Market Expectations Following Catastrophes: An Examination of Insurance Broker Returns

Marc A. Ragin* Martin Halek

University of Wisconsin-Madison

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Abstract

We examine the investment market reaction to large insured-loss catastrophes, focusing on publicly-traded commercial insurance brokers. We propose that investors expect the disaster to negatively shock financial capacity in the insurance market, raising prices and thus commission revenue for brokers. We test this theory and find the size of the relative shock has a positive and significant effect on cumulative abnormal returns of brokers. We also find evidence that insurance price changes are inversely related to returns. From this, we infer that large catastrophes are expected to increase insurance prices, and that those price increases are not expected to be offset by decreases in quantity.

*Contact author: 770-712-4647 ragin@wisc.edu
Organizations of all sizes and across all industries should generally expect favorable market conditions in 2014 as long as capacity and competition remain plentiful and catastrophe losses remain relatively low. - Dave Bidmead, CEO of Marsh U.S. on February 4, 2014

1 Introduction

Catastrophes are a central concern for the insurance market. Large or frequent disasters impact profits for insurance companies, who must balance offering competitive prices against maintaining financial stability. To manage this balance when claims are high, insurers may raise prices or restrict coverage. Reducing supply can help to recoup lost financial capital (“capacity”).

The total effect of this reduction in supply is uncertain. If demand remains static, $P^*$ increases and $Q^*$ decreases as supply shifts left. In this situation, the elasticity of demand dictates the total effect on industry revenue. If demand increases (as some evidence suggests), the industry may see an overall increase in revenue ($PQ$) as the increase in price dominates the reduction (if any) in quantity.

In this paper, we use an event study methodology to isolate the effect of a catastrophe from other factors that may impact the insurance market. Rather than look at the realized revenue changes in the quarter following the disaster (which would be influenced by interest rates, investment returns, inflation, and other losses), we study the stock market’s immediate reaction in the days following the 43 largest insured-loss catastrophes since 1970. This captures the expected change in insurance premium revenues as a direct result of the disaster.

We conduct this event study on insurance brokers, rather than insurance companies. While insurers bear the risk of loss payments following a disaster, insurance brokers facilitate the transaction of insurance contracts and are not substantially exposed to loss payments. A substantial portion of revenue for these brokers is from commissions on premiums paid, so insurance broker revenues proxy for insurer revenues. Because brokers do not pay losses following disasters, changes in equilibrium price and quantity are positively correlated with profits for brokers. We examine broker stock returns to evaluate the expected change in broker profits.

With the results of our event studies, we conduct a cross-sectional regression to examine what factors are associated with the size of the cumulative abnormal returns (CARs) for brokers. Our primary variable of interest is a proxy for “shock”—the size of the catastrophe relative to available capital in the insurance market, measured by policyholder surplus (PHS). A second variable of interest captures trends in insurance prices, which may measure the insurance cycle’s propensity to turn. We also include the type of disaster, location of the disaster, and broker-specific attributes as control variables.
We consistently find that positive and significant CARs for insurance brokers exist following the largest natural disasters. On average over the 10 events with the largest insured losses, broker stocks earned abnormal returns of 0.79% on the day of the catastrophe. In the 10- and 30-day windows following the top 10 catastrophes, broker stocks generated 2.74% and 5.95% cumulative average abnormal returns. Consistent with this result, we find that the CARs are positively related to the impact of the disaster on existing insurer financial capacity. Specifically, for every 1% of policyholder surplus affected by the size of the loss, the CAR in the 10 days following increases by 0.45%. We also find that CARs are positively related to sustained price decreases—for each consecutive quarter of insurance price decreases leading up to the event, the average 10-day broker abnormal return increases by 1 percentage point.

These results provide evidence that the equilibrium price of insurance is expected to increase and dominate any potential reduction in the quantity of insurance supplied. This may be due to anticipated increases in insurance demand, or an assumption that demand for insurance is relatively inelastic. While we are unable to determine the source of this expectation, the net effect remains—from an insurer’s perspective, catastrophes are expected to have a positive overall impact on the market for commercial insurance.

The remaining paper is organized as follows. In the next section we discuss related research on brokers, insurance cycles, and event studies. Section 3 develops our hypotheses. Section 4 describes our data, while Section 5 describes our methodology. Our results are presented in Section 6, and Section 7 concludes.

2 Related Research

2.1 Insurance cycles and capacity constraint theory

In the underwriting cycle (or insurance cycle), insurers experience an ebb and flow of premiums and profitability while increasing or reducing the amount of insurance available to customers. This trend is prominent in the property-casualty (P&C) insurance market. Historically, this cycle has a period of approximately six years, and some researchers have matched this to a second order autoregressive equation (Cummins and Outreville 1987, Smith and Gahin 1983, and Venezian 1985, among others). In the "hardening" period of the cycle, insurers begin with near-zero profits and subsequently increase premiums, decrease available limits, and change policy wording to be more restrictive. Once profits sufficiently increase, industry competition slowly reverses these effects until profits have returned to near-zero, after which the cycle begins again. Much research has been dedicated to determining the cause(s) of this cycle, but there is no general agreement among academics as to the primary cause.
Winter (1988, 1991) developed and formalized the idea that constrained capacity is the primary cause of the insurance cycle. Capacity may be reduced by any shock to net worth, such as inflation, claims, increases in interest rates, or poor investment performance. Winter theorized that, since external capital is more expensive and difficult to raise, firms whose financial capacity is reduced will choose to improve profitability by raising revenue and cutting expenses rather than turn to the capital markets for funds. Internal capital adjusts slowly in this manner, creating a cycle in which the market must remain hard for a long period. Winter’s initial theory of capacity constraint was supported, refined, and tested by Gron (1994). When capacity is reduced, the insurance supply curve shifts to the left, increasing premiums and decreasing the “quantity” of insurance in the market. This paper tests such a theory, so literature related to capacity constraint is of primary interest.

An extension of the capacity constraint hypothesis is the financial quality hypothesis (Cummins and Danzon, 1997; Harrington and Danzon, 1994). In this theory, net worth shocks affect both demand and supply, as insureds will have a higher willingness to pay for financial quality following a shock to capacity. Prices will increase due to an upward shift of the demand curve (due to the higher willingness to pay for the same coverage) and a leftward shift of the supply curve (due to capacity constraint). Our analysis will only test for an anticipated leftward shift of the supply curve, as we are not able to determine whether the quantity demanded changes.

Capacity constraint theory has been tested empirically many times over the past 20 years. Winter (1994) found empirical support for his theory, estimating a positive and significant relationship between surplus and the economic loss ratio (the reciprocal of price). Gron (1994) found a negative relationship between industry relative capacity and underwriting margins. Other research finding evidence for capacity constraint includes Cagle and Harrington (1995), Derien (2008), Doherty and Garven (1995), Fenn and Vencappa (2005), Higgins and Thistle (2000), Niehaus and Terry (1993), and Weiss and Chung (2004).

Choi et al. (2002) tested six of the most widely accepted hypotheses of insurance cycle determinants. They found support for the capacity constraint model, but not the financial quality hypothesis. Capacity constraint was supported by positive long-run and short-run relationships between interest rates and the economic loss ratio, positive short-run and neutral long-run relationships between surplus and the economic loss ratio, and negative short-run and neutral long-run relationships between variance and the economic loss ratio.

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1The primary difference between these theories is that Winter assumes that regulation reduces the probability of bankruptcy to zero, while Gron does not make such an assumption. Gron assumes that insurers hold net worth to comply with regulatory requirements, rather than to reduce the probability of insolvency (though that is the intent of the regulatory requirements). Both generate an upward-sloping short-run supply curve that shifts with changes in capacity.
2.2 Catastrophe event studies

A number of event studies have examined the effect of particular catastrophes on the insurance industry, though most have focused on insurers and have found negative returns. In many of these studies, the authors describe the possibility of offsetting effects—insurers must pay claims in the short term, but may be able to raise rates in the long term to recoup their losses. Both Shelor et al. (1992) and Aiuppa et al. (1993) studied the effect of the 1989 Loma Prieta earthquake in California, finding that insurance company stock prices experienced positive returns following the event. Lamb (1995) found that insurers with significant operations in Florida or Louisiana experienced negative abnormal returns following Hurricane Andrew in 1992, while stock returns for insurers not writing business in those states were not affected. Following Lamb’s work, Angbazo and Narayanan (1996) investigated both Hurricane Andrew and a subsequent freeze of American International Group’s premium rates. The authors found negative stock price effects for both events and provided some evidence that expectations of higher prices may have offset the negative effects of Hurricane Andrew until the premium freeze. Cagle (1996) identified negative abnormal returns for insurers following Hurricane Hugo in 1989, and the 1995 Hanshin earthquake in Japan created the same for Japanese insurers according to Yamori and Kobayashi (2002). Looking past simple returns, Blau et al. (2008) identified increases in short selling of insurer stocks beginning two days after Hurricane Katrina made landfall and several days before Hurricane Rita hit 28 days later.

The 9/11 terrorist attacks were a unique event—virtually unpredictable, economically significant across the globe, and man-made. Cummins and Lewis (2003) tested the effect of the 2001 World Trade Center (WTC) terrorist attacks on insurance company stocks and found that insurer stocks were negatively affected by the attacks, though financially strong insurers recovered their stock losses within a few weeks. They found similar negative results for insurers following Hurricane Andrew and the Northridge Earthquake in replicating Lamb’s (1995) event study on those disasters’ effects on insurer stocks. Finding similar effects for insurers, Doherty et al. (2003) also examined the effect of the WTC attacks on insurer stock returns, using the capacity constraint model to predict the impact of the attacks on insurers. The authors noted that insurance brokers fared well following the attacks, as exposure to the risk is limited and revenue is directly related to premium levels.

In the context of insurer event studies, expectations about claim payments appear to dominate anticipated price increases. To examine the expected net effect of catastrophes on the insurance market, we look to insurance brokers, who are compensated based on total premiums but who do not pay claims.
2.3 Brokers

The primary role of a commercial insurance broker is to purchase insurance coverage from retail insurers on behalf of their commercial clients. Brokers also may engage in benefits brokerage and consulting, wholesale or reinsurance brokerage, alternative risk financing, risk analysis, and human resources consulting, among other activities. These brokers are primarily compensated one of two ways. Most often, brokers are paid a percentage of the premium for each policy they manage, called a “direct commission.” In 2011, the average commission rate was 10.3% and the industry paid a net of $45.55 billion in commissions on $447.44 billion in net written premiums (Best’s Aggregates and Averages, 2012). Brokers may also be paid a flat fee for placing coverage, which is often negotiated annually and generally does not vary directly with the amount of coverage placed.

Although the flat fee approach is becoming more common, commissions continue to drive broker revenue. Maas (2010) conducted a series of interviews with brokers and found that the role of an insurance broker in the past has been primarily transactional, implying that brokers were compensated with direct commissions for placing coverage. Only in recent years have brokers migrated to more of a “consultant” role. It is possible that positive abnormal returns for brokers following catastrophes are due to investors’ expectations of an increased demand for loss control services or consulting, rather than a hardening of the market. This effect is difficult to disentangle, as brokers rarely report consulting revenue separate from insurer commission revenue. One aggregate estimate, the 2011 Business Insurance Market Sourcebook, found that commercial retail insurance accounted for 52.0% of broker revenue on average. A.J. Gallagher’s 2012 10-K reported that 52% of revenues came from direct brokerage commissions, 16% came from brokerage fees, 22% came from risk management and consulting fees, and 5% came from supplemental and contingent commissions.

In addition to regular compensation, brokers also may receive contingent commissions. These commissions are most often based on profitability, but also can be based on revenues, growth, or other metrics. While contingent commissions are a source of revenue for brokers, they do not comprise a major portion of revenue—overall, they amounted to only about 1.1% of premiums billed in 2004 (Cummins and Doherty, 2006). For commercial lines, contingent commissions comprise on average 5 to 6% of brokerage revenue. Because contingent commission revenue makes up such a small portion of overall revenue, we expect that changes in premiums paid (and thus direct commissions) will be the primary driver of broker revenue changes.

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2The average commission was 8.6% for earthquake insurance, 13.4% for fire, and 16.4% for commercial non-liability multi-peril. These commissions are averaged over both independent agents (such as brokers) and captive agents, so they may not accurately reflect the commissions earned by the brokers in this study.
3 Hypotheses

We begin by testing whether stocks of U.S.-traded brokers consistently experience nonzero abnormal returns following catastrophes. We hypothesize that broker stocks on average earn significant and positive abnormal returns in the days after a major catastrophe.

**Hypothesis 1:** Insurance broker stocks will earn positive abnormal returns following a catastrophe with large insured losses.

Once we calculate the abnormal returns, we consider what attributes of a catastrophe contribute to abnormal returns and what effect they have on those returns. Our primary interest is in how the financial markets react to the disaster’s impact on the insurance market. The impact of a large catastrophe depends on insurers' financial capacity to pay claims—if the insurance market has capacity available, even a large insured-loss disaster may not change prices, while a relatively small catastrophe may raise prices if capacity is already constrained. Price increases will boost broker revenues, and the abnormal returns should reflect any expectation of that effect.

We use policyholder surplus (PHS) as our measure of capacity available in the market. PHS is the difference between insurer assets and insurer liabilities, which serves as a proxy for the industry’s ability to pay claims and write new business. Catastrophe losses have a very direct negative effect on the capacity available in the market, as they lead immediately to higher expenses for insurers. However, there may be other factors that offset this effect, such as investment returns and inflation. PHS should capture many measures of capacity effects, as insurer balance sheets are affected by all of these factors.

**Hypothesis 2:** A catastrophe’s shock to insurer capacity will have a positive relationship with abnormal returns for insurance broker stocks.

The state of the insurance market may help to measure the market’s propensity to harden (increase prices). If the insurance market is already hardening, a new catastrophe might not improve broker revenues (which had already been improving with the hard market). In a soft market, however, brokers are facing decreased commission revenue. A catastrophe may have a greater proportional effect on the brokers’ revenue in such a market. We expect that catastrophes during soft (hard) markets will have a positive (neutral) impact on broker abnormal returns.

**Hypothesis 3:** Decreases in the price of insurance preceding a catastrophe will have a positive relationship with abnormal returns for insurance broker stocks.
As our price variable, we use Winter’s Economic Loss Ratio (ELR), which is the discounted ratio of premiums to losses after accounting for non-loss expenses. The data and methodology section details our calculation of ELR. In particular, we examine the relationship between the number of consecutive quarters of ELR decreases leading up to the event and the size of the abnormal return.

4 Data

4.1 Catastrophes

Information on the largest catastrophes in terms of insured loss from 1970 to 2010 comes from the 2010 and 2011 Swiss Re Sigma lists of the most costly insurance losses during that time. Table 1 describes the 10 largest losses.

As illustrated in Table 1, the size of losses is highly skewed. The largest catastrophe loss, Hurricane Katrina, is more than double the size of the next-largest loss, the Tōhoku Earthquake ($75 billion versus $35 billion). The mean insured loss is $10.01 billion with a standard deviation of $12.41 billion, while the median insured loss is $6.13 billion. We collect PHS for the P&C insurance industry in aggregate on a quarterly basis and convert to 2011 dollars. Hurricane Katrina also is the largest insured loss relative to market capacity, comprising over 15% of the existing PHS. The average loss size is 2.41% of PHS, while the median is 1.24%.

All but one of the events—the 9/11 terrorist attacks (“WTC”)—were natural disasters. Table 2 provides summary statistics on insured loss size for the studied catastrophe types. The most frequent catastrophes were hurricanes, though earthquakes had the largest average insured loss when considering disaster types that occurred more than once. Earthquakes also possess the most evident “event date,” since the onset of an earthquake is essentially unpredictable. The weather-related events, on the other hand, may be predicted several days prior to their onset.\(^3\) The primary results of this paper are based on the “event date” as the first full trading day after the weather began causing widespread destruction. In most cases, this was the date of landfall in the U.S. for hurricanes, the date of landfall in Japan for typhoons, and the date of widespread damage and business closures for flooding or winter storms in Europe. We also considered the time of day, so if an earthquake struck in the early morning hours of a trading day (such as the Tōhoku Earthquake in

\(^3\)To test if investors anticipate weather events we conducted a t-test for different average abnormal returns (AARs) between weather events and non-weather events. We found that weather event AARs are 0.7% higher on day -7 and 0.2% higher on day -5 (significant at the 1% and 10% levels respectively). No other prior days between -10 and 0 had significantly different abnormal returns. This may indicate that investors react when an upcoming weather catastrophe is first forecast, but do not make any further investment in brokers until the damage begins. We do not believe this reaction will affect the CARs.
2011, which struck at 12:45am New York time) we would consider that same day the “event date.”

WTC was unique in several ways. First, this event had the highest cumulative average abnormal return (12.96% in the five trading days following, and 23.34% in the 30 trading days following), which is our primary dependent variable of interest. Second, the stock markets were closed on September 11, 2001 during this catastrophe and did not reopen until September 17. This may have led to pent-up demand for investment in certain stocks and thus a run-up in prices once the markets reopened. Finally, this is the only intentionally man-made catastrophe on the list,\textsuperscript{4} creating a question about whether stock market effects related to the WTC attacks are representative of the rest of the sample. We subsequently conduct this analysis both with and without WTC.

The year with the most catastrophes was 2011, which had two earthquakes, one major flood, two storm systems with tornadoes in the U.S., and one hurricane. However, 2005 had the highest level of insured loss due to Hurricanes Katrina, Rita, and Wilma, which together caused over $100 billion in insured losses. From our original dataset of 46 events, there were three incidences of events that had the same or nearly the same event date. To avoid double-counting the abnormal returns, we collapsed the data for both catastrophes into the observation for the event causing more damage. We merged data for the Chilean earthquake (ranked #15) with Winter Storm Xynthia (#39) on 3/1/2010, Winter Storm Lothar (#17) with Winter Storm Martin (#36) on 12/27/1999, and Hurricane Frances with Typhoon Songda (#30) on 9/7/2004. This provides a final dataset of 43 events for our event study.

### 4.2 Brokers

We compile a list of commercial P&C brokers who were publicly traded on U.S. exchanges during the period surrounding the disaster. We limit our search to commercial P&C brokers because these brokers are highly commission driven, and the P&C insurance market has direct exposure to the catastrophic events. To get a comprehensive list of the brokers, we search the SEC EDGAR database under SIC code 6411 (Insurance Agents, Brokers, and Service) and examine each firm’s most recent 10-K to establish that they derived a substantial amount of their revenue from retail commercial P&C brokerage.\textsuperscript{5} We also double-check similar SIC codes and several editions of the annual Business Insurance Market Sourcebook, which lists the top 100

\textsuperscript{4}The California East Bay Hills Fire of October 1991 (ranked #40 by insured loss) was started by a small grass fire that was not completely extinguished by firefighters. The cause of the original grass fire is unknown.

\textsuperscript{5}We also considered including some measure of the amount of revenue derived from P&C brokerage, but reporting is inconsistent among brokers. Often, that information is reported as an aside in management’s discussion of financials, and the measure may not be exactly the same for each broker. Because of this inconsistency, we feel that it is not appropriate to use this information as a control in our later regressions.
brokers each year. We eliminate brokers with a very small amount of revenue, brokers primarily traded on
foreign exchanges, brokers who operate as insurance companies, and specialty or wholesale brokers. Due to
IPOs, acquisitions, and the like, the firms come in and out of the dataset throughout the period from 1987
to 2011. There was one broker (Acordia) who was only traded during four events, while four brokers (Aon,
Brown & Brown, A.J. Gallagher, and Marsh & McLennan) were traded during all 45 events. Table 3 on
page 25 provides the list of brokers that comprise our 264 broker-events.

We use stock return data from The Center for Research in Security Prices (CRSP) to estimate abnormal
returns for the brokers traded surrounding the catastrophe. We only examine events between 1987 and 2011,
which is why five of the brokers in Table 3 have “end dates” of December 31, 2011.6

4.3 Insurance Prices

Our measure of price is Winter’s Economic Loss Ratio (ELR),7 which we calculate on a quarterly basis and
define as:

\[
ELR \, Price = DiscountFactor \left( \frac{EarnedPremium}{IncurredLoss} \right) (1 - ExpenseRatio)
\]

(1)

\[
DiscountFactor = \sum_{t=1}^{8} \beta_t \frac{1}{(1+r)^t}
\]

(3)

where the discount factor is:

The loss ratio is calculated as incurred losses divided by the earned premiums. The incurred losses are
a proxy for the realized claims during quarter \(t\), plus the expected future claims to be paid on those losses.
Earned premiums are an appropriate denominator for this ratio, as they represent the amount of premium
that corresponds to those incurred losses over the same period (the net written premium, on the other hand,

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6There are two events added to the Swiss Re Sigma catastrophe report for 2012. Hurricane Sandy, which devastated the
U.S. East Coast in October 2012, is now the #3 largest insured-loss event since 1970 with an estimated $35 billion in insured
losses (2012 dollars). The drought in the Corn Belt of the U.S. during the summer of 2012 is also a new event on the list (#13),
with an estimated $11 billion in insured losses.

7This actually is the reciprocal of Winter’s ELR—a proxy for price, rather than losses—as our analysis is focused on how
price changes affect broker returns. Any mention of ELR in this paper refers to price.
corresponds to the whole policy year). The expense ratio is calculated as non-loss expenses (such as overhead and commissions) divided by net written premiums. Expenses are not tied as closely to a particular loss or portion of the policy period, so the net written premium is a more accurate denominator for this ratio. To calculate the expense ratio and the loss ratio, we collect quarterly aggregate financial data for P&C insurers as reported by the Insurance Services Office (ISO). To our knowledge, no other research has calculated ELR on a quarterly basis.

We also calculate ELR using annual measures as reported in ISO’s annual *Fact Book*, following Winter’s model. This is a much smoother measure of prices, but these measures do not closely match the environment surrounding each catastrophe period. For example, Hurricane Katrina occurred during a year where the Annual ELR increased by 0.69%, but the year-over-year price changes from 2004 to 2005 were 6.35% in Q1, 7.03% in Q2, -8.43% in Q3 and -2.41% in Q4.

For our estimate of the discount factor, we follow Winter’s assumption that all claims are paid in eight years.\(^8\) \(\beta_t\) is the fraction of claims paid in each year after the policy is written. Winter estimated the \(\beta\) vector (annual \(\beta_t\) for eight years) by examining the industry-wide loss triangles for each line of business in the “Schedule P” (long-tail) and “Schedule Q” (short-tail) sections reported in *Best’s Aggregates and Averages*. He took a weighted average of each line based on the 1986 premium volume to estimate an eight-year \(\beta\) vector of \((0.435, 0.266, 0.107, 0.055, 0.034, 0.034, 0.034, 0.034)\)—we use these \(\beta\) vector estimates in our analysis.\(^9\) Finally, we use the market yield on U.S. Treasury securities at three-month constant maturity for \(r\).

We are able to calculate ELR beginning with Q3 1988. There is one event that occurs before this period (“Storm and Floods in Europe,” ranked #21), so it will be dropped from our cross-sectional regression. We considered other measures of price, such as the reinsurance rate on line and insurance research firm Advisen’s *ADVx Composite Index*, but these measures were not available for the full sample period. Both alternative measures of price are positively correlated with ELR for the period available—the reinsurance rate on line has a Pearson correlation coefficient of 0.626 and the ADVx Composite Index has a correlation coefficient of 0.517. This gives us confidence that ELR is an appropriate measure of insurance prices.

\[^8\text{As a robustness check, we observed no significant change in price trends under an alternate assumption that all claims are paid in five years.}\]

\[^9\text{We checked these vectors with current data and found no significant difference.}\]
5 Methodology

Event studies examine the difference between a security’s expected return and its observed return over a period of time. The expected return is most often calculated by using return data from an “estimation window” prior to the event of interest to estimate parameters to predict returns in the future. The abnormal return is the deviation from these predictions during an “event window” surrounding the event of interest. This is the common formulation in Brown and Warner (1985) and Scholes and Williams (1977), among others, which normally estimate parameters using the capital asset pricing model (CAPM). To predict returns as accurately as possible, we use the Fama-French (1993) Three-Factor model outlined in Equation (4) below.\textsuperscript{10}

Our standard benchmark estimation period for estimating a broker’s expected return ends 46 trading days before the event date. The estimation period is set at 255 trading days long if possible, with a minimum of 60 days. We test windows 10 days prior to the event through 90 days following the event.

In many cases, shocks cause abnormal returns to become more volatile. In order to improve the fit of event studies with induced volatility, Lamoureux and Lastrapes (1990) examined the variance of daily abnormal returns and found that errors followed a generalized autoregressive conditionally heteroskedastic (GARCH) framework. Cheng et al. studied the effect of the 2004 Spitzer bid-rigging lawsuits on the stock returns for publicly-traded brokers in the U.S. and found that daily abnormal returns for insurance brokers also follow a GARCH (1,1) framework. We specify the same GARCH errors in our analysis.

To calculate expected returns, we estimate coefficients in the following model using benchmark data from the estimation period:

\[ R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML_t + \epsilon_{it} \]  \hspace{1cm} (4)

where \( R_{it} \) is the actual return of the stock of firm \( i \) on day \( t \); \( R_{mt} \) is the rate of return of a market index \( m \) (we chose the CRSP equally-weighted index) on day \( t \); \( SMB_t \) is the return on a portfolio of small market-capitalization stocks minus the average return on three portfolios of large market-capitalization stocks; \( HML_t \) is the average return on two portfolios of stocks with high book-to-market ratios minus the average return of two portfolios of stocks with low book-to-market ratios; \( \epsilon_{it} \) is a random error variable with a conditional expectation of zero given \( \Psi_{t-1} \) (the information available at time \( t - 1 \)) and conditional variance:

\[ \sigma^2(\epsilon_{it}|\Psi_{t-1}) = h_{it} = \omega_i + \delta_i h_{it-1} + \gamma_i \epsilon_{it-1}^2 \]  \hspace{1cm} (5)

\textsuperscript{10}For robustness, we conduct the same analysis using various alternative estimation models (market model, market adjusted returns) without significant differences in results.
where $\omega_i > 0$, $\gamma_i > 0$, $\delta_i \geq 0$ and $\gamma_i + \delta_i < 1$. We use maximum likelihood to estimate these coefficients.

The abnormal return of stock $i$ on day $t$ is the empirical difference between the observed return and the expected return during the event window:

$$ AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt} + \hat{s}_i SMB_t + \hat{h}_i HML_t) $$

where $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{s}_i$, and $\hat{h}_i$ are the estimates of the coefficients in Equation (4) using an OLS regression on data from the estimation window. We chose to use this multifactor model to reduce the variance of the abnormal return as much as possible. As MacKinlay (1997) states, the marginal explanatory power (and thus variance reduction) of using such a model over a standard market model will be greatest with similar firms.\(^{11}\)

This provides us with an estimate of the abnormal return for a particular broker stock each day during the event window. We then sum these abnormal returns over a specified window starting at day $T_1$ and ending at day $T_2$ to determine the cumulative effect of the event for each broker as shown in Equation (7).

$$ CAR_{ik} = \frac{T_2}{T_1} \sum_{t=T_1}^{T_2} AR_{ikt} $$

We have a $CAR_{ik}$ for each broker $i$ traded during catastrophe $k$. This provides a single observation per broker, per event, and consolidates each broker stock’s reaction to each catastrophe. Table 4 shows summary statistics for the CARs on a per-broker basis over all events. Some of these statistics (such as the large minimum and maximum for Gallagher) indicate that each broker stock may react differently to each catastrophe. Because of this, we include a fixed effect for brokers in our later cross-sectional regressions. We also calculate the cumulative average abnormal returns (CAARs), which are the average return of the traded brokers over the catastrophe. This provides one observation (the average CAR) per event. Table 4 summarizes the results of the event studies for each broker.

$$ CAAR_k = \frac{1}{n} \sum_{i=1}^{n} CAR_{ik} $$

To test our first hypothesis that abnormal returns are positive and significant, we use the Patell (1976) test.
test. This test assumes abnormal returns are serially uncorrelated, which may not be a correct assumption. However, the bias resulting from this assumption is generally small when the event window is shorter than 60 days (Karafiath and Spencer, 1991; Cowan, 1993). While we report CAARs up to 90 days post-event, our primary interest is on CAARs under 30 days. The Patell Z-scores are calculated using a standardized abnormal return (SAR) for each insurance broker, $i$:

$$\text{SAR}_{ikt} = \frac{\text{AR}_{ikt}}{s_{A_{ikt}}}$$  \hfill (9)\hfill

where $s_{A_{ikt}}$ is the standard deviation of the abnormal returns, adjusted for any missing trading days. The Z-score from $T_1$ to $T_2$ is then:

$$Z_{T_1, T_2} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} Z_{i}^{T_1, T_2}$$  \hfill (10)\hfill

where for each broker, $i$:

$$Z_{i}^{T_1, T_2} = \frac{1}{\sqrt{Q_{i}^{T_1, T_2}}} \sum_{t=T_1}^{T_2} \text{SAR}_{ikt}$$  \hfill (11)\hfill

and:

$$Q_{i}^{T_1, T_2} = (T_2 - T_1 + 1) \frac{M_i - 2}{M_i - 4}$$  \hfill (12)\hfill

with $M_i$ being the number of nonmissing trading days in the estimation window. Assuming cross-sectional independence of $Z_{i}^{T_1, T_2}$, $Z_{T_1, T_2}$ follows a standard normal distribution.

Once the CARs are calculated for each of the 264 broker-events, we use them as the dependent variable in cross-sectional regressions to test Hypotheses 2 and 3. We use a representative CAR with a window from day 0 to day +10. Table 5 shows that this CAR window is highly correlated with both shorter and longer windows, indicating it is representative of many other returns in the sample. CARs appear to differ by broker, but not by time (in other words, the CARs do not appear to have behaved differently in the 1990s than they did in the 2000s). There is some intraclass correlation of CAR within events, so we cluster standard errors by event in our regressions.

[Table 5 about here.]
The variable of interest in testing our second hypothesis is a “shock” variable. We theorize that the size of the shock to insurers’ financial capacity will be positively related to the broker CAR. Our measure of the shock is the size of the P&C industry’s insured loss divided by the industry’s PHS. It does not seem appropriate to use PHS from the same quarter as the event, since that value has not yet been aggregated and reported. In collecting our data, we found that PHS was generally reported 3-4 months after quarter’s close. We use the PHS from the preceding quarter to calculate our shock variable:

$$SHOCK_k = \frac{INSUREDLOSS_k}{PHS_{q=-1}}$$  \hspace{1cm} (13)$$

for event $k$’s effect during quarter $q = 0$, the quarter in which the catastrophe occurred.

Finally, our third hypothesis tests the relationship between CARs and the price trends leading up to the event. We propose that a “soft” market (where prices are decreasing) affected by a catastrophe may turn to a hard market, benefiting brokers. Similar to the shock measure, insurance prices leading up to the event quarter may not be known. Instead, we examine how long (if at all) insurance prices have been decreasing up to the most recently reported quarter. Prices for quarter 0 (the event quarter) will not be known when the event occurs. We measure this as the number of consecutive quarters of price decreases leading up to the event. This variable equals 0 if prices have been increasing, 1 if prices have been decreasing for only one quarter, etc. We expect a positive relationship between sustained insurance price decreases and CARs following a catastrophe.

Our model for testing Hypotheses 2 and 3 is:

$$CAR_{i,k} = \alpha + \alpha_i + \beta_1 SHOCK_k + \beta_2 CONSECNEGELRCHG_{q=-1} + \beta_3 US_k + \beta_4 EARTHQUAKE_k + \beta_5 NEWS_{i,k} + \beta_6 EARNINGS_{i,k} + \beta_7 WTC_i + \epsilon_{i,k}$$  \hspace{1cm} (14)$$

with $i$ indicating the broker, $k$ indicating the event, and $q$ indicating quarters relative to the event quarter. Our primary independent variables of interest are $SHOCK$ and $CONSECNEGELRCHG$. A positive relationship between $SHOCK$ and $CAR$ would provide support for Hypothesis 2, while a positive relationship between $CONSECNEGELRCHG$ and $CAR$ would provide support for Hypothesis 3. We include control variables for event type ($EARTHQUAKE$) and event location ($US$).

We also control for broker-specific items that may be affecting the CARs for a particular firm, such as

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12 Generally, we found that Q1 results were reported in mid-June, Q2 results were reported in late September, Q3 results were reported in late December, and Q4 results were reported in early April.
company news surrounding the event\cite{footnote13} or earnings announcements.\cite{footnote14} To account for heterogeneity between brokers that is not accounted for in the NEWS and EARNINGS variables (e.g., larger brokers may benefit more from a hardening market, as their negotiating power draws new customers), we include a fixed effect for each broker. Our analysis uses ordinary least squares (OLS) cross-section regressions with standard errors clustered at the event level to control for intraclass correlation.

6 Results

6.1 Hypothesis 1: Positive CAARs following catastrophes

Testing Hypothesis 1 requires an event study surrounding each major insured-loss catastrophe. Our findings are outlined in Table 6, where the results are reported as the difference in percentage return. For example, the CAAR of 2.75 in the (0,+5) window for the top 10 events (in column c) means that on average broker returns were 2.75 percentage points higher than would be expected based on how broker stocks normally trend with the rest of the market. We find a significant and positive abnormal return of 0.34% for brokers on the event date (day 0) when considering all 43 events in the sample (column a).\cite{footnote15} None of the later windows have significant CAARs for the full sample. When we restrict the sample to the 20 largest events (column b), we find a larger and more persistent positive return. The (0,0) window is twice as large as for the full sample, with a CAAR of 0.71%. The five-day window following the event is not significant, which may indicate some hesitance by the investment market until loss estimates are calculated. Later windows are positive and significant, indicating that the 20 largest catastrophes have a lasting positive effect on expectations for broker profits. The positive and significant results for the 10 largest catastrophes (column c) reinforce this idea and provide some indication that we might find support for Hypothesis 2 (a positive influence of relative loss size on CARs).

\begin{table}[h]
\centering
\caption{CAARs following catastrophes.}
\end{table}

These results are subject to two potential problems. One is that the WTC event is included, and as previously discussed, this event appears to be distinct from the other catastrophes. Figure 2 illustrates the unique response of the WTC event relative to the other events. We remove WTC from our sample and find that the day 0 CAAR window for the 42 remaining events decreases from 0.34% to 0.17% but remains

\cite{footnote13} We searched the Wall Street Journal with a 10-day window surrounding each event for any news item related to a particular broker. We found few overlaps, mostly related to bond issues, hiring or firing executives, or upcoming acquisitions or divestitures. We included a binary indicator variable when there was a news item, as it was difficult to ascertain whether the news would be received well or poorly by the markets.

\cite{footnote14} We categorized earnings announcements relative to average analyst expectations. Beating expectations was categorized as a 1, and missing expectations was categorized as a -1. We expect this control to be positively related to CAR.

\cite{footnote15} Columns are denoted with letters rather than numbers to illustrate the same event study model was used with a different subset of data in each column.
significant at the 10% level. Similar results hold for longer event windows, though we do not report these results alone in a table—we must first address the second issue.

The second potential problem is that some of the event windows overlap with a subsequent event, which may artificially boost calculated returns in the earlier event window(s). For example, Tropical Storm Allison (ranked #28) had a CAAR of 8.59% in the (0,+90) day window, but the WTC event (ranked #4) occurred on day +68 of Tropical Storm Allison. WTC certainly impacts abnormal returns associated with the Tropical Storm Allison event for day +68 and later, as illustrated by Figure 3. To account for these overlapping events, we conduct a subsequent event study dropping abnormal returns for days on or after a subsequent event. For example, we dropped the abnormal returns from day +68 to day +90 following Tropical Storm Allison in conducting our CAR calculation and significance tests. For events with dropped observations in particular window, the CAR for that window is also dropped. In the Tropical Storm Allison example, the CARs are calculated and reported for the (0,0), (0,+5), (0,+10), and (0,+30) windows, but not for the (0,+90) window. A final event study using this methodology and dropping the WTC event is reported in Table 7. These results show positive and significant CAARs for the top 20 and top 10 event subsamples. Overall, these event study results provide strong and robust support for Hypothesis 1.

6.2 Hypotheses 2 and 3: Effects of shock size and insurance price trends

Table 8 displays results for our regression model in Equation (14) that utilizes the day (0,+10) event window CARs as the dependent variable. Column (1) is the regression result for the sample of 43 events. Column (2) adds an indicator variable to the model to control for the influence of the WTC event. Columns (3) and (4) replicate the models in columns (1) and (2), dropping events that are followed by other events within 20 days to ensure that our results are not confounded by overlapping events.

Considering the disproportionate influence of WTC, we believe columns (2) and (4) best represent the “normal” investor reaction to a catastrophe. Our first independent variable of interest, SHOCK, has a

16Data was not available to calculate ELR for the quarters surrounding the earliest event (“Storms and Floods in Europe” on 10/15/1987), so that event is dropped from our regressions.
coefficient that is positive and significant for all four model specifications, providing support for Hypothesis 2—events with a larger impact on PHS are associated with larger abnormal returns. The estimated coefficients imply that for every 1% of policyholder surplus impacted by a particular catastrophe, brokers CARs increase by approximately 0.45 percentage points. These results indicate that the investment market considers the impact of the loss on capacity when buying broker stocks, and increase their demand as the effect on policyholder surplus increases.

Our second independent variable of interest is the number of consecutive quarters of price decreases leading up to the event, \( CONSECNEGELRCHG \). The coefficient on this variable is positive, indicating that sustained decreases in prices are associated with positive abnormal returns for brokers following a catastrophe. For each additional quarter of price decreases, the average 10-day CAR increases by 1 percentage point. This implies that the investment market considers the existing insurance market environment. This response, in addition to the positive coefficient on \( SHOCK \) indicates that the potential impact on insurance prices is associated with higher returns for brokers following a major catastrophe.

We include controls for catastrophe type and location, whether there was a significant news item about the broker in the days surrounding the catastrophe, and whether the broker announced earnings in the days before and after the event. The negative signs of the coefficients of news item variables imply that many of the news items were negative.\(^{17}\) The positive coefficient of the EPS announcement variable indicates that confounding effects of earnings announcements were properly controlled for.

[Table 8 about here.]

7 Conclusion

We propose that the investment market increases demand for insurance broker stocks following catastrophes, generating positive abnormal returns. The market expects catastrophes to constrain insurers’ financial capacity, leading to increased insurance premiums and higher commission revenue for brokers. The expected price increases outpace any expected decrease in equilibrium quantity, either due to a perception of inelastic demand or an expected shift in the demand curve to the right. We find evidence that insurance broker stocks earn positive and significant cumulative abnormal returns (CARs) following catastrophes. This effect is particularly striking for large catastrophes. We find that the relative size of the catastrophe is positively related to broker abnormal returns, and that returns are larger when insurance prices have been decreasing.

\(^{17}\)During data collection we noticed that many of the news items we categorized were regarding upcoming acquisitions, management changes, or bond issues. Stockholders often react negatively to each of these activities.
Specifically, we find a strong positive relationship between the insured loss size relative to policyholder surplus (PHS) and the CARs following the catastrophe event. A proposed explanation for this relationship is that capacity is more likely to be constrained if the loss is large relative to PHS. We find evidence of a positive relationship between sustained decreases in insurance prices and CARs, implying that the financial markets may consider the insurance market’s potential to harden when buying broker stocks in reaction to a catastrophe.

Our findings allow us to better understand how investment markets react to catastrophes. It appears that investors consider the surrounding environment and full sequence of events following a catastrophe to make a reasoned investment decision. Investors understand the state of the insurance market and how changes might influence brokers’ business.

Future research might examine the extent to which investors are correct in buying broker stocks following catastrophes. While our research shows that investors expect broker revenues to increase as a result of the catastrophe, it does not determine whether revenues actually increase as a result of the disaster. A comparison of broker CARs to insurer CARs following catastrophes also may be an interesting avenue for future research.
Appendix: Added Variable Plots of CAR vs. Variables of Interest

Figure 4 illustrates the relationship between $SHOCK$ and the 10-day CAR for each event using an added-variable plot, which displays the relationship after controlling for other influencing factors (see Frees, 2004, for more information). Figure 5 illustrates the relationship between $SHOCK$ and $CONSECNEGELRCHG$ using this same methodology.

[Figure 4 about here.]

[Figure 5 about here.]
References


<table>
<thead>
<tr>
<th>Rank</th>
<th>Event</th>
<th>Date</th>
<th>Insured Loss ($) (B, 2011)</th>
<th>Shock (% of PHS)</th>
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<tr>
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<td>H. Katrina</td>
<td>8/29/05</td>
<td>74.7</td>
<td>15.65</td>
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<td>2</td>
<td>Tōhoku EQ</td>
<td>3/11/11</td>
<td>35.0</td>
<td>6.20</td>
</tr>
<tr>
<td>3</td>
<td>H. Andrew</td>
<td>8/24/92</td>
<td>25.6</td>
<td>9.90</td>
</tr>
<tr>
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<td>9/11 Attacks</td>
<td>9/17/01</td>
<td>23.8</td>
<td>6.66</td>
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<td>21.2</td>
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<td>H. Ike</td>
<td>9/15/08</td>
<td>21.1</td>
<td>4.23</td>
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<tr>
<td>7</td>
<td>H. Ivan</td>
<td>9/16/04</td>
<td>15.4</td>
<td>3.49</td>
</tr>
<tr>
<td>8</td>
<td>H. Wilma</td>
<td>10/24/05</td>
<td>14.5</td>
<td>2.94</td>
</tr>
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<td>9</td>
<td>Thailand Floods</td>
<td>7/27/11</td>
<td>12.0</td>
<td>2.23</td>
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<td>New Zealand EQ</td>
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<td>12.0</td>
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Table 2: Summary Statistics of Insured Loss, by Catastrophe Type

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<th>SD</th>
<th>Min</th>
<th>Max</th>
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<td>17.34</td>
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<td>Winter Storm</td>
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<td>8.04</td>
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<td>Earthquake</td>
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<td>Floods</td>
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<td>7.39</td>
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<td>Tropical Storm</td>
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<td>Hail</td>
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<td>2.80</td>
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<td>-</td>
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<td><strong>Total</strong></td>
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<td>10.01</td>
<td>6.13</td>
<td>12.41</td>
<td>2.57</td>
<td>74.69</td>
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Table 3: Commercial P&C Brokers Traded on U.S. Exchanges

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<th>Ticker</th>
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<td>2/21/1997</td>
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<td>Aon Corp.</td>
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<td>4/24/1987</td>
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<td>Hilb, Rogal &amp; Hobbs Co.</td>
<td>HRH, HRHC</td>
<td>7/15/1987</td>
<td>10/1/2008</td>
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<td>Marsh &amp; McLennan Companies Inc.</td>
<td>MMC</td>
<td>2/16/1968</td>
<td>12/31/2011</td>
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<tr>
<td>Willis Group Holdings Plc.</td>
<td>WSH</td>
<td>6/12/2001</td>
<td>12/31/2011</td>
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Table 4: Summary Statistics of CAR(0,+10), by Broker

<table>
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<tr>
<th>Broker</th>
<th>Mean</th>
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<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
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<tr>
<td>Acordia</td>
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Table 5: Pearson Correlation between CAR Windows

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<th>CAR Window</th>
<th>(0,+0)</th>
<th>(0,+1)</th>
<th>(0,+5)</th>
<th>(0,+10)</th>
<th>(0,+30)</th>
<th>(0,+45)</th>
<th>(0,+90)</th>
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<tbody>
<tr>
<td>(0,+0)</td>
<td>1.000</td>
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<td></td>
<td></td>
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<td>(0,+1)</td>
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<td>1.000</td>
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<td>(0,+5)</td>
<td>0.636</td>
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<td>(0,+10)</td>
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<td>(0,+30)</td>
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<td>0.755</td>
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Table 6: Cumulative Average Abnormal Returns, by 2011 Rank

<table>
<thead>
<tr>
<th>Window</th>
<th>(a) All Events</th>
<th>(b) Top 20</th>
<th>(c) Top 10</th>
</tr>
</thead>
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<tr>
<td></td>
<td>CAAR (%)</td>
<td>CAAR (%)</td>
<td>CAAR (%)</td>
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<td>(-11,-1)</td>
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<td>0.60*</td>
<td>0.26</td>
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<tr>
<td></td>
<td>(139:125)</td>
<td>(70:55)</td>
<td>(34:29)</td>
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<tr>
<td>(0,0)</td>
<td>0.34**</td>
<td>0.71***</td>
<td>1.65***</td>
</tr>
<tr>
<td></td>
<td>(145:119)</td>
<td>(78:47)</td>
<td>(51:12)</td>
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<tr>
<td>(0,+5)</td>
<td>0.20</td>
<td>1.02</td>
<td>2.75***</td>
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<tr>
<td></td>
<td>(124:140)</td>
<td>(67:58)</td>
<td>(44:19)</td>
</tr>
<tr>
<td>(0,+10)</td>
<td>0.67</td>
<td>1.99***</td>
<td>3.91***</td>
</tr>
<tr>
<td></td>
<td>(137:127)</td>
<td>(77:48)</td>
<td>(46:17)</td>
</tr>
<tr>
<td>(0,+30)</td>
<td>0.24</td>
<td>3.25***</td>
<td>4.38***</td>
</tr>
<tr>
<td></td>
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<td>(78:47)</td>
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<tr>
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<td>2.17*</td>
<td>4.80***</td>
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<td>Obs.</td>
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<td>63</td>
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Note: The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using Patell’s standardized abnormal return Z-test. Figures in parentheses are the number of securities with (positive:negative) CAARs within that event window.
Table 7: Cumulative Average Abnormal Returns, Dropping Returns During Subsequent Events and WTC, by 2011 Rank

<table>
<thead>
<tr>
<th>Window</th>
<th>(a) All Events CAAR (%)</th>
<th>(b) Top 20 CAAR (%)</th>
<th>(c) Top 10 CAAR (%)</th>
</tr>
</thead>
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<tr>
<td>(-11,-1)</td>
<td>0.17* (139:125)</td>
<td>0.60* (70:55)</td>
<td>0.26 (34:29)</td>
</tr>
<tr>
<td>(0,0)</td>
<td>0.17* (140:124)</td>
<td>0.38* (75:50)</td>
<td>0.79* (48:18)</td>
</tr>
<tr>
<td>(0,+5)</td>
<td>0.00 (119:140)</td>
<td>0.53* (65:60)</td>
<td>1.50*** (40:26)</td>
</tr>
<tr>
<td>(0,+10)</td>
<td>0.16 (114:123)</td>
<td>1.29*** (68:49)</td>
<td>2.74*** (39:19)</td>
</tr>
<tr>
<td>(0,+30)</td>
<td>-0.08*** (83:92)</td>
<td>1.14*** (41:20)</td>
<td>5.95*** (20:7)</td>
</tr>
<tr>
<td>(0,+90)</td>
<td>-2.59 (68:80)</td>
<td>6.85*** (37:13)</td>
<td>8.28*** (21:6)</td>
</tr>
<tr>
<td>Events</td>
<td>42</td>
<td>20</td>
<td>10</td>
</tr>
</tbody>
</table>

Note: The symbols *, **, *** and **** denote statistical significance at the 0.10, 0.05, 0.01, and 0.001 levels, respectively, using a generic one-tail test. Significance was tested using Patell’s standardized abnormal return Z-test. Figures in parentheses are the number of securities with (positive:negative) CAAR within that event window.

The number of broker-events included in each CAAR estimation can be calculated by adding the values inside the parentheses.
Table 8: OLS Regression Analysis of Factors Influencing CAR (0,+10)

<table>
<thead>
<tr>
<th></th>
<th>All Events</th>
<th>Drop 20 Day Overlap</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Shock</td>
<td>0.578***</td>
<td>0.447***</td>
</tr>
<tr>
<td>Consec. Qtr of Neg ELR Chg</td>
<td>0.012***</td>
<td>0.012***</td>
</tr>
<tr>
<td>US Ind</td>
<td>0.023*</td>
<td>0.021*</td>
</tr>
<tr>
<td>Earthquake Ind</td>
<td>-0.0009</td>
<td>0.002</td>
</tr>
<tr>
<td>News Ind (-5,+5)</td>
<td>-0.011</td>
<td>-0.018</td>
</tr>
<tr>
<td>EPS Results Ind (-10,+10)</td>
<td>0.031**</td>
<td>0.03*</td>
</tr>
<tr>
<td>WTC Ind</td>
<td>0.160***</td>
<td>0.161***</td>
</tr>
<tr>
<td>Broker FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Obs.</td>
<td>259</td>
<td>259</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.232</td>
<td>0.368</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.185</td>
<td>0.326</td>
</tr>
</tbody>
</table>

Note: Standard errors clustered by event in parentheses. Stars *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.
Figure 1: ELR Year-Over-Year Price Changes Over Time
Figure 2: Unique Response to WTC Event
Figure 3: WTC Event Following Tropical Storm Allison

CAAR: Tropical Storm Allison

Day
CAAR

0 10 20 30 40 50 60 70 80 90

9/17/2001
Figure 4: Added Variable Plot of CAR vs. Shock (H2)
Figure 5: Added Variable Plot of CAR vs. Prior ELR (H3)