\tilde{R}_{mt}$ = rate of return on the CRSP equally-weighted index of all NYSE/AMEX stocks on day t,
β_{i0} = market-independent rate of return on firm i,
β_{im} = sensitivity of firm i's rate of return to changes in the market's rate of return, and
$\tilde{\varepsilon}_{it}$ = error term which is assumed to be normally distributed and serially independent.

The parameters $\hat{\beta}_{i0}$ and $\hat{\beta}_{im}$ for both events are estimated based on an ordinary least squares procedure over an estimation period of 110 days (day −120 to day −11) prior to the day Hurricane Andrew first hit Florida (August 24, 1992).[6] The abnormal return for firm i on any (event) day t is given by

$$A_{it} = R_{it} - \hat{\beta}_{i0} - \hat{\beta}_{im}R_{mt}. \tag{2}$$

The day t sample mean abnormal return is given by $\overline{A}_t = \frac{1}{N}\sum_{i=1}^{N} A_{it}$, and the statistic used to test the significance of $\overline{A}_t$ is given by

[5] A few examples of such studies are Schipper and Thompson (1983) (on merger regulations), Cornett and Tehranian (1990) (on bank regulations), and Binder (1988) (on antitrust regulations).

[6] We use the same estimation period for both events since they occurred close to each other in calendar time.

$$\frac{\overline{A}_t}{\hat{S}(\overline{A}_t)}, \tag{3}$$

where $\hat{S}(\overline{A}_t)$ is the standard deviation of the mean abnormal returns calculated from the estimation period time series of mean abnormal returns and is given by

$$\hat{S}(\overline{A}_t) = \sqrt{\frac{1}{109} \sum_{t=-120}^{-11} (\overline{A}_t - \overline{\overline{A}})^2},$$

where $\overline{\overline{A}} = (1/110)\sum_{t=-120}^{-11} \overline{A}_t$. If $\overline{A}_t$ are independent, identically distributed, and normal, the test statistic in equation (3) is distributed Student-t under the null hypothesis of $\overline{A}_t = 0$. By using a time series of sample mean abnormal returns (portfolio abnormal returns), the test statistic takes into account cross-sectional dependence between the individual firms' abnormal returns.

In addition to testing the daily abnormal returns, we also test for the significance of the cumulative abnormal returns (CAR). The sample CAR that begins with event day t_1 and ends with event day t_2 is given by CAR = $\sum_{t_1}^{t_2} \overline{A}_t$. The test statistic for CAR is given by

$$\frac{\sum_{t_1}^{t_2}\left[\left(\frac{\overline{A}_t}{\hat{S}(\overline{A}_t)}\right)\Big/(t_2 - t_1 + 1)\right]}{\sigma\left[\sum_{t_1}^{t_2}\left[\left(\frac{\overline{A}_t}{\hat{S}(\overline{A}_t)}\right)\Big/(t_2 - t_1 + 1)\right]\right]} = \frac{\sum_{t_1}^{t_2}\left[\frac{\overline{A}_t}{\hat{S}(\overline{A}_t)}\right]}{\sqrt{t_2 - t_1 + 1}}. \tag{4}$$

This statistic is distributed as standard normal under the null hypothesis of CAR = 0.

Generalized Least Squares Approach

Schipper and Thompson (1983) propose a multivariate GLS regression approach that employs an expanded version of the market model with a zero-one dummy variable appended to reflect the occurrence or nonoccurrence of each event:

$$\tilde{R}_{it} = \beta_{i0} + \beta_{im} \tilde{R}_{mt} + \sum_{k=1}^{K} \beta_{ik} D_{kt} + \tilde{\varepsilon}_{it}, \tag{5}$$

where D_{kt} = a dummy variable equal to one if event k (k = 1, 2,..., K) occurred on day t (t = 1, 2,..., T) and zero otherwise (K = 2 in this study), and

β_{ik} = sensitivity of firm i's rate of return to event k; it captures the firm's share price reaction to the event and is analogous to the market model abnormal returns in equation (2).

Following Theil (1971, p. 306), we can express the regressions in equation (5) as a single regression in partitioned form:

$$\begin{bmatrix} \tilde{\mathbf{R}}_1 \\ \tilde{\mathbf{R}}_2 \\ \vdots \\ \tilde{\mathbf{R}}_N \end{bmatrix} = \begin{bmatrix} \tilde{\mathbf{X}} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{X}} & \cdots & \mathbf{0} \\ \vdots & \vdots & & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \tilde{\mathbf{X}} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{bmatrix} + \begin{bmatrix} \tilde{\varepsilon}_1 \\ \tilde{\varepsilon}_2 \\ \vdots \\ \tilde{\varepsilon}_N \end{bmatrix}, \tag{6}$$

where $\tilde{\mathbf{R}}_1 = (\tilde{R}_{i1}\ \tilde{R}_{i2} \ldots \tilde{R}_{iT})$ (a $1 \times T$ vector),

$\tilde{\mathbf{X}}$ = a $T \times J$ matrix of independent variables which is the same for each equation in the system,

β_i = a $J \times 1$ vector of coefficients, and

$\tilde{\varepsilon}_i$ = a $T \times 1$ vector of disturbances,

or more simply as

$$\tilde{\mathbf{R}} = \tilde{\mathbf{X}}\beta + \tilde{\varepsilon}. \tag{7}$$

This model assumes that the disturbances are independent and identically distributed within each firm in equation (6) but allows the disturbance variance to differ across firms. It also assumes that their contemporaneous covariances $E(\tilde{\varepsilon}_{it}\,\tilde{\varepsilon}_{jt})$ can be nonzero, but their noncontemporaneous covariances $E(\tilde{\varepsilon}_{it}\,\tilde{\varepsilon}_{j,t-h})$ are zero. These assumptions imply that the covariance matrix in equation (7) is

$$\mathbf{V}(\tilde{\varepsilon}) = \Sigma \otimes \mathbf{I},$$

where Σ is the $N \times N$ covariance matrix of $(\tilde{\varepsilon}_{1t}\,\tilde{\varepsilon}_{2t} \ldots \tilde{\varepsilon}_{Nt})$, $\mathbf{I}$ is the $T \times T$ identity matrix, and $\otimes$ is the Kronecker product.

Estimation of equation (7) is based on Zellner's (1962) seemingly unrelated regression model. When the covariance matrix Σ is known, the GLS estimate of β is maximum likelihood and best unbiased. When Σ is replaced by the OLS residual covariance matrix, the GLS estimate of β is consistent and asymptotically efficient. These estimates and their t-statistics measure the size and significance of the abnormal return for each firm. But the overall significance of the average abnormal returns is inferred from a set of joint hypotheses on the β_{ik}'s in equation (5). These hypotheses can be expressed as constraints on the coefficients of the form

$$\mathbf{L}\hat{\beta} = \mathbf{1},$$

where **L** is a $P \times J$ matrix of constants with rank $P (\leq K)$, $\hat{\beta}$ is the $NJ \times 1$ vector of coefficients estimated from equation (6), **1** is a $P \times 1$ vector of constants, and P is the number of restrictions tested in the system. As described in Theil (1971, pp. 314, 402), the test statistic

$$\frac{NT - NJ}{P}(\mathbf{1} - \mathbf{L}\,\hat{\beta})' \{\mathbf{L}[\mathbf{X}'(\hat{\Sigma}^{-1} \otimes \mathbf{I})\mathbf{X}]^{-1}\,\mathbf{L}'\}^{-1}(\mathbf{1} - \mathbf{L}\,\hat{\beta}) \tag{8}$$

is asymptotically distributed as $F(P, NT - NJ)$.

Within this framework, we test three hypotheses concerning the β_{ik} parameters. The first hypothesis (H_1) tests the significance of the total, sample-wide influence of the events. The sample-wide "abnormal returns" for an event k is given by the sum (across the N firms) of the parameter β_{ik}. Under the null hypothesis of no significant effect, this sum is equal to zero; that is,

$$H_1 : \sum_{i=1}^{N} \beta_{ik} = 0 \text{ for each event } k. \tag{9}$$

While the above hypothesis looks for the overall impact of an event on the sample, our second hypothesis (H_2) tests whether an event had a significant impact on each sample firm individually, that is, is each firm's event parameter β_{ik} equal to zero.

$$H_2 : \beta_{1k} = \beta_{2k} = \beta_{3k} = \ldots = \beta_{Nk} = 0 \text{ for each event k.} \tag{10}$$

The final hypothesis (H_3) is based on the assumption of a constant cross-sectional covariance matrix of residuals. Schipper and Thompson (1983) show that there is a portfolio interpretation of the coefficients estimated from the pooled time series cross-sectional regressions (assuming the same β_{ik} for each firm), where the portfolio weights are constant through time. Accordingly, the return-generating process for an equally-weighted portfolio of sample firms is

$$\frac{1}{N}\sum_{i=1}^{N} \tilde{R}_{it} = \beta_{p0} + \beta_{pm}\,\tilde{R}_{mt} + \sum_{k=1}^{K} \beta_{pk}\,D_{kt} + \tilde{\varepsilon}_{pt}, \tag{11}$$

where β_{p0} is the intercept, β_{pm} is portfolio's sensitivity to the market, and β_{pk} is the portfolio's sensitivity to the kth event. We can interpret the parameter β_{pk} as measuring the "industry" effect of event k. The regression estimate of β_{pk} and its t-statistic provides an indication of the size and significance of this "industry" effect. This leads to the following null hypothesis:

$$H_3 : \beta_{pk} = 0 \text{ for each event k.} \tag{12}$$

The first two hypotheses are tested using the F-test in equation (8), and the final hypothesis is tested using the standard t-test. Since the F-test is unsigned, rejection of the null hypothesis in the first two cases does not indicate whether an event had a positive or negative impact on stock returns. But the t-test for Hypothesis 3 allows us to sign the event's impact on stock returns.

Cross-Sectional Analysis

The cross-sectional analysis is performed using a multivariate regression approach to test whether the stock price impact of the two events was related to any firm-specific characteristics. The regression equation is given by

$$\beta_{ik} = \delta_0 + \delta_1 (EXP)_i + \delta_2 (RSV)_i + \delta_3 (REINS)_i + \tilde{\varepsilon}_i , \qquad (13)$$

where β_{ik} = stock price impact of event k for firm i,
$(EXP)_i$ = direct premiums written in Florida and Louisiana as a percentage of total direct premiums written by firm i at the end of 1991,
$(RSV)_i$ = loss reserves as a fraction of net premiums written for firm i at the end of 1991, and
$(REINS)_i$ = total amount recoverable from reinsurers for all losses as a fraction of net premiums written for firm i at the end of 1991.

We are able to obtain complete cross-sectional data for 45 out of the 48 firms in our sample (data on EXP are missing for three firms). The above variables exhibit substantial cross-sectional variation. The mean (median) value of EXP is 4.19 percent (0.90 percent), and it varies from 0 to 20.30 percent. Nearly half (22) of the 45 firms have no exposure to Florida or Louisiana, and nine of the remaining 23 firms have exposures in both Florida and Louisiana. RSV has a mean (median) of 133.29 percent (116.19 percent), and it ranges from 17.11 to 410.87 percent. Finally, REINS has a mean (median) of 67.33 percent (40.97 percent), and it ranges from 0 to 439.38 percent. Only one firm in our sample has no reinsurance protection.

EMPIRICAL RESULTS

Modified Event Study Results

The event study results are presented in Table 1. Panel A presents data on the sample average abnormal returns ($\overline{A}_t$) and the cumulative abnormal returns (CAR) for the entire period ranging from ten days before the hurricane to ten days after the regulatory environment change. Panel B presents data on the cumulative abnormal returns for certain selected event windows. We define day 0 for the hurricane event as August 24, 1992, the day Andrew first hit Florida.[7] Day 0 for the regulatory event is September 9, 1992, the day on which the Florida insurance commissioner warned insurers against rate increases.

Statistically significant negative abnormal returns for Andrew occurred on event days 0 and +1 (August 24 and 25) (see Panel A). The larger negative effect on day +1 compared to day 0 may be because investors needed a little time to assess the property damage from the hurricane and because of the impending threat to Louisiana on the following day. The negative day –3 (August 19) abnormal return suggests that the market may have anticipated Andrew's damages to some extent.[8] The significantly negative return on August 31 may be a random occurrence as no new information about Andrew was released on that day. We also see that a significant majority of the firms experienced negative abnormal returns during the hurricane period. Finally, the CARs during the event period are significantly negative (Panel B). For example, the CAR for the three-day period –1, 0, and +1 was –1.97 percent, which is significant at the 1 percent level. Based on all of these findings, we conclude that Andrew had a negative impact on insurance stocks.

We now examine the effect of the regulatory change event. As shown in Panel A, this event caused significantly negative abnormal returns on event days –3, –1, and +1 (September 3, 8, and 10). Day 0 abnormal returns were also negative but not significant. A significant majority of the firms experienced negative abnormal returns on days –3, –2, –1, and +1. In Panel B, we see that the CAR for the three-day period –1, 0, and +1 was –1.55 percent (significant at the 5 percent level). These results suggest that the market reacted negatively to the insurance commissioner's warning against rate increases. The negative returns before the announcement are consistent with information leakage or market anticipation of the warning. We can infer from these results that the negative effect of Andrew masked a smaller positive effect in anticipation of premium increases. This explains the negative market reaction to the warning because it made them unlikely.

But there are other plausible explanations for the negative market reaction during the second event period. One explanation could be that, given Andrew's massive devastation, many insurance firms may have raised their claims estimates in the days that followed and this may account for the negative effects during the second event period. Our examination of the newspapers reveals no such upward loss revisions during the second event period.[9] But this argument may help to ex-

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[7] Andrew was classified as a tropical storm on August 17 and as a hurricane on August 21. It struck the Bahamas on August 23 and Louisiana early on August 26 (event day +2).

[8] It is possible that the day –3 returns were unrelated to Andrew. In fact, the next day's *Wall Street Journal* quoted an analyst who attributed the price decreases to heightened fears of real estate losses for insurance companies.

[9] Two large insurers, Allstate and State Farm, did release their initial loss estimates on September 8 and 9. But the *Wall Street Journal* claimed that these estimates did not come as a shock to investors and they were expected.

Table 1
Modified Event Study Estimation Results

Panel A: Average Abnormal Returns

Calendar Date	Average Abnormal Return ($\overline{A}_t$)	t-statistic for $\overline{A}_t$	Percentage of Negative $\overline{A}_t$	Cumulative Abnormal Return (CAR)
August 10, 1992	−0.0028	−0.72	66.7**	−0.0028
August 11, 1992	0.0003	0.07	56.3	−0.0025
August 12, 1992	−0.0011	−0.28	68.8***	−0.0036
August 13, 1992	−0.0042	−1.06	64.6**	−0.0078
August 14, 1992	0.0023	0.59	54.2	−0.0055
August 17, 1992	−0.0003	−0.07	45.8	−0.0058
August 18, 1992	−0.0025	−0.62	50.0	−0.0083
August 19, 1992	−0.0081	−2.03**	72.9***	−0.0164
August 20, 1992	0.0010	0.24	60.4	−0.0154
August 21, 1992	−0.0008	−0.21	47.9	−0.0162
August 24, 1992	−0.0068	−1.72*	68.8***	−0.0230
August 25, 1992	−0.0120	−3.04***	81.3***	−0.0350
August 26, 1992	0.0028	0.72	50.0	−0.0322
August 27, 1992	0.0003	0.08	66.7**	−0.0319
August 28, 1992	0.0069	1.54	60.4	−0.0250
August 31, 1992	−0.0117	−2.96***	66.7**	−0.0367
September 1, 1992	−0.0002	−0.06	58.3	−0.0369
September 2, 1992	0.0067	1.36	54.2	−0.0302
September 3, 1992	−0.0098	−2.47**	75.0***	−0.0400
September 4, 1992	0.0012	0.30	64.6**	−0.0388
September 8, 1992	−0.0056	−2.81***	64.6**	−0.0444
September 9, 1992	−0.0054	−1.36	60.4	−0.0498
September 10, 1992	−0.0045	−1.99**	64.6**	−0.0543
September 11, 1992	0.0011	0.29	45.8	−0.0532
September 14, 1992	0.0005	0.14	54.2	−0.0527
September 15, 1992	−0.0028	−0.71	64.6**	−0.0555
September 16, 1992	−0.0054	−1.38	62.5*	−0.0609
September 17, 1992	−0.0074	−1.89*	70.8***	−0.0683
September 18, 1992	0.0041	1.03	37.5*	−0.0642
September 21, 1992	0.0075	1.89*	54.2	−0.0567
September 22, 1992	−0.0049	−1.25	58.3	−0.0616
September 23, 1992	−0.0021	−0.54	64.6**	−0.0637

(Continued)

75 24 48 57

Table 1 (Continued)

Panel B: Selected Cumulative Abnormal Returns

	Hurricane Andrew		Regulatory Event	
Event Window	Cumulative Abnormal Return (CAR)	z-statistic	Cumulative Abnormal Return (CAR)	z-statistic
−5 to +5	−0.0312	−2.36**	−0.0242	−1.78*
−3 to +3	−0.0236	−2.24**	−0.0225	−2.10**
−2 to +2	−0.0158	−1.79*	−0.0132	−1.44
−1 to +1	−0.0197	−2.88***	−0.0155	−2.23**
−3 to +1	−0.0267	−3.01***	−0.0241	−2.89***
−1 to 0	−0.0076	−1.35	−0.0110	−1.94*
0 to +1	−0.0188	−3.35***	−0.0099	−1.74*
0 to +2	−0.0160	−2.33**	−0.0088	−1.25
0 to +3	−0.0157	−1.97**	−0.0083	−1.01

Note: This table presents the event study results for the two events. Panel A shows the average abnormal returns and cumulative abnormal returns for the period August 10, 1992 (10 days before Hurricane Andrew), to September 23, 1992 (10 days after the regulatory environment change). Event day 0 for Andrew is August 24, 1992, and for the regulatory event is September 9, 1992. The market model parameters for both events are estimated using 110 days of returns data from day −120 to day −11 prior to Andrew's day 0. Panel B shows the cumulative abnormal returns for some selected intervals around the two events.

* Statistically significant at the 10 percent level, two-sided tests.
** Statistically significant at the 5 percent level, two-sided tests.
*** Statistically significant at the 1 percent level, two-sided tests.

plain the significant abnormal returns on September 17, because, on that day, Travelers Corp. more than doubled its initial loss estimates from $70 million to between $175 and $225 million, and other insurers were expected to follow suit. Another explanation for the negative effect could be that it was in anticipation of Hurricane Iniki, which hit Hawaii late on September 11 (event day +2). But this explanation is unlikely to explain our results since none of our sample firms had any exposure in Hawaii. Finally, it can be argued that this event would have caused a negative effect regardless of whether Andrew raised expectations of premium increases, because the commissioner's warning may have prevented *all* premium increases, even those unrelated to the hurricane. However, the commissioner drew an explicit connection between Andrew and subsequent rate hikes, and he only ruled out Andrew-related premium increases. This implies that the negative effects of the second event can be attributed mostly to dashed expectations of premium increases in the wake of Andrew. But these alternative explanations imply that we can interpret the negative effects of the second event as only being consistent with, not proof of, a small positive effect during the hurricane.

Finally, we check the robustness of our event study results. First, we re-estimate the market model parameters in equation (1) using the Scholes-Williams and Dimson corrections to account for nonsynchronous trading. We find that these corrections do not alter any of the results that were obtained using an OLS procedure. Second, we take into account the possibility that Andrew may have increased firm variance. Such event-induced variance causes the test statistic in equation (3) to reject the null hypothesis of zero abnormal returns too often when it is true. Therefore, we adjust the test statistic to incorporate event-induced variance using the procedure outlined by Boehmer, Musumeci, and Poulsen (1991), and we find that our results are essentially unchanged.

Generalized Least Squares Results

We estimate equation (5) using two dummy variables for the two events (K = 2): D_{1t} for Hurricane Andrew and D_{2t} for the subsequent regulatory change event. The event window for each dummy variable includes the event days −1, 0, and +1.[10] The dummy variables take on a value of one for the days in the event window and a value of zero for the other days. We use a time series of daily returns of all the trading days in the event year 1992 (255 trading days) and run a seemingly unrelated regression of each firm's return on the market return and the dummy variables. The coefficients of the two dummies (β_{i1} and β_{i2}) measure the impact of the two events on each firm i.

In order to conserve space, we do not list these event coefficient estimates for each firm individually but instead present their summary statistics in Panel A of Table 2. The sample mean and median values of both coefficients are negative and highly significant. Also, a significant majority of the firms (more than 70 percent) had negative coefficients for both events. But we must interpret such results based on average event coefficients with caution since they are not very appropriate given cross-sectional dependence in firm returns. And, to the extent that the two events are not independent of one another, a form of multicollinearity is introduced which affects the average coefficient estimates and their t-ratios. Therefore, we complement the above results with tests of the three hypotheses discussed above.

As shown in Panel A of Table 2, the hypothesis H_1 ($\sum_{i=1}^{N} \beta_{ik} = 0$) can be rejected for both events at a better than 2 percent significance level. But we cannot reject hypothesis H_2 that the individual coefficients are all equal to zero for each event. These two results together imply that the individual event coefficients for the sample firms are all either mostly positive or mostly negative but not strongly so. In fact, even though 73 percent of the β_{i1} (β_{i2}) parameters are negative, only 16 percent (14 percent) of them are significantly negative. But the significance of H_2 is sensitive to the length of the time series of returns. When the time series length

[10] We chose these narrow event windows because broader ones may make inferences ambiguous given the close proximity of the two events in calendar time. In any case, our results did not change when we replicated the GLS and cross-sectional analyses for different broad windows.

is changed to 180 trading days in 1992, we can reject H_2 for both events at 5 percent significance levels.[11]

Table 2
Generalized Least Squares Estimation Results

Panel A: $\tilde{R}_{it} = \beta_{i0} + \beta_{im}\tilde{R}_{mt} + \sum_{k=1}^{2} \beta_{ik} D_{kt} + \tilde{\varepsilon}_{it}$

Event Coefficient	Mean (t-statistic)[a]	Median (p-value)[b]	Minimum/ Maximum	% Negative (z-statistic)[c]	H_1: F-value (p-value)	H_2: F-value (p-value)
β_{i1}	−0.0061 (−3.46***)	−0.0028 (0.006)	−0.0462/ 0.0161	72.92 (3.18***)	9.991 (0.001)	0.880 (0.704)
β_{i2}	−0.0071 (−2.37**)	−0.0037 (0.002)	−0.1282/ 0.0249	72.92 (3.18***)	5.740 (0.017)	0.946 (0.580)

Panel B: $\frac{1}{N}\sum_{i=1}^{N} \tilde{R}_{it} = \beta_{p0} + \beta_{pm}\tilde{R}_{mt} + \beta_{p1} D_{1t} + \beta_{p2} D_{2t} + \tilde{\varepsilon}_{pt}$

$\hat{\beta}_{p0}$ (t-statistic)	$\hat{\beta}_{pm}$ (t-statistic)	$\hat{\beta}_{p1}$ (t-statistic)	$\hat{\beta}_{p2}$ (t-statistic)	F-value (p-value)	R^2
0.0009 (2.64***)	0.5800 (7.19***)	−0.0062 (−2.40**)	−0.0053 (−1.98**)	21.47 (0.000)	0.3046

Note: This table presents the summary statistics of the event coefficient estimates and the tests of the three hypotheses using the GLS approach discussed in the text. Panel A shows the estimation results of equation (5), where coefficient β_{i1} measures the impact of Hurricane Andrew and β_{i2} measures the impact of the regulatory environment change for each firm i. The returns time series used comprises all the trading days in 1992 (255 trading days), and the event windows for the two dummy variables are event days −1, 0, and +1. In Panel B, the portfolio regression equation (11) is estimated to test Hypothesis 3.

[a] This is computed by dividing the mean parameter estimate by the sample cross-sectional standard error.

[b] This is from a Wilcoxon signed-ranks test for the zero median null hypothesis.

[c] This is given by $\frac{G - Np}{\sqrt{Np(1-p)}}$, where G is the number of negative sample coefficients, N is the total number of sample coefficients (48), and p is the probability of a negative estimate under the null hypothesis (0.50).

* Statistically significant at the 10 percent level, two-sided tests.
** Statistically significant at the 5 percent level, two-sided tests.
*** Statistically significant at the 1 percent level, two-sided tests.

[11] Schipper and Thompson (1983, p. 212) also find that the H_2 tests are sensitive to the number of time series observations. They claim that it results from the fact that H_2 has 48 degrees of freedom (in our study), whereas H_1 has only one degree of freedom.

We test the final hypothesis (H_3) by estimating equation (11) with an equally-weighted portfolio of our insurance stocks. The regression results are presented in Panel B of Table 2. The data show that both portfolio event coefficients, which measure the "industry" effects of the events, are significantly negative and so we can reject H_3.

The results from the GLS analysis are very similar to those from the event study, and they show that both events had a negative impact. Although our finding of a negative effect for Andrew differs from the findings of the above-mentioned studies of a zero effect for Hugo and a positive effect for the California earthquake, they are consistent with each other in the following sense: Since the damage claims from Andrew were much larger than those from the other two disasters, the expected premium increases would not recoup all of the losses, leading to a negative market reaction. For the smaller Hugo disaster, the market expected premium increases to recoup the losses, leading to no market reaction, and for the even smaller earthquake disaster, the market expected premium increases to more than recoup the losses, leading to a positive market reaction.

Cross-Sectional Analysis

As mentioned above, 22 firms in our sample have no claims exposure in Florida or Louisiana (EXP = 0), and 23 firms have some exposure in either or both states (EXP > 0). The data presented in Panel A of Table 3 facilitate comparison of the impact of the two events (β_{i1} and β_{i2}) across these two subsamples. The mean values of β_{i1} and β_{i2} for the exposed and unexposed firms are all significantly negative. Furthermore, although Andrew had a larger negative impact on the exposed firms than on the unexposed firms (and vice versa for the regulatory event), the differences are not statistically significant.[12]

These results are interesting because they suggest that both events had industry-wide *contagion* effects. Therefore, even though Andrew struck only Florida and Louisiana, the market expected it to adversely affect the solvency of the entire insurance industry. This caused the market to bid down all insurance stocks. Similarly, the Florida insurance commissioner's ban on Andrew-related rate hikes chilled the regulatory environment in all states and not just in Florida and Louisiana. A similar sentiment was expressed by a consumer advocate in the *Wall Street Journal* (September 10, 1992), who said that other states were likely to become more attentive to rate increases and that "this will not stop with Florida and Louisiana." Shelor, Anderson, and Cross (1992) also report a contagion effect for the California earthquake, although theirs is a positive contagion. But Cagle (1996) and Lamb (1995) find no evidence of contagion for Hugo and Andrew, respectively. Instead, they find that these disasters had an adverse effect only on the ex-

[12] The same results are obtained when we compare the median values of β_{i1} and β_{i2} for the two subsamples. In addition, none of our cross-sectional results change when event study CARs are used instead of GLS betas to measure event effects.

posed firms.[13] A useful avenue of future research would be to discover the factors that induce contagion effects in some disasters but not in others.

Table 3
Cross-Sectional Analysis Results

Panel A: Comparison of Means

Event Coefficient	Mean for EXP = 0 Firms	Mean for EXP > 0 Firms	t-statistic for Difference in Means
β_{i1}	-0.0054^{**}	-0.0071^{**}	0.46
β_{i2}	-0.0091^{*}	-0.0059^{**}	−0.50

Panel B: $\beta_{Ik} = \delta_0 + \delta_1(EXP)_i + \delta_2(RSV)_i + \delta_3(REINS)_i + \tilde{\varepsilon}_i$

Sample	$\hat{\delta}_0$ (t-statistic)	$\hat{\delta}_1$ (t-statistic)	$\hat{\delta}_2$ (t-statistic)	$\hat{\delta}_3$ (t-statistic)	F-value (p-value)	R^2
Full Sample	−0.0107	-3.04×10^{-5}	0.0034	3.99×10^{-5}	0.80	0.05
	(-2.53^{**})	(−0.08)	(1.30)	(0.02)	(0.50)	
EXP = 0 Subsample	−0.0140	N.A.	0.0063	−0.0011	1.83	0.16
	(-2.71^{**})		(1.79^{*})	(−0.40)	(0.19)	
EXP > 0 Subsample	−0.0086	N.A.	0.0007	0.0012	0.06	0.01
	(−1.63)		(0.18)	(0.20)	(0.94)	

Note: This table presents the results of the cross-sectional analysis for the two events. Panel A compares the mean effects of Hurricane Andrew (β_{i1}) and the regulatory event (β_{i2}) between those firms that had no claims exposure in Florida and Louisiana (EXP = 0 firms) and those firms that did (EXP > 0 firms). Panel B presents the results of the cross-sectional regression given by equation (13).

* Statistically significant at the 10 percent level, two-sided tests.
** Statistically significant at the 5 percent level, two-sided tests.
*** Statistically significant at the 1 percent level, two-sided tests.

We further analyze the cross-sectional variation of the stock price impact of Andrew by estimating regression equation (13) (see Panel B in Table 3).[14] The insignificance of the EXP coefficient implies that Andrew's stock price impact on a firm is unrelated to its claims exposure in Florida and Louisiana. This is consistent with our earlier argument of a contagion effect for Andrew. The positive coefficient on the RSV variable is in line with our expectation that firms with ample loss reserves would be better able to weather the storm without having to resort to fire sale liquidations of their asset portfolios, and so their stocks would be less ad-

[13] We attribute the difference between our results and those of Lamb (1995) to differences in the samples and in the methodologies used to measure event effects.

[14] The regression results for the regulatory change event are omitted because they are similar.

versely affected. But the weak statistical significance of this coefficient is a warning against inferring too much from this result. Another problem is that our loss reserves measure is a liability account and may be an imperfect measure of the actual amount of assets set aside to meet losses (which is unobservable). Finally, the insignificance of the REINS variable implies that firms with ample reinsurance protection did not fare any better during Andrew than unprotected firms. One possible reason for this could be that the market expected reinsurers to raise their premiums significantly after Andrew in order to offset their losses. Therefore, the market expected firms with relatively large amounts of reinsurance coverage to find their premiums going up the most, and this would offset the beneficial effects of the reinsurance protection. Shelor, Anderson, and Cross (1992) make a similar point in a different context, and there is some evidence that reinsurance premiums did rise in the wake of Andrew (see the *Wall Street Journal,* February 22, 1993, p. A3).

One possible reason for the insignificance of the EXP, RSV, and REINS variables may be due to interactions between them. In order to explore this possibility, we rerun the above regression with the interaction (cross-product) terms included in the regression (not shown). But we find no change in any of our results, and none of the interaction terms are significant. We also run the regression of Andrew's effect on RSV and REINS for the EXP = 0 and EXP > 0 subsamples separately (see the second and third rows of Panel B, Table 3). The positive coefficient on the RSV coefficient is due mainly to the EXP = 0 firms. In other words, only the unexposed firms benefited from building their reserves, whereas the exposed firms found their market values eroded by Andrew irrespective of their reserves. But once again we must caution against inferring too much from these results given the small size of the subsamples and the weak significance levels.

These results also have some operational implications for insurance firms. First, we find limited support for the oft-repeated prescription that firms should build up their loss reserves so that they are less negatively affected by catastrophes. Second, we do not find any evidence that firms benefit from reinsuring their risks. Firms may be overestimating the value of catastrophic reinsurance because reinsurance premiums tend to rise rapidly in the aftermath of large disasters, maybe even faster than primary insurance premiums.

CONCLUSION

Hurricane Andrew had a significant negative impact on property-liability insurance stocks. But Andrew's negative effect was offset to some extent by the market's expectations of premium increases. When Florida (and Louisiana) subsequently dashed these expectations by banning Andrew-related premium increases, insurance stocks fell further. Andrew and the regulatory event negatively affected most insurers, not just those exposed to the affected states (Florida and Louisiana). Andrew had a negative stock price reaction on firms irrespective of their extent of reinsurance, but this reaction was (weakly) less negative for unexposed firms with ample reserves.

APPENDIX
SAMPLE OF 48 PROPERTY-LIABILITY INSURERS

Aetna Life and Casualty Co.	Horace Mann Educators Corp.
Alfa Corp.	Kemper Corp.
Allcity Insurance Co.	Lawrence Insurance Group
Ambac Inc.	Lincoln National Corp.
American Indemnity Financial Corp.	Merchants Group Inc.
American International Group Inc.	NAC Re Corp.
Amwest Insurance Group Inc.	National Security Group Inc.
Aon Corp.	Ohio Casualty Corp.
Avemco Corp.	Orion Capital Corp.
Chubb Corp.	Physicians Insurance Co. OH
CIGNA Corp.	Progressive Corp. OH
Citizens Inc.	Reliance Group Holdings Inc.
CNA Financial Corp.	RLI Corp.
Continental Corp.	Safeco Corp.
Cotton States Life Health Insurance	St. Paul Co.
First Central Financial Corp.	SCOR US Corp.
Fremont General Corp.	Selective Insurance Group
Frontier Insurance Group Inc.	Torchmark Corp.
Fund America Enterprises Holding	Travelers Corp.
Gainsco Inc.	Unicare Financial Corp.
Geico Corp.	United Fire & Casualty Co.
General Re Corp.	USF&G Corp.
Harleysville Group Inc.	USLICO Corp.
Hartford Steam and Boiler Insurance	Zenith National Insurance Corp.

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