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Catastrophic Losses and Insurer Profitability: Evidence From 9/11

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Abstract

We examine the effects of 9/11 on the insurance industry, hypothesizing a short-run claim effect, resulting from insufficient premium *ex ante* for catastrophic losses, and a long-run growth effect, resulting from *ex post* insurance supply reductions and risk updating. Following Yoon and Starks (1995) we use short- and long-run abnormal forecast revisions to measure both effects, analyzing them as a function of firm-specific characteristics. We find that firm type, loss estimates, reinsurance use, and tax position are important determinants of the short-run position. Firm type, loss estimates, financial strength, underwriting risk, and reinsurance are key determinants of the firm's long-run position.

Introduction

The terrorist attack on the World Trade Center (WTC) on September 11, 2001, had an enormous impact on the insurance industry. Swiss Reinsurance estimates WTC losses at US$21 billion (Swiss Re, 2004), making it one of the most costly natural or man-made catastrophes in history. The WTC attack resulted in immediate and unexpected

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increases in insurer claim payments as well as a reduction in their capacity to supply catastrophe insurance. In theory, the WTC attack may have led to risk updating by insurers, resulting in a subsequent increase in insurance demand. Prior work suggests that both supply reduction by insurers and risk updating by insurers positively affect insurer long-run growth and profitability (Gron, 1994; Winter, 1994; Cummins and Danzon, 1997; Froot and O'Connell, 1999). The purpose of this study is to investigate the effect on insurers of both the large unexpected losses experienced in the short term (a "claim effect") and the long-run potential growth opportunities for insurers due to supply reduction and potential risk updating (a "growth effect") following 9/11.

The prior literature using event study methodology provides mixed evidence on the effect of catastrophic events on insurers. Shelor, Anderson, and Cross (1992) find positive abnormal returns for property and liability insurers after the Loma Prieta earthquake, positing that this is due to increased demand for insurance coverage, consistent with a growth effect. Conversely, Lamb (1995) finds a negative stock price reaction for insurers with direct business exposure following Hurricane Andrew, consistent with a short-run insurance claim effect. Similarly, Cummins and Lewis (2003) examine the WTC attack, the Northridge earthquake, and Hurricane Andrew, and find a strong negative impact (i.e., a claim effect) on insurer stock prices immediately following the catastrophe.

The conventional event study methodology, however, does not allow separation of short- and long-run effects that may occur with a mega-catastrophe like the WTC attack. Consequently, we adopt the Yoon and Starks (1995) approach, using short-run abnormal forecast revisions to measure changes in firms' existing assets and long-run abnormal forecast revisions to measure firms' future growth opportunities. We use 1-year earnings forecasts for short-run analysis and 5-year earnings growth forecasts for long-run analysis. Instead of focusing on the industry-level response to 9/11 we test short- and long-run abnormal forecast revisions as a function of individual firm characteristics. Prior studies provide some insight on firm characteristics that may explain insurer performance following a catastrophe. Kleffner and Doherty (1996) show that the supply of earthquake coverage is a function of insurer leverage, level of diversification, and profitability. Doherty, Lamm-Tennant, and Starks (2003) argue that leverage, level of new capital, expected growth, and losses may affect post-WTC stock price performance. Gron and Winton (2001) find that insurer product concentration, specifically in riskier or longer-tail lines of business, affects firm performance. Cummins and Lewis (2003) suggest insurer financial ratings to be an important predictor of postloss stock performance.

Using data from the Institutional Brokerage Estimate System (IBES) database, we obtain analysts' forecasts of earnings per share for a sample of public U.S. insurers in order to test short- and long-run abnormal forecast revisions as a function of firm characteristics. We match the IBES data with Compustat, Lexis Nexis, National Association of Insurance Commission (NAIC), and A.M. Best's data on firm financial and other variables. Our results are consistent with a short-run claim effect and a long-run growth effect. Specifically, there is a statistically significant relationship between the short-run abnormal forecast revision and firm type (property-liability vs. non-property-liability insurer), estimated loss, use of reinsurance, and the insurer's tax position. We find evidence consistent with a long-run growth effect as well. There is a statistically significant relationship between the long-run abnormal forecast revision and firm type, estimated losses, financial strength, underwriting risk, and use of reinsurance.

Our study makes several contributions to the literature. Unlike previous event studies that jointly consider the short- and long-run effects of catastrophes and capital shocks on insurers, we bring a new approach for evaluating this issue by using short-term and long-term earnings forecasts as proxies for expected short-term and long-term insurer performance. Using earnings forecast revisions we are able to separate the immediate claim effect and the longer-term growth effect, two potentially competing impacts on insurer profitability. We conduct cross-sectional regression analysis using firm-specific characteristics to provide additional insight on insurer performance. Our study should be of interest to analysts, regulators, shareholders, and industry participants in evaluating market dynamics in the aftermath of large disaster events.[1]

The remainder of the paper is organized as follows: The "Claim and Growth Effects" section explores the potential claim and growth effects of the WTC attack. The "Data" section describes the data set. The "Methodology" section introduces our research methodology. The next section presents the empirical results, and the final section "Summary and Implications" discusses the implications of our findings.

CLAIM AND GROWTH EFFECTS

Claim Effect

Insurers did not anticipate the WTC attack, one of the largest insured losses in history, so they did not charge *ex ante* for the terrorism risk or receive additional premium *ex post* to cover losses. In a Letter to Berkshire Hathaway shareholders discussing 2001 third-quarter earnings results, Warren Buffett wrote, "We were foolish . . . we and the rest of the industry included coverage for terrorist acts in policies covering other risks, and received no additional premium for doing so."[2] The unexpectedly large WTC claim cost resulted in higher expenses for insurers and substantially lowered short-run earnings and profitability. Here we define the impact of the unexpected loss on insurer short-run profitability as the *claim effect*. In this study, our focus is on how the claim effect varies across insurers as a function of firm characteristics.

In our empirical analysis, we use short-run abnormal forecast revisions (*SAFR*) to measure the claim effect and we anticipate that analysts revise downward the forecasts of earnings per share for individual firms more affected by the WTC attack. We hypothesize that insurers providing more property-liability coverage will experience a greater claim effect, holding other variables constant. We expect that firms

[1] Our study should be of interest to financial behavioralists. Prior studies, for example, De Bondt and Thaler (1990), Teoh and Wong (2002), and Easterwood and Nutt (1999), report that financial analysts under react or over react to new information. Here we find evidence that analysts are responding rationally to a major catastrophic event, which adds a new twist to the literature on analyst behavior.

[2] Failure by insurers to charge sufficient premium has occurred before. For example, insurers have undercharged for natural catastrophe risk (such as earthquakes or hurricanes), but correcting for this in the aftermath of the catastrophe is relatively easier, given that there are far more observations to use in forecasting than there are with the terrorism risk.

with higher loss estimates will experience more negative short-run forecast revisions. We anticipate that firms with more reinsurance backing will experience less negative short-run abnormal forecast revisions since reinsurers help cover big claims, relieving primary insurers of additional asset liquidation (e.g., stock sales) at a time when asset values are falling because of widespread sell orders from other insurers liquidating assets as well as market jitters due to the catastrophe itself. In addition, firms with a relatively greater tax burden will receive relatively more tax benefit in the short run from unexpectedly large losses, yielding a positive relationship between the average tax rate and short-run forecast revisions.

Growth Effect

In this study we hypothesize a long-run growth effect for insurers post-9/11 profitability due in theory to supply constraints and/or probability updating. Following a catastrophic event, insurers face large loss payouts, leading to depletion of capital. The demand for additional capital is both immediate and industrywide, resulting in increases in the cost of capital. Theory and empirical evidence suggest that higher costs of capital as well as solvency requirements limit the ability of insurers to supply insurance, both for policy renewals and issuance of new coverage (see Winter, 1991, 1994; Gron, 1994; Cummins and Danzon, 1997; Froot and O'Connell, Forthcoming; Cummins and Lewis, 2003). Given supply constraints, insurers are able to adopt stricter underwriting standards as well as increase price for any given level of risk.[3] If price increases dominate quantity reductions of issued coverage, insurer profitability increases, leading to better growth opportunities. In our study we hypothesize that supply constraints following the WTC attack are a component of a long-run *growth effect* for insurers.

It is important to note that not all insurers are equally well positioned to recover from a capital shock (see, e.g., Cummins and Danzon, 1997; Cummins and Lewis, 2003). For example, some insurers with good credit histories and outstanding financial ratings have the ability to replenish external capital at a relatively lower cost. Alternatively, many insurers concerned by the high cost of raising external capital will have to rely on slower capital recovery using internal capital. On average, the faster the recovery of an individual insurer, the better reshuffled position it achieves in the market and the greater its profitability, which is reflected in analysts' long-run forecasts of earnings for the firm. Here we investigate the relationship between various firm characteristics and long-run abnormal forecast revisions.

In addition to capacity constraints, the hypothesized growth effect could be explained by policyholder risk updating after the WTC attack. Froot and O'Connell (1999) discuss probability updating as an increase in the actual or perceived actuarial loss

[3] Following the WTC attack insurers began excluding the terrorism risk from the coverage that they were writing. In response, the Terrorism Risk Insurance Act of 2002 (TRIA) was passed in November 2002 that required insurers to write terrorism coverage but provided the industry with some protection through government reinsurance. TRIA primarily affects terrorism insurance (see Brown et al., 2004) whereas the supply effect we consider here involves all lines of insurance as a consequence of capital shortage. Our study largely ignores the impact of TRIA because we are investigating a hypothesized growth effect using analysts' forecasts made by December 2001, at which time the passage of TRIA was uncertain.

covered by a given contract following a catastrophe. That is, increases in either the expected loss probability distribution or in the policyholder perception of expected loss will result in increased insurance demand. Policyholder awareness of what is and is not covered by existing contracts can result in demand for higher limits or broader scope of coverage. In addition, Lewis and Murdock (1996) and Cummins and Lewis (2003) point to the role of parameter uncertainty in probability updating. They suggest that risk updating is especially likely when there is relatively greater uncertainty about the true probability distribution of loss, for example, the terrorism risk.[4] Taken together, both updating of average or perceived losses and uncertainty about loss parameters constitute a second economic explanation for the hypothesized growth effect. Here we test for a growth effect and expect greater growth for insurers specializing in property-liability lines, those lines that had greater 9/11 exposure to terrorist-related risk.

While theory suggests that these supply and/or demand factors may underlie a possible growth effect, disentangling these two effects would require data not available at this time (e.g., firm-level information on quantity increases or price increases by line of coverage following a catastrophe). Thus, our purpose here is to test for a hypothesized growth effect and explore firm characteristics related to long-run growth potential.

In our study we use long-run abnormal forecast revisions (*LAFR*) to test for a hypothesized growth effect. Using long-run abnormal forecast revisions allows us to avoid compounding impacts inherent to event studies using stock performance analysis. We hypothesize relatively greater positive long-run growth effects for property-liability insurers and for insurers with greater expected loss estimates. We anticipate that insurer financial strength, which affects the firm's ability to raise capital for postcatastrophe recovery, is positively related to long-run abnormal forecast revisions. Since consistent underwriting results over time allow better client retention and attraction of new business, we expect a negative relationship between growth and underwriting risk, as measured by the variation in the loss ratio of an insurer over the past decade. We hypothesize long-run abnormal forecast revisions to be positively related to the use of reinsurance and negatively related to firm leverage because greater use of reinsurance and lower leverage correspond to greater firm capacity to absorb unexpected losses and greater flexibility for recovery.

Data

Our initial sample of insurers is obtained from the IBES database. IBES includes five insurance-related segments: life insurers, multiline insurers, property and liability insurers, mortgage and title insurers, and insurance brokerage firms. We exclude mortgage and title insurers to focus on the impact of the WTC attack on conventional life-health and property-liability insurers. We also exclude insurance brokerage firms because they do not underwrite risk and pay for losses in the WTC attack. This yields an initial sample of 104 U.S. insurers with either 1-year analysts' earnings forecasts (for short-term claim effect analysis) or 5-year earnings forecasts (for long-run growth

[4] Consistent with the view of parameter uncertainty, we find that forecast dispersion, measured by the standard deviations of the forecasts submitted by different analysts, greatly increased after the WTC attack.

effect analysis) between August 2001 and December 2001. Next, we confirm that a firm is either a property-liability insurer or a life-health insurer using the Standard Industrial Classification (SIC) codes in the Compustat database and information from Moody's Bank and Finance Manual. The verification process eliminates 18 firms from the sample.[5] We then remove four firms that have fewer than 12 observations of historical short-run forecast revisions or long-run forecast revisions. Our final sample includes 82 firms. Among them, 80 firms are included in the short-run analysis and 66 firms are included in the long-run analysis.

We identify insurers as either property-liability (PL) or non-property-liability (non-PL) firms, using both IBES and Compustat database identifiers. In Compustat, a firm with the SIC code of 6330 and 6331 is a property-liability insurer. In IBES, a firm with its Sector / Industry / Group (SIG) code of 010503 is a property-liability insurer. Accordingly, we classify a firm as a PL firm if (1) IBES and Compustat both classify it as a property-liability insurer (35 PL firms are identified) and (2) in cases where only one database identifies a firm as a PL firm, we check the firm's websites to confirm its specialization (an additional 19 PL firms are identified). In sum, we identify a sample of 54 PL firms and 28 non-PL firms. Table 1 provides names of the 82 sample firms classified by type.

To facilitate the cross-sectional analysis, we match our sample with the NAIC database to obtain insurer financial and underwriting-related information. IBES and Compustat data are reported at the holding level while the NAIC data are provided at the subsidiary level with identified group names. If a firm in the NAIC database belongs to an insurance group, we aggregate the firm-level data into the group level in the NAIC database and then match NAIC group names with IBES / Compustat firms.[6] If a firm in the NAIC database is a stand-alone firm, we match it with the IBES / Compustat sample by company name. We find that 76 firms in our sample are covered in the NAIC database.

Finally, we obtain the company ratings from the A.M. Best Key Rating Guide for property-casualty and life-health insurers. Here again we match data by insurer name to obtain the Best's group code (if they are affiliated companies) or the company code (if they are stand-alone companies). We obtain Best's ratings for 67 firms in our sample.

METHODOLOGY

Abnormal Earnings Forecast Revisions

IBES provides detailed and summarized forecasts from security analysts for more than 18,000 companies worldwide. Forecast items include earnings per share, cash flow,

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[5] Three are non-U.S. insurance firms, one is an insurance auto auction firm, four are mortgage bankers, one is a security broker, one is the parent company of an insurer, and 10 are insurance brokerage firms.

[6] The NAIC database covers property-liability insurers and life insurers separately. For property-liability insurers, it provides information at both the individual firm level and the insurance group level. For life insurers, it only provides individual firm information, but it specifies the insurance group for each firm where applicable. Since the procedure used by the NAIC to aggregate individual firm information of property-liability insurers to the group-level data is not publicly available, we do not use the group data provided by the NAIC database.

TABLE 1
Sample Insurance Firms

PL Insurance Companies		
21st Century Insurance Group	Everest Re Group	PMA Capital Corp
Ace Ltd	FPIC Insurance Corp	ProAssurance Corp
Alfa Corp	Harleysville Group	Progressive Ohio Corp
Allmerica Financial	Hartford Financial Service	PXRE Group Ltd
Allstate Corp	HCC Insurance Holdings Inc	Reliance Group Holding
American Physicians Svc Group	Horace Mann Education	RenaissanceRe Holding Corp
American Financial Group	IPC Holdings Ltd	RLI Corp
American International Group	Mercury General Corp	Safeco Corp
American Safety Insurance	Midland Corp	SCPIE Holdings Corp
Argonaut Insurance Group	MIIX Group Corp	Selective Insurance Corp
Berkley W R Corp	Navigators Group	St Paul Inc
Berkshire Hathaway	NYMAGIC Inc	State Auto Financial Corp
Chubb Corp	Ohio Casualty Insurance Group	Transatlantic Holding Corp
Cincinnati Financial	Old Republic International Corp	Trenwick Group Ltd
CAN Financial Corp	PartnerRe Ltd	Unitrin Inc
CAN Surety Corp	Penn-America Insurance Group	VESTA Insurance Corp
Commerce Group Inc	Philadelphia Consolidating Holding	XL Capital Ltd
Donegal Group		Zenith National Insurance Corp
Erie Indemnity		
Non-PL Insurance Companies		
Aegon N.V.	Jefferson-Pilot Corp	Protective Life Corp
AFLAC Inc	John Hancock	Prudential Plc
American National Insurance Group	Kansas City Life Insurance	Reinsurance Group of America
Amerus Group Corp	Leucadia National	Scottish Annuity Corp
Annuity and Life Reinsurance	Lincoln National Insurance Group	Stancorp Financial Corp
AXA SA	Metlife Inc	Torchmark Corp
CIGNA Corp	Mutual Risk Management	UICI
Conseco Inc	Nationwide Financial	Universal American Financial
Delphi Financial Group	Presidential Life Insurance Corp	UnumProvident Corp
FBL Financial Group		

long-term growth projections, and stock recommendations. The specific forecasts vary from one-quarter forecasts to long-term (greater than 10-year) growth projections. The summary file, also known as the consensus file, contains the mean, median, and standard deviation as well as other statistics of the analysts' forecasts on a monthly basis.

Yoon and Starks (1995) suggest that short-run analysts' earnings forecast revisions reflect changes in firms' existing assets, while long-run growth forecast revisions correspond to firms' future growth. We adopt their methodology and use the 1-year abnormal earnings forecast revisions to represent the short-term claim effect. We examine the earnings forecast changes for year 2001 (short-run) as well as the 5-year earning growth rate (long-run) made before and after September 2001. We use the forecast in August as the before-attack forecast and the forecasts in October, November, and December, respectively, as the postattack forecasts.

Following Brous (1992) and Yoon and Starks (1995), we measure the raw short-run forecast revision, $SFR_{i,j}$, using the following formula:

$$SFR_{i,j} = \frac{F_{i,\tau+j} - F_{i,\tau-1}}{P_{i,\tau-1}}, \tag{1}$$

where i represents a specific firm i, $j = 1$, 2, or 3, and τ stands for September 2001, the month of the WTC attack. Accordingly, $\tau - 1$ denotes August 2001, and $\tau + j$ represents October, November, or December 2001. $F_{i,\tau-1}(F_{i,\tau+j})$ is the mean or median year 2001 earnings forecast for firm i made in month $\tau - 1$ $(\tau + j)$ and $P_{i,\tau-1}$ is the price for firm i in month $\tau - 1$.

The raw short-run forecast revision provided in Equation (1) suffers from some drawbacks. This concern comes from two biases in analysts' forecasts highlighted by the prior literature. One is an optimism bias shown in O'Brien (1988) and Brous (1992). When making their forecasts, analysts tend to be optimistic at the beginning of the fiscal year and gradually revise their forecasts down as fiscal year-end approaches. The other is a sequential updating bias identified in Brous (1992). On average, approximately 20 percent of the analysts update their forecast each month, resulting in serial correlation among the consensus earnings forecasts. These biases may lead to nonzero average raw forecast revisions without an event occurring. To control for forecast biases and assess the actual effect of the WTC attack on short-run earnings forecast made by financial analysts, we estimate the abnormal forecast revision by subtracting the expected forecast revision from the raw forecast revision.

Defining $E(SFR_{i,j})$ as the expected forecast revision for firm i from month $\tau - 1$ to $\tau + j$, we have the following expression for the short-run abnormal earnings forecast revision (*SAFR*) from $\tau - 1$ (August 2001) to $\tau + j$ (jth month after the WTC attack):

$$SAFR_{i,j} = SFR_{i,j} - E(SFR_{i,j}). \tag{2}$$

$E(SFR_{i,j})$ is the expected forecast revision during the nonevent period plus a disturbance term. Consistent with Brous (1992), we model the disturbance using a fourth-order moving average process. The formula for $E(SFR_{i,j})$ is:

$$E(SFR_{i,j}) = k_{i,j} + \frac{1}{5}\sum_{1}^{4} \varepsilon_{i,j,\tau-c}. \tag{3}$$

In Equation (3), $k_{i,j}$ is the expected forecast revision, evaluated as the average of the 1-year forecast revisions from month $t - 1$ to $t + j$, where t is any available month in the IBES database except months (−6, +6) relative to September 2001.[7] That is,

[7] As noted by a reviewer, the estimation of E(SFR) uses past data that could be affected by previous major catastrophes. To control for this we exclude the forecast revisions around the

$k_{i,j}$ is the time-series average forecast revision calculated with available data in IBES excluding the time period from March 2001 to March 2002. The second term in (3) is a disturbance term following a fourth-order moving average process, where $\varepsilon_{i,j,\tau-c}$ is the unexpected forecast revision for "event" month $\tau - c$ ($1 \leq c \leq 4$). We express $\varepsilon_{i,j,\tau-c}$ as the difference between the actual forecast revision in month $\tau - c$ and the average forecast revision. That is, $\varepsilon_{i,j,\tau-c} = SFR_{i,j,\tau-c} - k_{i,j}$.

We calculated long-run abnormal forecast revisions (*LAFR*) as the difference in the actual long-term earnings growth forecast revisions, *LFR*, and the expected forecast revisions, *E*(*LFR*).

$$LAFR_{i,j} = LFR_{i,j} - E(LFR_{i,j}). \tag{4}$$

Consistent with Yoon and Starks (1995) and Best, Best, and Hodges (1998), we compute long-run forecast revisions (*LFR*) as:

$$LFR_{(i,j)} = \frac{F_{i,\tau+j}}{F_{i,\tau-1}} - 1, \tag{5}$$

where τ refers to September 2001. $F_{i,\tau+j}$ and $F_{i,\tau-1}$ are the mean or median forecasts of the annual earnings growth rate for the next 5 years for firm i in month $\tau + j$ and $\tau - 1$, respectively. $E(LFR_{i,j})$ is estimated as the average of the *LFR*s using 3 years of monthly data from March 1998 to March 2001. The long-run forecast revisions are not standardized by stock price because the long-run forecast provided by IBES is the annual growth rate of earnings per share. We do not include a disturbance term in *E* (*LFR*) as we do in *E*(*SFR*) because long-run forecasts are not subject to the sequential updating bias.

Determinants of the Claim Effect

We investigate firm characteristics that explain insurer performance following a catastrophe. The characteristics that are expected to predict the short-run firm effect of the WTC attack are whether the firm is a property-liability insurer, the magnitude of estimated losses following the attack, the extent of reinsurance usage, and the firm's tax position. We also consider the effects of several other factors, including product diversification within the firm, firm size, firm leverage, and forecast dispersion.

The insurance industry has been organized into two branches, the property-liability and the life-health insurance sectors. Since the majority of claims from the WTC attack were for property-liability losses, the attack had the most negative impact on property-liability insurers. To capture this effect, we use an indicator variable, *PLDUMMY*, equal to 1 for property-liability insurers, and 0 otherwise. A concern of using the above simple classification of PL and non-PL insurers is that many insurers write both property-liability and life-health insurance policies. To control for limitations of

three largest natural catastrophes prior to 9/11, namely, Hurricane Hugo (September 1989), Hurricane Andrew (August 1992), and the Northridge earthquake (July 1994). Specifically, we exclude forecast revisions made in the 3 months before and the 3 months after the catastrophe. We find virtually no change in our results.

the bivariate classification, we construct a continuous measure, namely, the percentage of the firm's sales in property-liability lines, *PLPCT*. The segment sales information is obtained from the Compustat segment database where segment SICs of 6330 and 6331 are considered as property-liability business. We expect short-run abnormal forecast revisions to be negatively correlated with both loss measures, *PLDUMMY* and *PLPCT*.

We expect that analysts' short-run forecast revisions are affected by the magnitude of expected losses following the attack. We include two loss measures. One is the estimated posttax loss net of reinsurance standardized by total assets in year 2001 (Compustat item 6). We denote this first loss measure as *LOSS1*. We obtain the attack-related loss information from the quarterly reports (10Q), the annual reports (10K), and the unscheduled material events reports (8K). All these data come from Lexis-Nexis. Sixty-nine out of the 82 insurers covered in our sample report the attack-related losses net of reinsurance.[8] For insurers reporting their pretax attack related losses, we estimate their income tax rate using income tax (Compustat item 135) divided by pretax income (item 170) and then compute their posttax losses as pretax losses multiplied by (1 − estimated income tax rate). Alternatively, we measure WTC-related losses indirectly with *LOSS2*, the reduction in an insurer's net income (item 172) from year 2000 to 2001, scaled by total assets (item 6). We expect short-run abnormal forecast revisions to be negatively related to *LOSS1* and *LOSS2*.

We expect firms purchasing more reinsurance to be relatively better off in the short run following a mega-catastrophe. Insurers transfer risk to reinsurers, reducing the claim effect on insurers when a covered event occurs. We measure reinsurance use (*REINS*) as the ratio of the ceded written reinsurance premium to the sum of the direct written premium (paid by policyholders) plus the assumed written reinsurance premium. Since the public insurers in the IBES database typically correspond to insurance groups in the NAIC database, we average *REINS* weighted by firm assets at the end of year 2000 across individual insurers within an insurance group, including both property-liability and non-property-liability segments. The same procedure is applied to computing other insurance characteristic measures. We expect a positive relationship between analysts' short-run abnormal forecast revisions and *REINS*.

The firm's average tax rate (*TAX*) is another determinant of how some insurers fare in the short run following the WTC attack. Increased claim costs potentially offer a tax benefit to insurers since claim payments are business expenses which lower pretax income. Firms with a higher tax rate benefit relatively more from claims payout. We expect analysts' short-run forecast revisions to be positively related to *TAX*. In addition, because the largest component of liability is unpaid losses, we expect firms with lower leverage (*LEVERAGE*) to have less exposure to unexpected losses. We calculate leverage as the insurer's total liabilities divided by total assets.

We include the Herfindahl index by line of business, *HERF*, as a measure of product (or line) diversification within the firm. It is calculated as the sum of the squared

[8] The reporting on WTC-related losses varies across firms. For example, Chubb Corporation reports in its 10K filing that the pre- and post-tax costs net of reinsurance ceded and additionally incurred losses are \$645 and \$420 million, respectively, from the 9/11 attack, whereas, in the 10K of SAFECO Corporation, \$25 million is reported as pretax 9/11 losses net of reinsurance.

percentages of insurance premium earned in each business line to the total premium written in all property-liability and life-health lines. To be specific, for firm i, $HERF_i = \sum_{l=1}^{35}(PW_{i,l}/TPW_i)^2$ where $PW_{i,l}$ is its net premium written in business line $l(l = 1, 2, \ldots,$ and 35), and TPW_i is its total net premium written for all business lines.[9,10] The more diversified a firm is by line of business, the lower the Herfindahl index.[11] More diversified firms are better able to handle a catastrophic loss; thus, we expect analysts' short-run forecast revisions to be negatively related to *HERF*.

We control for firm size since larger firms may be more diversified and are therefore better able to handle large losses. We measure firm size (*LGSIZE*) as the logarithm of the total assets at the end of 2000, where assets are aggregated across firms within each insurance group. We expect analysts' short-run forecast revisions to be positively related to *LGSIZE*. In addition, we control for the earnings forecast dispersion across analysts (*FCSTDISP*). We calculate *FCSTDISP* as the standard deviation of earnings forecasts made by different analysts.

Determinants of the Growth Effect

The firm characteristics that are expected to affect long-run results are firm type (i.e., whether the firm is a property-liability insurer), expected losses, firm financial strength, firm underwriting risk, use of reinsurance, and tax rate. We control for firm diversification by line of coverage, firm size, firm leverage, and forecast dispersion.

As in the short-run analysis we control for firm type (i.e., property-liability insurers) using an indicator variable, *PLDUMMY* as well as a variable that measures the percentage of the firm's business in property-liability lines (*PLPCT*). Since property-liability insurers are expected to experience greater supply constraints, controlling for other factors, we anticipate a positive relationship between property-liability measures and long-run abnormal forecast revisions.

Two loss-related industry-wide growth measures are considered. Sectors of the insurance industry experiencing more losses in the WTC attack may have greater future growth potential. However, the two loss measures (*LOSS1* and *LOSS2*) that were used in the claim effect analysis are problematic because they involve firm-specific losses. With firm-specific losses, an affected firm cannot increase premium and the growth effect may not apply. If a loss is sustained by all firms in a line, then the affected firms will increase their premiums, get through the shock and have long-run revenue growth. In order to address this problem, we regress the two loss measures, *LOSS1* and *LOSS2*, on the proportions of premiums in the lines expected to be highly affected by the WTC attack. Specifically, we consider six lines, namely, fire, workers' compensation, general liability, commercial multiple perils, aircraft, and allied lines to be related lines. We compute the percentage of written premiums in each of these lines using the written premium in affected lines divided by total written premiums

[9] Based on Part1B of the insurer annual statement, property-liability insurance business is broken down into 34 business lines. We treat life-health insurance as the 35th business line.

[10] Net written premium is the direct written premium paid by policyholders plus the difference between an insurer's assumed and ceded written reinsurance premiums.

[11] Following Kleffner and Doherty (1996) in our preliminary analysis we also used a state Herfindahl index to measure diversity with little change in the result.

from all other property-liability and life-health lines. Information for a specific related line is obtained from Part 2B of the Underwriting and Investing Exhibit of an insurer's 2001 annual statements. We use the predicted value from the regressions to construct the predicted loss measures, *PLOSS1* and *PLOSS2*. We expect analysts' long-run forecast revisions to be positively related to these two measures.[12]

We expect firm financial strength to be an important determinant of long-run growth following a catastrophic event. Here we use A.M. Best ratings (*RATING*) as a proxy for financial strength. Higher ratings indicate superior financial strength and capacity, which allow insurers to better recover from catastrophic losses. We define the rating of an insurer following the classification used in Colquitt, Sommer, and Godwin (1999). *RATING* equals 5 for firms rated A++ or A+ and FPR9, equals 4 for A or A− and FPR7 or FPR8, equals 3 for B++ or B+ and FPR5 or FPR6, equals 2 for B or B− and FPR4, equals 1 for C++ or C+ and FPR3, and equals 0 for C, C−, or D and FPR2.[13] Following Cummins and Lewis (2003) better rated insurers have more financial capacity to recover from the attack. Therefore we expect a positive relationship between long-run abnormal forecast revisions and *RATING*.

Underwriting risk is also expected to affect an insurer's long-run growth potential following a catastrophe. Following Lamm-Tennant and Starks (1993) we measure *UWRISK* as the standard deviation of the loss ratios for the firm from 1990 to 2000. We expect a negative relation between *LAFR* and *UWRISK* because firms with more volatile underwriting results (or profitability) are less able to take advantage of growth opportunities in the postcatastrophe environment.

Another determinant of a potential growth effect is leverage, measured as the firm's long-term liability over total assets. Cummins and Sommer (1996) and Kleffner and Doherty (1996) find that the cost of risk bearing for insurers is positively related to leverage. Lower leverage provides greater capacity for unexpected losses and more flexibility in recovery. We expect that the lower a firm's leverage, *LEVERAGE*, the greater the potential growth effect.

As in the short-run estimation, here we also include a measure of firm diversification by line (*HERF*). More diversified firms are better able to handle catastrophic losses and we expect analysts' long-run forecast revisions to be negatively related to *HERF*. We include two control variables, firm size (*LGSIZE*) and analysts' forecast dispersion (*FCSTDISP*).

Table 2 Panel A provides descriptive statistics for variables used in both the short-run and long-run analyses. The average reported WTC-related losses scaled by total assets, denoted by *LOSS1*, accounts for 0.91 percent of insurers' total assets, with the maximum value being 11.52 percent. The asset-scaled net income change, LOSS2, shares a similar magnitude. As implied by the mean value for *PLPCT*, property-liability lines on average account for about half of the written premium of insurers in

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[12] For the sake of completeness we also estimated the long-run abnormal forecast revision equations using *LOSS1* and *LOSS2* (as in the short-run abnormal forecast revision estimation) with virtually no change in results.

[13] Based on the Best Rating Guide, the FPR measures the financial strength of small or new companies not eligible for a Best's Rating. The FPR scale ranges from a 9 for financially strong companies to a 2 for financially weak companies.

TABLE 2
Summary Statistics

Panel A: Descriptive Statistics

	Mean	Std. Dev.	Min.	Max.	*N*
LOSS1 (%)	0.91	2.06	0.00	11.52	69
LOSS2 (%)	0.88	2.53	−5.51	8.80	80
PLPCT (%)	49.44	43.73	0.00	100	65
REINS (%)	34.27	21.52	0.00	97.95	76
TAX (%)	25.10	18.44	−45.52	59.42	82
RATING	4.15	0.79	0.00	5.00	67
UWRISK (%)	12.03	9.83	2.16	48.92	76
LEVERAGE (%)	49.75	16.03	4.21	80.24	76
HERF (%)	47.02	34.17	7.52	100.00	76
SIZE (billion $)	23.07	47.74	0.02	226.62	76

Panel B: Correlation Coefficients

	PLDUMMY	*LOSS1*	*LOSS2*	*PLPCT*	*REINS*	*TAX*	*RATING*	*UWRISK*	*LEV*	*HERF*
LOSS1	0.35									
LOSS2	0.25	0.62								
PLPCT	0.79	0.31	0.28							
REINS	0.41	0.38	0.31	0.36						
TAX	−0.09	0.02	0.01	0.12	−0.31					
RATING	0.16	0.24	0.15	−0.02	0.08	−0.02				
UWRISK	−0.15	−0.04	−0.06	0.09	−0.01	0.09	−0.21			
LEVERAGE	0.20	−0.05	−0.07	0.08	−0.16	0.08	0.02	0.04		
HERF	−0.42	−0.33	−0.38	0.13	−0.50	0.13	−0.05	0.21	0.27	
SIZE	−0.13	0.24	0.26	0.03	0.02	0.03	0.34	−0.06	−0.03	−0.08

Notes: Panel A reports the descriptive statistics for the attributes of sample insurers. Panel B reports the correlation among these variables. *PLDUMMY* is the dummy equal to 1 for a property-liability insurer, and 0 otherwise. *LOSS1* (in percent) is estimated loss related to the WTC attack standardized by its total assets at the end of year 2000. *LOSS2* (in percent) is the difference in net income between 2000 and 2001, standardized by total assets in 2000. *PLPCT* is the percentage of an insurer's business in property-liability lines obtained from Compustat segmentation data. *REINS* (in percent) is the ratio of the ceded written reinsurance premiums to the sum of the direct written premiums and the assumed written reinsurance premiums. *TAX* (in percent) is the average tax rate, estimated as income tax divided by taxable income. *RATING* is an insurer's Bests' rating, equal to 5 for firms rated A++ or A+ and FPR9, 4 for A or A− and FPR7 or FPR8, 3 for B++ or B+ and FPR5 or FPR6, 2 for B or B− and FPR4, 1 for C++ or C+ and FPR3, and 0 for C, C−, or D and FPR2. *URISK* (in percent) is the standard deviation of the loss ratios of each insurer from 1990 to 2000. *LEVERAGE* (in percent) is an insurer's total liabilities to its total assets. *HERF* (Herfindahl index, in percent) is the sum of the squared percentage of the premiums of an individual line to total premiums of the insurer. *SIZE* is total assets at the end of 2000. For *REINS*, *LEVERAGE*, and *HERF*, we calculate the measures for individual firms and then average across each insurance group weighted by firm assets at the end of year 2000. We calculate *SIZE* for individual firms and then aggregate across each insurance group.

our sample. Firms in our sample tend to have strong insurance ratings; the Bests' rating sample average is 4.15 out of a possible 5 points (whereas the average across all insurers is 3.12). Table 2 Panel B reports the correlation between insurer characteristics. The two loss measures are highly correlated (correlation = 0.62). In addition, they appear to be correlated with business-type measures (*PLDUMMY* and *PLPCT*). In addition, the insurance rating and firm size variables are positively correlated.

Statistical Inference: Bootstrapping Approach

Since our analysis only involves a single-event period (September 2001) and all sample firms come from a single industry (the insurance industry), forecast revisions of individual firms are expected to be correlated. As a consequence, the conventional t-statistics may be misspecified because they typically assume the observations to be independent. One way to solve the cross-sectional dependence problem is to use multivariate regression models (MVRM) suggested in Binder (1985) and Bernard (1987). The MVRM approach, however, is not applicable here because we do not apply the time-series regressions to estimate abnormal forecast revisions. Therefore, we instead base the statistical inference on a bootstrapping procedure to obtain p-values of the t-statistics. The intuition of the bootstrapping approach is straightforward. We use the "abnormal" forecast revisions in the normal "sample" period without a known catastrophic event as a benchmark to evaluate the effect of the WTC attack. As long as the cross-sectional dependence is constant during the event period and the normal sample period, the bootstrapping approach provides an inference on the magnitude of the event on analysts' forecast revisions. As suggested in Freeman (1981) and Hall (1992), an apparent advantage of the bootstrapping approach is that it does not rely on any parametric assumption of sample distributions.

Specifically, we construct a nonevent sample that assumes the "event" month to be September 2000, where no substantial event occurs in this period in the insurance industry. As a result, we do not expect the average abnormal forecast revisions for our sample insurers to be significantly different from zero. With replacement, we randomly draw from the nonevent sample the same number of observations as that in the WTC attack period and compute bootstrapped test statistics. We repeat this procedure 1,000 times to form the bootstrapped distribution of the test statistic. We then compute the bootstrapped p-value as the relative ranking of the test statistic calculated from the real sample in the bootstrapped distribution.[14] The details of the bootstrapping procedure are given in the Appendix.

EMPIRICAL RESULTS

Evidence on a Claim Effect

Table 3 presents the results for univariate comparisons of abnormal forecast revisions based on mean and median forecasts for the full sample and for subsamples. The first three columns of Panel A show the mean and median of the full-sample short-run abnormal forecast revisions (*SAFR*) for event month windows $(-1, 1)$, $(-1, 2)$, and $(-1, 3)$, which respectively represent the forecast revisions from August to October, August to November, and August to December. The t-statistic for the mean and z-statistic for the median and bootstrapped p-values are reported as well.

Our findings are consistent with a negative industry-wide impact of the WTC attack as reflected by analysts' short-term forecast revisions. The mean and median *SAFR*s

[14] Following Hall (1992) we bootstrap t-statistics rather than abnormal forecast revisions because t-statistics have better convergence properties.

TABLE 3
Univariate Comparisons of Abnormal Forecast Revisions

Panel A: Full Sample

	SAFR			*LAFR*		
Relative Months	Mean (%)	Median (%)	*N*	Mean (%)	Median (%)	*N*
(−1, +1)	−0.63	−0.59	69	−0.76	−0.54	60
	(−1.79 / 0.11)	(−1.82 / 0.13)		(−0.70 / 0.76)	(−0.35 / 0.70)	
(−1, +2)	−0.79*	−0.81*	79	−0.24	−0.31	64
	(−1.87 / 0.08)	(−1.93 / 0.08)		(−0.33 / 0.75)	(−0.28 / 0.69)	
(−1, +3)	−2.14***	−2.11***	80	0.69	0.52	66
	(−2.97 / 0.00)	(−2.88 / 0.00)		(0.73 / 0.44)	(0.55 / 0.39)	

Panel B: PL Insurers vs. Non-PL Insurers (month window (−1, +3) forecast revisions)

	SAFR			*LAFR*		
Insurer Type	Mean (%)	Median (%)	*N*	Mean (%)	Median (%)	*N*
$PLDUMMY = 1$	−3.92***	−4.00***	49	1.37*	1.42*	43
	(−3.14 / 0.01)	(−3.26 / 0.01)		(1.74 / 0.10)	(1.78 / 0.09)	
$PLDUMMY = 0$	−0.20	0.10	31	−0.94	−0.86	23
	(−0.34 / 0.47)	(0.23 / 0.62)		(−0.43 / 0.72)	(−0.71 / 0.77)	
DIFF	−3.72***	−4.10***		2.31*	2.28*	
	(−2.98 / 0.00)	(−3.17 / 0.00)		(1.84 / 0.05)	(1.96 / 0.05)	

Notes: This table reports the results for univariate comparisons of abnormal forecast revisions based on mean and median forecasts for full sample and subsamples. Panel A presents abnormal forecast revisions, both short-run forecast revisions (*SAFR*) and long-run forecast revisions (*LAFR*), for three event windows: month (−1, 1), (−1, 2), and (−1, 3) surrounding the event month of September 2001. Panel B compares the forecast revisions between property-liability insurers ($PLDUMMY = 1$) and non-property -liability insurers ($PLDUMMY = 0$) in the month window (−1, +3). The t-statistics of mean analysis, z-statistic of the median analysis, and respective bootstrapped p-values are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

for the (−1, 1) month window are both negative (−0.63 percent and −0.59 percent), however, insignificantly different from 0.

The mean and median *SAFR*s for the (−1, 2) month window are −0.79 percent and −0.81 percent, significant at the 10 percent level. Further, the mean and median *SAFR*s in the (−1, 3) month window are −2.14 percent and −2.11 percent, respectively, both significant at the 1 percent level. The less significant results for the (−1, 1) and (−1, 2) month windows are driven by the fact that only 20 percent of analysts update their earnings forecasts each month (e.g., Brous, 1992). Since the (−1, 1) and (−1, 2) month windows may not include adequate analyst updates regarding the WTC attack, we focus on forecast revisions in the (−1, 3) month window in the remaining analyses.[15]

[15] Analyst updates are performed on a voluntary basis rather than a fixed schedule. After an adequately long event window (such as 3 months used in our analysis) analysts should have updated their forecasts. A stale forecast is more reflective of an analyst's decision not to update

In Panel B, we compare short-run forecast revisions for the property-liability insurers and non-property-liability insurers. The mean forecast revision for property-liability insurers is −3.92 percent, which is statistically significant at the 1 percent level, whereas that for the non-property-liability insurers is −0.20 percent, insignificantly different from 0. This contrast indicates that the WTC attack has a strong negative impact on forecasts made by financial analysts for property-liability insurers and an insignificant impact on non-property-liability insurers. The analysis based on median short-run abnormal forecast revisions presents consistent results.

In Table 4, we examine the cross-sectional determinants of the short-run abnormal forecast revisions. All of the ratios in the regressions (e.g., short-run abnormal forecast revisions, the percentage of premiums in PL lines, and the tax ratio) are expressed in percentage points. We separately include the four claim factors discussed earlier in our regression.[16] Specifically, we include *PLDUMMY* in column A. As expected the coefficient is −2.32, statistically significant at the 5 percent level. This confirms our finding in by-group comparison, suggesting a negative short-run effect on property-liability insurers. In column B we use *PLPCT*, the percentage of the insurer's business that is in property-liability lines, as a proxy for the insurer's major business type. Consistent with our results on *PLDUMMY*, the coefficient estimate for *PLPCT* is −0.53, which is statistically significant at the 10 percent level.[17] Further, we alternatively evaluate the WTC claim effect using the percentage of estimated losses to total assets (*LOSS1*) and the percentage of earnings reduction around the WTC attack (*LOSS2*), and report the regression results in columns C and D. The coefficient estimates for these two variables are also negative and statistically significant at the 1 percent level. In other words, greater losses coming from the WTC attack lead to more negative short-run abnormal forecast revisions.[18]

The coefficient estimate for *REINS* is positive and statistically significant, consistent with our conjecture that greater use of reinsurance reduces the claim effect. Similarly, the estimated coefficient for *TAX* is positive and statistically significant as expected given the tax benefit of a loss payout. Further, the coefficient on *FCSTDISP* is negative and statistically significant, suggesting that analysts revise downward the earnings forecasts for insurers with greater forecast dispersion after the WTC attack. However,

given individual interpretation of the news rather than of an analyst's ignorance or laziness. As a result, nonupdated forecasts contain useful information of analysts' expectations and thus are included in our analyses.

[16] The correlation between *LOSS1* and *PLDUMMY* is 0.35 as reported in Panel B of Table 2. As a result, we do not simultaneously include the business type variables (*PLDUMMY* or *PLPCT*) and loss variables (*LOSS1* or *LOSS2*) because they are highly correlated.

[17] In unreported tests, we interact a dummy variable *NOLOSS* (equal to 1 for property-liability insurer having no loss and 0 otherwise) with *PLDUMMY* and *PLPCT*. We find a positive coefficient for the interacted variable in the short-run analysis, indicating that the claim effect is weaker for property-liability insurers not suffering significant losses in the WTC attack.

[18] We perform other robustness checks. The test shows a low degree of multicollinearity, as indicated by the fact that variance inflation factors of all variables are smaller than 3.5. Diagnostics indicate that only one observation (Trenwick Group Limited) is a high-leverage data point. The coefficient estimates are similar to those reported after excluding this observation.

TABLE 4
Regressions of Short-Run Abnormal Forecast Revisions on Firm Characteristics

Independent Variables	A	B	C	D
Intercept	0.20	−0.14	−1.38*	−1.57**
	(0.04 / 0.46)	(−0.12 / 0.50)	(−1.74 / 0.09)	(−2.18 / 0.04)
PLDUMMY	−2.32**			
	(−2.40 / 0.04)			
PLPCT		−0.53*		
		(−1.87 / 0.09)		
LOSS1			−0.94***	
			(−3.69 / 0.00)	
LOSS2				−1.07***
				(−3.15 / 0.00)
REINS	2.33*	2.59*	2.41*	2.34*
	(1.94 / 0.09)	(2.01 / 0.08)	(1.92 / 0.09)	(1.95 / 0.08)
TAX	4.85*	4.83*	4.54	3.86*
	(1.67 / 0.09)	(1.84 / 0.08)	(1.55 / 0.13)	(1.63 / 0.10)
LEVERAGE	0.07	0.12	0.10	0.10
	(1.31 / 0.19)	(1.56 / 0.13)	(1.49 / 0.17)	(1.52 / 0.16)
HERF	0.05	0.06	0.05	0.06
	(0.71 / 0.39)	(0.95 / 0.43)	(0.75 / 0.50)	(0.81 / 0.52)
LGSIZE	0.56	1.03	0.95	1.14
	(0.73 / 0.31)	(1.52 / 0.23)	(1.47 / 0.22)	(1.43 / 0.25)
FCSTDISP	−11.74***	−12.41***	−9.57***	−11.06***
	(−2.93 / 0.00)	(−3.29 / 0.00)	(−3.15 / 0.00)	(−3.06 / 0.00)
Adjusted R^2	22%	26%	24%	25%
No. of observations	69	69	57	69

Notes: This table reports the results of ordinary least squares regression for short-run abnormal forecast revision (*SAFR*, in percent). *PLDUMMY* equals 1 if the firm is a property-liability firm and 0 otherwise. *PLPCT* is the percentage of an insurer's business in property-liability lines. *LOSS1* (in percent) is estimated loss related to the WTC attack standardized by its total assets at the end of year 2000. *LOSS2* (in percent) is the reduction in net income from 2000 to 2001 scaled by total assets. *REINS* (in percent) is the ratio of the ceded written reinsurance premiums to the sum of the direct written premiums and the assumed written reinsurance premiums. *TAX* (in percent) is the average tax rate, estimated as income tax divided by taxable income. *LEVERAGE* is an insurer's total liabilities to its total assets. *HERF* (Herfindahl index, in percent) is the sum of the squared percentage of the premiums of an individual line to total premiums of the insurer. *LGSIZE* is the logarithm of an insurer's total assets at the end of 2000. *FCSTDISP* is the dispersion of analyst forecasts, measured as the standard deviation of earnings forecasts made by different analysts. The *t*-statistics of the coefficients and respective bootstrapped *p*-values are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the coefficient estimate for the Herfindahl index is not statistically significant. In other words, there is no evidence that more diversified insurers experience a weaker claims effect. In addition, the empirical evidence for *LGSIZE* here suggests no difference in a claim effect for large firms and small firms.[19]

[19] For completeness, we include here in the short-run analysis two additional variables used later in the long-run analysis, *RATING* and *UWRISK*. The coefficients on *RATING* and

Evidence on a Growth Effect

Similar to our analysis for the claim effect, we first perform univariate analyses for the full sample and subsamples of insurers included in the study. The results are presented in Table 3. The attack seems to have little effect on the full sample. In Panel B we compare long-run abnormal forecast revisions between property-liability and non-property-liability insurers. The average long-run abnormal forecast revision for property-liability firms is positive (1.37 percent) and statistically significant at the 10 percent level, whereas that of non-property-liability firms is −0.94 percent and is not statistically significant. This result is in sharp contrast to the finding for short-run forecast revisions. The evidence suggests that analysts on average positively revise their expectation of the long-run earnings growth for property-liability insurers, which is consistent with a growth effect.

Note that price increases and supply constraints are also characteristics of a hardening insurance market even without a capital shock. An astute reader may wonder if the same growth effect occurred prior to 9/11 when the property-liability market was hardening. We explore this by examining analysts' long-run growth abnormal forecast revisions around each month in the first half year of 2001 (January 2001 to June 2001) using the (−1, 3) month window. Our results, not reported here, suggest that none of the six long-run abnormal forecast revision coefficients are statistically signficant. This finding is different from the long-run abnormal forecast revision after the WTC attack reported in Table 3. The pattern in the long-run abnormal forecast revisions made around 9/11 is apparently different from that prior to 9/11. Nevertheless, it is still unknown if the change, that is, the evidence on the growth effect shortly after 9/11, is shock-related or due to a natural force the market hardening starting before 9/11. Perfectly separating these two force requires the ability to simulate a "9/11" market environment without the WTC attack, which is not feasible. Rather, we shed light on this issue by performing cross-sectional regressions on long-run abnormal forecast revisions including factors directly associated with the attack.

Table 5 presents the results of cross-sectional regression analysis of the effect of insurer characteristics on long-run abnormal forecast revisions. In columns A through D, we alternatively include the four market wide growth factors in the analysis. It is clear that, irrespective of the choice of the market wide growth factor, our results are consistent with the growth effect hypothesis. We find that whether classified as a property-liability insurer or identified by the amount of property-liability coverage written, there is a positive relationship between property-liability concentration and long-run abnormal forecast revisions. The coefficient estimates on *PLDUMMY* and *PLPCT* are 1.24 and 0.26 respectively, statistically significant at the 5 percent and 10 percent levels. Similarly, the coefficient estimates for the loss variables are both positive and statistically significant at the 10 percent level. Firms with greater predicted losses, whether measured as predicted estimated losses reported by each insurer (*PLOSS1*)

UWRISK are not statistically significant and results on other variables are consistent with Table 4. The effect of these variables on short-run abnormal forecast revisions, if any, may be explained by loss variables and *PLDUMMY*.

TABLE 5
Regressions of Long-Run Abnormal Forecast Revisions on Firm Characteristics

Independent Variables	A	B	C	D
Intercept	−9.52	23.80	12.55	−4.07
	(−0.59 / 0.55)	(1.17 / 0.24)	(1.00 / 0.43)	(−0.38 / 0.72)
PLDUMMY	1.24**			
	(2.07 / 0.02)			
PLPCT		0.26*		
		(1.87 / 0.09)		
PLOSS1			0.47*	
			(1.76 / 0.10)	
PLOSS2				0.65*
				(1.75 / 0.09)
RATING	2.79**	2.26*	2.58*	2.60*
	(2.00 / 0.05)	(1.92 / 0.07)	(1.95 / 0.07)	(2.03 / 0.06)
UWRISK	−0.24*	−0.27**	−0.28***	−0.27**
	(−2.14 / 0.05)	(−2.34 / 0.03)	(−2.73 / 0.00)	(−2.54 / 0.01)
REINS	0.50**	0.52**	0.41*	0.48**
	(2.01 / 0.04)	(2.18 / 0.05)	(1.95 / 0.07)	(2.14 / 0.05)
TAX	0.12	0.07	−0.09	0.06
	(0.05 / 0.49)	(0.26 / 0.44)	(−0.28 / 0.54)	(0.23 / 0.49)
LEVERAGE	0.32	0.41	0.38	0.42
	(1.46 / 0.47)	(0.92 / 0.52)	(0.84 / 0.46)	(0.93 / 0.45)
HERF	0.17	0.24	0.15	0.19
	(0.25 / 0.46)	(0.79 / 0.42)	(0.77 / 0.46)	(0.99 / 0.39)
LGSIZE	−0.85	−0.75	−0.86*	−0.80
	(−1.60 / 0.12)	(−1.64 / 0.11)	(−1.75 / 0.10)	(−1.60 / 0.14)
FCSTDISP	0.52	0.61	0.73	0.59
	(0.94 / 0.55)	(0.45 / 0.43)	(0.91 / 0.45)	(0.62 / 0.46)
Adjusted R^2	18%	18%	19%	18%
No. of observations	52	52	47	52

Notes: This table reports the results of ordinary least squares regression for long-run abnormal forecast revision (*LAFR*, in percent). *PLDUMMY* equals 1 if the firm is a property-liability firm and 0 otherwise. *PLPCT* is the percentage of an insurer's business in property-liability lines. *PLOSS1* (in percent) is the predicted estimated loss related to WTC attack standardized by year 2000 total assets. *PLOSS2* (in percent) is the predicted reduction in net income from 2000 to 2001 scaled by total assets in 2000. *RATING* is an insurer's Bests' rating, equal to 5 for firms rated A++ or A+ and FPR9, 4 for A or A− and FPR7 or FPR8, 3 for B++ or B+ and FPR5 or FPR6, 2 for B or B− and FPR4, 1 for C++ or C+ and FPR3, and 0 for C, C−, or D and FPR2. *UWRISK* (in percent) is the standard deviation of the loss ratios of each insurer from 1990 to 2000. *REINS* (in percent) is the ratio of the ceded written reinsurance premiums to the sum of the direct written premiums and the assumed written reinsurance premiums. *TAX* (in percent) is the average tax rate, estimated as the total income tax divided by taxable income. *LEVERAGE* (in percent) is an insurer's total liabilities to its total assets. *HERF* (Herfindahl index, in percent) is the sum of the squared percentage of the premiums of an individual line to total premiums of the insurer. *LGSIZE* is the logarithm of an insurer's total assets in year 2000. *FCSTDISP* is the dispersion of analyst forecasts, measured as the standard deviation of earnings forecasts made by different analysts. The *t*-statistics of the coefficients and respective bootstrapped *p*-values are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

or predicted reduction in earnings per share from 2000 to 2001 (*PLOSS2*), have more positive long-run abnormal forecast revisions holding other factors constant.

We also find strong evidence of a positive and statistically significant relationship between firm financial rating (*RATING*) and long-run abnormal forecast revisions. This is consistent with our expectation that firms with high insurance ratings are better able to raise adequate capital following 9/11.[20] Having adequate capital allows insurers to attain a better competitive position for achieving greater growth potential after the WTC attack. Our results support the "flight to quality" argument in Cummins and Lewis (2003).

We also find that insurers with higher underwriting risk (*UWRISK*) have lower long-run growth expectation. Our findings suggest that firms with relatively greater variability in losses have more difficulty in attracting capital to enable growth following unexpectedly large losses. As expected we find the coefficient estimate for REINS to be positive and statistically significant. Greater reinsurance purchase mitigates the risk of uncertain, large claims payout and improves the insurer's ability to recover from 9/11 or potential future catastrophes.

We do not find a statistically significant relationship between long-run abnormal forecast revisions and the firm's tax position (*TAX*), firm leverage (*LEVERAGE*), or firm concentration by product line (*HERF*).

SUMMARY AND IMPLICATIONS

Unlike previous studies that jointly consider the short-run and long-run effects of catastrophes and capital shocks on the insurance industry, here we separate the immediate "claim effect" and the longer term "growth effect" of the WTC attack on insurers. We use short-run and long-run earnings forecast revisions as proxies for expected short-term and long-term insurer performance. We demonstrate that catastrophic claims have a negative effect on short-run, but not on long-run, profitability. We provide firm-level analysis to investigate the role of specific firm characteristics on insurer short- and long-run performance. We find that firm type (i.e., property-liability vs. non-property-liability insurers), the size of estimated losses, the firm's tax position, and the extent of reinsurance usage are statistically significant predictors of short-run abnormal forecast revisions. We show that firm type, firm losses, firm financial strength, firm underwriting risk, and firm reinsurance usage are statistically significant predictors of long-run abnormal forecast revisions.

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[20] In fact, we collected information on insurers' debt and equity financing between 2001/09 and 2001/12 from the Securities Data Corporate (SDC) database. Based on issuance/announcement dates, 14/15 insurers in our sample raised debt and equity capital during this period. We construct a variable on external financing either using aggregate external capital raised by an insurer or a dummy variable for insurers raising external capital shortly after the WTC attack. We expect the external financing variable to be positively related to long-run abnormal forecast revisions because raising capital may improve an insurer's ability to improve long-run performance. The result, however, shows that the coefficient on neither form of the external financing variables is significant. It is likely that some financing activities shortly after the WTC attack may have been scheduled before 9/11 and thus are not attack related.

Clearly, evidence of a claim effect is somewhat apparent in the wake of catastrophic loss. The growth effect, however, less obvious and our study provides initial evidence of this as well as insight into firm characteristics that are related to the potential for growth. The growth effect is important in understanding that the industry is not necessarily damaged in the long run by a catastrophe, and, in fact, insurers actually can thrive by providing risk transfer for catastrophic loss. These results, however, assume that the industry as a whole has the capacity to absorb catastrophic losses. Cummins, Doherty, and Lo (2002) suggest that the property-liability industry could sustain a mega-catastrophe up to \$100 billion.

Given evidence of a growth effect, additional research is needed to better understand factors underlying this result. Work is warranted on disentangling the supply and demand effects, which may drive long-run growth following a catastrophic loss. Pursuing this avenue of inquiry would require data not yet publicly available, such as postcatastrophe firm-level data on changes in the quantity of insurance demanded versus changes in prices of coverage supplied. This line of research would assist regulators in shaping public policy on catastrophe risk management.

APPENDIX: BOOTSTRAPPING METHOD

We use a bootstrapping procedure to deal with the cross-sectional dependence in abnormal forecast revisions caused by the same event date and industry clustering. Statistical inference is based on the t-statistics (z-statistics) of the mean (median) abnormal forecast revisions, rather than the mean (median) abnormal forecast revisions themselves, because these t-statistics (z-statistics) are pivotal and have better convergence properties (Hall, 1992). We conduct three types of analyses: (1) the average abnormal forecast revisions, (2) comparisons of abnormal forecast revisions for property-liability insurers and non-property-liability insurers, and (3) regression analyses of abnormal forecast revisions. Below we discuss the specific bootstrapping procedures for each type of analysis.

Bootstrapping Procedures for Unisample Tests

Step 1: Computing t-statistics of the mean and z-statistics of the median of the actual abnormal forecast revisions for the sample firms. Using τ to represent September 2001, we estimate abnormal forecast revisions (*AFR*s) based on Equations (2) and (5). The actual t- or z-statistic are denoted as $\Gamma(AFR_\tau)$.

Step 2: Computing bootstrapped t-statistics for the mean test and bootstrapped z-statistics for the median test. We first calculate abnormal forecast revisions around September 2000 (an "event" period without any major event), denoted as $AFR_{\tau'}$ (using τ' to denote September 2000). Then we draw 1,000 random samples with replacements from the above nonevent sample the same number of observations as the actual sample (e.g., 80 observations during the event window from August 2001 to December 2001 for short-run abnormal forecast revisions). In each random sample, we calculate the t-statistic for the mean or z-statistic for the median. This process results in 1,000 bootstrapped t- or z-statistics, denoted as $\Gamma^*(AFR_{\tau'})$.

Step 3: Computing bootstrapped p-values for the test statistics. For the analyses on short-run forecast revisions, the bootstrapped p-value is computed as the percentage of bootstrapped t-/z-statistics less than the sample t-/z-statistic. That is,

$$p = \frac{1}{1000} \sum_{j=1}^{1000} I_{\Gamma_j^* < \Gamma}, \tag{A1}$$

where $I_{\Gamma_j^* < \Gamma}$ is an indicator function with value 1 if $\Gamma_j^*(AFR_{\tau'}) < \Gamma(AFR_\tau)$. For the analyses on long-run forecast revisions, the bootstrapped p-value is computed as the percentage of bootstrapped t-/z-statistics that exceeds the sample t-/z-statistic. That is,

$$p = \frac{1}{1000} \sum_{j=1}^{1000} I_{\Gamma_j^* > \Gamma}, \tag{A2}$$

where $I_{\Gamma_j^* > \Gamma}$ is an indicator function with value 1 if $\Gamma_j^*(AFR_{\tau'}) > \Gamma(AFR_\tau)$.

Bootstrapping Procedures for Bisample Comparisons

Step 1: Computing t-statistic on the mean difference and z-statistic of the Wilcoxon ranked sum test on the median difference in abnormal forecast revisions between property-liability (PL) insurers and non-property-liability (non-PL) insurers during the actual event period, denoted as $\Gamma(AFR_\tau)$.

Step 2: Computing bootstrapped t- and z-statistics for mean and median differences in abnormal forecast revisions between PL and non-PL insurers around September 2000. Specifically, we first calculate abnormal forecast revisions around September 2000 for PL and non-PL firms. We draw random samples with replacements 1,000 times from the nonevent PL and non-PL samples with the same number of observations as PL and non-PL firms in the actual event period (e.g., for short-run forecast revisions, there are 49 and 31 firms in PL and non-PL groups). This results in 1,000 bootstrapped t-/z-statistics, denoted as $\Gamma^*(AFR_{\tau'})$.

Step 3: Computing bootstrapped p-values for the test statistics. For the short-run analyses, we test if the mean / median abnormal forecast revisions of PL firms are more negative than that of non-PL firms. Following (A1), we compute the bootstrapped p-value as the percentage of bootstrapped t-/z-statistics less than the sample t-/z-statistic. For the long-run analysis, we test if the mean / median abnormal forecast revisions of PL firms are more favorable than that of non-PL firms. Following (A2), we compute the bootstrapped p-value as the percentage of bootstrapped t-/z-statistics that exceeds the sample t-/z-statistic.

Bootstrapping Procedures for Regression Analysis

Step 1: Performing cross-sectional regression of abnormal forecast revisions in the actual event period and obtaining t-statistics for the intercept and the coefficients on the independent variables. The actual t-statistic for a specific variable x_j is denoted as $\Gamma(AFR_\tau, x_j)$.

Step 2: Computing bootstrapped t-statistic for the intercept and each coefficient when regressing abnormal forecast revisions around September 2000. To do this, we first calculate abnormal forecast revisions around September 2000. Repeated 1,000 times and with replacement, we randomly draw the same number of abnormal forecast revisions as the actual sample. We simultaneously draw the same number of insurers, with replacement, and randomly match them with the randomly generated abnormal forecast revisions. Bootstrapped abnormal forecast revisions are regressed on firm characteristics. This process results in 1,000 sets of bootstrapped *t*-statistics for the intercept and each of the coefficients, denoted as $\Gamma^*(AFR_{\tau'}, x_j)$.

Step 3: Computing bootstrapped *p*-values for the sample *t*-statistics. To test if a coefficient is negative, we follow (A1) to compute bootstrapped *p*-value as the percentage of bootstrapped *t*-statistics is less than the sample *t-/z*-statistic. To test if a coefficient is positive, we follow (A2) to compute bootstrapped *p*-value is computed as the percentage of bootstrapped *t-/z*-statistics that exceeds the sample *t-/z*-statistic. For the variables without a specific prediction, we perform two-sided tests and compute bootstrapped p-value as twice of the lower *p*-value estimated by (A1) or (A2).

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