Catastrophic Losses versus Growth Potential:
Analysis of Post-WTC Attack Earnings Forecasts of Insurance Industry

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Abstract

We examine the short-run claim effect due to the catastrophic losses of the World Trade Center attack and the post-attack long-run growth effect due to rising insurance demand and more prudent underwriting practice. We find that the claim effect measured by short-run earnings forecast revisions is more negative for firms with higher claim costs. On the other hand, long-run forecast revisions are positive associated with firm's growth opportunities. Long-run forecast revisions of property and liability (P&L) insurance firms, particularly those specializing in commercial product lines, are greater than those of non P&L firms. Our findings demonstrate the importance for investors to consider the combined effects of a catastrophe on firms' existing assets and future growth.

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I. Introduction

The terrorist attack on the World Trade Center (WTC) on September 11th, 2001 had an enormous impact on the insurance industry. According to Swiss Reinsurance (2002), estimated insured loss is between \$30 and \$58 billion. Such large claim losses push the insurance industry into a hard market where insurance coverage is limited and prices are high. Simultaneously, this event has greatly changed how the insurance industry and the public view terrorist risks. As Warren Buffett wrote to Berkshire Hathaway's shareholders, "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."[1] The general public has come to consider terrorist attacks as a virtual threat, and their overall perception of risk has also changed. Subsequently, the demand for insurance, especially for commercial property-liability (P&L) insurance, has greatly increased after the WTC attack.

The main objective of our study is to examine the short-run catastrophic claim effect and the long-run growth effect after the WTC attack. The literature has provided mixed results about the effects of catastrophic events using an event study approach. For example, Shelor, Anderson and Cross (1992) find a positive abnormal return for P&L insurers during the California (Loma Prieta) earthquake in 1989. They argue that their findings are contributable to demand growth after the earthquake. Conversely, Lamb (1995) renders support for the claim effect by showing that Hurricane Andrew caused negative stock price reactions for P&L insurers with direct business exposure. Since changes in stock prices reflect both the short-run claim effect and the long-run growth effect, it is natural to observe a differential stock valuation effect if the relative magnitudes of the two effects differ.

[1] See Warren Buffet's "Letter to Berkshire Shareholders discussing 2001 Third Quarter Earnings Results".

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. In the case of the WTC attack, the large increases of claim costs reduced insurers' existing assets. At the same time, both insurers and policyholders would update the probability of future occurrence of extreme events in P&L business, particularly in those lines most affected by the WTC attack, such as fire, business interruption, and workers compensation. Risk updating increases insurance demand in the affected lines, and hence improves insurers' growth potential after the attack. Therefore, we propose that (1) short-run analysts' earnings forecast revisions capture the WTC attack's claim effect, and (2) long run growth forecast revisions encapsulate insurers growth potential following the attack.

We find that short-run earnings forecast revisions after the attack are more negative for insurers with higher claim costs. For example, insurers that experienced greater reduction in earnings in year 2001 had more negative short-run forecast revisions. Additionally, insurers specializing in commercial P&L lines experienced more negative short-run earnings forecast revisions than those specializing in personal lines such as homeowners' insurance. On the other hand, we find that long-run forecast revisions for P&L firms are significantly higher than those of non P&L firms. Moreover, long-run forecast revisions are greater for P&L firms specializing in commercial lines than for P&L firms specializing in personal lines. These results are consistent with anecdotal evidence that stocks of P&L firms outperformed stocks of non P&L firms from the occurrence of the WTC attack to August 2002 (Hartwig, 2002).

Our contributions are twofold. First we effectively separate the post WTC attack claim effect and the growth effect using measures built upon analysts' earnings forecasts. Second, we demonstrate that, while the claim effect has negative impact on P&L firms' short-run profitability, the growth effect has positive impact on P&L firms' long-run profitability. Unraveling these two effects enables us to identify the cause of value change in a firm's existing assets and growth potential separately. The great magnitude of the WTC attack makes both effects most pronounced in the insurance industry, but our analysis is also applicable to studying the impact of unfavorable external shocks on other industries. Investors and regulators should consider both the damaging short run impact and possible favorable impact on firms' growth.

The remainder of the paper is organized as follows: Section 2 discusses the claim and growth effects of the WTC attack. Section 3 describes the data and our measures of these two effects. Section 4 presents the empirical results. We provide robustness checks in Section 5. Finally, Section 6 concludes and discusses implications of our findings.

2. Claim and Growth Effects of the WTC Attack

To better understand the claim and growth effects of a major catastrophe such as the WTC attack, it is important to consider the impact of capital shocks on the underwriting cycle prevalent in the insurance industry. The insurance industry has repeatedly experienced capital shocks that significantly reduced its capacity to supply insurance. As a result, the insurance market is cyclical. Low price and ample coverage in soft markets are followed by high price and constrained coverage in hard markets. A typical example of the insurance hard market is the liability insurance crisis in the mid 1980s, when insurance firms experienced large shortfalls of capital due to drastic increases in liability claims costs.[2]

Figure 1 illustrates the capacity constraint framework provided in Gron (1994) and Winter (1994). The short-run supply curve (S_1) is upward sloping, showing that the cost of supplying insurance is an increasing function of quantity supplied. This is because it is costly for insurance firms to adjust their capacities. A capital shock causes a reduction in insurance supply and the short-run supply curve shifts leftward to S_2. Price is higher and quantity is lower under the new equilibrium in hard markets. However, hard markets are transitory, thus the long-run supply curve, S, is flat, indicating that insurance companies frictionlessly adjust their capacity to

[2] See Harrington and Niehaus (2001) for a review.

meet any insurance demand in the long-run. The insurance supply curve would shift back to the long-run flat curve once companies replenish their capital.

Large catastrophes also generate industry-wide capital shocks and greatly reduce the available capital within the industry. Doherty (1997) suggests that catastrophic events like Hurricane Andrew and the Northridge earthquake "have imposed costs on the insurance industry an order of magnitude not thought possible only a decade ago." Cummins, Doherty and Lo (2002) suggest that the insurance industry can afford a mega-catastrophe of $100 billion in insured losses, however, they also conclude that such an event would cause numerous insolvencies and severely destabilize insurance markets. Large catastrophes will cause decline in insurers' capital, but insurance buyers may also update their knowledge of catastrophic risks accordingly and increase the demand after the catastrophe. Froot and O'connell (1999) differentiate these two forces in the reinsurance market. They find the capacity constraint effect dominates the increasing demand of insurance during the post-catastrophe periods.

The main implication of the capacity constraint theory is on the short-run impact of capital market imperfection on the insurance market, while little emphasis is put on the long-run impact of catastrophic events. In addition, prior analyses focus on the aggregate impact of external capital shocks on the insurance industry and the cross-sectional difference among different insurers has largely been overlooked. In this paper, we propose a unified framework to analyze how changes in the supply and demand result in the differential short-run claim effect and long-run growth effect after the WTC attack.

2.1 Claim Effect

The WTC attack caused insured losses larger than any other natural or man-made event in history. The estimated payment by P&L insurers is approximately $37.5 billion and approximately $2.7 billion by life insurers (Hartwig, 2002). However, insurance companies received no additional premium for terrorism coverage before the WTC attack. Rise in claim costs increases expenses of insurance firms, and lowers their short-run earnings and profitability.

In this paper we define the impact of the unexpected loss on insurance firms' short-run profitability as *the claim effect*.

Figure 2 illustrates this claim effect under a hypothetical framework that assumes policyholders and insurance firms had known the true probability of terrorist attacks before September 11 2001. D_1/D_2 is the demand curve of terrorism insurance either supplied by insurers with more/less specialization in underwriting terrorism risks, or demanded by firms with high/low exposure of terrorist attacks. S is the long run supply curve of terrorism insurance.[3] P is the equilibrium price; Q_1 and Q_2 are equilibrium quantities associated with the equilibrium points A and B. Thus, areas under rectangles $OPAQ_1$ and $OPBQ_2$ represent the fair premium income under different demand schemes. Since insurance firms received no premium for terrorism coverage prior to the WTC attack, areas $OPAQ_1$ and $OPBQ_2$ reflected unexpected losses insurers sustain from the attack, i.e. claim effects of different insurers.

An insurer's unexpected claim costs would be greater if the demand for its terrorism insurance coverage had been higher ($OPAQ_1 > OPBQ_2$). In addition, insurers providing P&L coverage, especially those specializing in commercial lines, are more likely to be firms offering free terrorism coverage before the WTC attack. Therefore, the claim effect would be greater for P&L insurers, for insurers underwriting more business in New York, and for insurers operating in commercial products lines. We refer to this hypothesis as *the claim effect hypothesis*. Accordingly, we measure the claim effect with short-run analysts' earnings forecast revisions and argue that firms with higher claim losses should experience more negative earnings revisions.

2.2 Growth Effect

The WTC attack caused the greatest capital shock to the P&L insurance industry in the history. Affected P&L lines include property, business interruption, workers' compensation, aviation, environmental, general liabilities and others. The attack cautions insurers and policyholders of future extreme events in these affected lines. Therefore insurance buyers would subsequently update their probability distribution of P&L risks, and increase the demand for P&L coverage.[4] Hence, the WTC attack cause the demand increase for insurers specializing in P&L lines to be higher than insurers specializing in non-P&L lines. In addition, insurers would adopt a more rigorous standard for their P&L underwriting businesses as they update the probability distribution of extreme events after the WTC attack. The growth effect reflects the joint impacts of greater demand due to risk updating and changed supply as the result of more rigorous underwriting standard.

Figure 3 provides an equilibrium framework to analyze the growth effect. Unlike short-run supply shrinkage caused by capacity constraint, the long-run supply curve of P&L insurance moves upward (from A_1B_1 to A_2B_2) as long as insurance firms update the probability distribution of the occurrence of extreme events in P&L lines. Prior to the WTC attack, A_1 is the equilibrium point of P&L coverage provided by firms specializing in P&L business, while B_1 is the equilibrium point of P&L coverage provided by firms specializing in non P&L insurance. The WTC attack increases the overall demand for P&L insurance and then both demand curves shift to the right. More importantly, we should observe greater increase in demand for insurance offered by insurers specializing in P&L lines rather than insurers specialized in non-P&L insurance. Although the overall revenue change depends on the interactions between higher demand and less supply, we should still expect P&L insurers to have higher growth potential as long as the demand increase is higher for P&L insurers than for non-P&L insurers. We refer to this hypothesis as *the growth effect hypothesis*.

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[3] The assumption that insurers with more/less specialization share the same supply curve simplifies our analysis but is not essential. Our conclusion holds under the alternative assumption that more specialized firms or firms charge higher premium.

[4] See the article by Adrian Michaels in Financial Time, November 5, 2001.

3. Data and Methodology

3.1 Data

We retrieve analysts forecast data from the Institutional Brokerage Estimate System (IBES) database. Specifically, the IBES database provides the summary database that reports monthly mean and median forecasts of earnings per share for individual firms. Based upon IBES industry classification, we obtain 116 insurance firms that either have 1-year earnings forecast or have 5-year earning-growth forecast between August 2001 and December 2001. However, 15 of them are excluded because they do not underwrite insurance business or are non-US insurance firms.[5] Additionally, we require firms to have at least 15 months of estimation history for short-run forecasts and 12 months of estimation history for long-run forecasts. Subsequently, we remove 5 firms from short-run forecast analysis and 4 firms from long-run forecast. Table 1 provides our final sample of 96 firms. Among them, 94 firms are used in our short-run analysis and 72 firms are used in the long-run analysis.

We then use the IBES and Compustat databases to identify property-liability (P&L) insurance firms.[6] We classify a firm as a P&L firm if IBES and Compustat agree on its industrial identification (37 P&L firms are identified). We further classify a firm as a P&L firm if it is categorized as a P&L firm in Compustat and as a multi-line insurer in IBES (15 P&L firms are identified). In cases where only one database identifies a firm as a P&L firm, we check the firm's websites to confirm its specialization (12 additional firms are identified). Overall we identify a sample of 64 P&L firms. The rest 32 firms in our sample are classified as non-P&L firms.

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[5] Specifically, we remove two non-US insurance firms, one insurance auto auction firm, four mortgage bankers, one security broker, and seven insurance brokerage firms.

[6] IBES classifies insurance firms into five categories: life insurance, multi-line insurance, property and liability insurance, mortgage and title insurance, and insurance brokerage. At the same time, Compustat uses standard industrial classification (SIC) codes to identify industries. We regard SIC codes 6330, 6331, 6350, 6351, 6360 and 6361 as property and liability firms in our analysis. In addition, our robustness checks in Section 5 show our results are not sensitive to sample construction.

We obtain detailed underwriting data of P&L insurance firms from the A.M. Best Company's Key Rating Guide (A.M. Best) database Property-Casualty 2002 edition. Our sample from IBES covers both insurance holding companies and standalone insurers. The A.M. Best database provides data in the individual firm level and the group level. If an insurer is a standalone insurer, we match the company name in our IBES sample with the name in the A.M. Best database. Otherwise, we match an insurance holding company in the IBES sample with the group level insurer in the A.M. Best database. This process results in a list of 53 P&L firms with insurance operation data.

Next, we classify whether a P&L firm's primary business is commercial lines or personal lines using the A.M. Best database. We include aircraft, commercial lines, excess & surplus, reinsurance, aviation, inland marine, medical malpractice, workers' compensation, and ocean marine as commercial lines. Personal lines, personal auto, physical auto damage, and homeowners are considered as personal lines. If a firm engages in a unique business line, we classify its primary business as either commercial or personal based on its unique specialty in the A.M. Best database. If a firm has a multi-line specialty in the A.M. Best database, we use the top-five business lines to classify firms. If over fifty percent of a firm's business is related to commercial lines, we regard it as a commercial P&L insurer. Finally, if we cannot identify a firm's specialization from the A.M. Best database we check its website. Overall, we identify 37 commercial P&L firms and 17 personal P&L firms.

Similarly, we distinguish whether an insurance firm's major operation is in New York. If the A.M. Best database shows the New York State is among an insurer's top-five business states, we classify the firm as one that operates in the New York state.[7] Otherwise, we treat the firm

[7] Ideally, we should consider firms having a significant amount, e.g., fifty percent, of insurance operation in the New York *city* when we conduct this analysis. However such data is not available and quite few firms mainly operate in the New York City.

having no operation in the New York state. This process identifies 19 firms with operation in New York State and 32 firms without operation in New York State.

3.2 Methodology

A. Measures of the Claim effect

We measure the claim effect by the short-run raw forecast revisions (SFRs) and abnormal forecast revisions (SAFRs). We first calculate $SFR_{i,(T-1,T+3)}$, price-adjusted 1-year earnings per share forecast revision from August 2001 to December 2001, as follows:

$$SFR_{i,(T-1,T+3)} = \frac{(MDF_{i,T+3} - MDF_{i,T-1})}{P_{i,T-1}} \tag{1}$$

where T refers to September 2001. $MDF_{i,T+3}$ and $MDF_{i,T-1}$ are the median forecast for firm i in December 2001 and August 2001, respectively. $P_{i,T-1}$ is the stock price for firm i in August 2001.

Previous studies find an optimism bias and sequential updating bias in annual earnings forecast data (e.g., Brous, 1992), and they show that the above unadjusted SFR may be imprecise.[8] Figure 4 displays a similar pattern of a downward trend of annual EPS forecast for fiscal year 2000 and 2001. Such biases may cause average raw forecast revisions different from zero without any event. To control for the optimism and sequential updating biases, we estimate the expected forecast revisions following Brous (1992). The expected forecast revision for firm i in month t is estimated as

$$E(SFR_{i,t}) = k_i + \frac{1}{5}\sum_{c=1}^{c=4}\varepsilon_{i,t-c} \tag{2}$$

[8] Brous (1992) shows that analysts tend to be more optimistic at the beginning of the fiscal year when forecasting annual EPS, and they will gradually revise their forecasts down as fiscal year end approaches (optimism bias). He also suggests that, on average, approximately 15-20% of the analysts update their forecast each month, so it takes on average five months to have a complete update (sequential updating).

The forecast component (k_i) is estimated for each firm as the average forecast revision during an estimation period that consists of all months for which forecasts are available excluding the relative month (-6, +6) to September 2001. The unexpected component ($\varepsilon_{i,t-c}$) is measured as the difference between k_i and the actual forecast revision in month *t-c*. Based on equation 2 shown above, we calculate expected forecast revisions from August 2001 to December 2001 as

$$E(SFR_{i,(T-1,T+3)}) = \sum_{j=-1}^{2} E(SFR_{i,(T+j,T+j+1)}) \tag{3}$$

Therefore, the short-run abnormal forecast revisions (SAFR) from August 2001 to December 2001 is expressed as:

$$SAFR_{i,(T-1,T+3)} = SFR_{i,(T-1,T+3)} - E(SFR_{i,(T-1,T+3)}) \tag{4}$$

B. Measures of the Growth Effect

We proxy the long-run growth effect with the long-run raw forecast revisions (LFRs) and abnormal forecast revisions (LAFRs). IBES provides long-term earnings growth forecasts that represent an expected annual increase in earnings per share over next five years. Consistent with Yoon and Starks (1995) and Best, Best and Hodges (1998), we calculate raw long-run forecast revisions (LFR) as:

$$LFR_{i,(T-1,T+3)} = \frac{(1+MDF_{i,T+3}/100)^5}{(1+MDF_{i,T-1}/100)^5} - 1 \tag{5}$$

where T refers to September 2001. $MDF_{i,T+3}$ and $MDF_{i,T-1}$ are the median forecast of annual increase in earnings per share for next five years for firm i in December 2001 and August 2001, respectively.

Following Yoon and Starks (1995), we calculate the expected long-run abnormal forecast revisions E(LFR) by taking average of LFRs for pre-attack periods from March 1998 to March

2001. LAFR is the difference in the actual revisions and average estimation-period long-run earnings forecast revisions.

$$LAFR_{i,(T-1,T+3)} = LFR_{i,(T-1,T+3)} - E(LFR_{i,(T-1,T+3)}) \qquad (6)$$

C. Factors Influencing Claim Effect and Growth Effect

We examine various factors associated with the claim and growth effects. As discussed in Section 2, we expect claim effect and growth effect to be stronger for firms with primary business in commercial lines and in the New York State. Thus, following discussions in Section 3.1, we classify P&L firms into commercial lines and personal lines. We also separate out P&L firms with operation in New York from the rest of the sample.

Additionally, we use ΔEPS, the difference in actual annual earnings per share between 2001 and 2000, to measure gross claim losses due to WTC attack up to the end of 2001. The relationship between ΔEPS and short-run forecast revisions shows how changes of insurers' claim costs affects analysts' expectations surrounding the terrorist attack.

Finally, we apply two proxies to measure firms' growth opportunities. One is Tobin's q that is typically used as an ex-ante measure of firm growth. We calculate Tobin's q as the ratio of a firm's market value of assets to assets' book value. In addition, we also use firms' sales growth as an ex-post measure of growth opportunities. Sales growth is the difference in net sales between fiscal year 2002 and 2001 standardized by net sales in 2001. We obtain these data from the Compustat database.

4. Empirical Results

4.1 Analysis of the Claim Effect

Our claim effect hypothesis suggests that, the WTC attack has a negative impact on insurance firms' expected profitability, and such impact is stronger for insurers with more exposure in the attack. Table 2 presents raw and abnormal forecast revisions of the overall sample and univariate comparison of abnormal forecast revisions of subsamples based on different classifications. Panel A provides raw short-run forecast revisions (SFRs) and abnormal short-run forecast revisions (SAFRs) around the WTC attack for all insurance firms. SFRs for all different monthly windows (-1, +1), (-1, +2) and (-1, +3) are significantly negative. Similarly, SAFR for month (-1, +1) and month (-1, +3) are significantly negative. Our results suggest that the WTC attack has a negative impact on insurance companies' earnings forecasts. Since only 20 percent analysts report their earnings forecasts in each month, tests using monthly windows (-1, +1), (-1, +2) may not fully capture the impact of the WTC attack, thus we focus on the three-month window in the remaining analyses.

To demonstrate short-run forecast revisions effectively measure the claim effect, we examine how changes in actual earning are related to these measures. We find that, on average, earnings per share for insurance firms dropped 250 percent from 31 cents per share in the second quarter of 2001 to –17 cents per share in the third quarter of 2001. In addition, total earnings of insurance firms dropped approximately $23 billion in 2001 from $40 billion in 2000. The earnings drop for insurance firms in the post-attack can largely be attributed to increasing claim costs, therefore we expect SFRs and SAFRs to be more negative for firms with larger EPS drop.[9]

Panel B of Table 2 supports our supposition. Specifically, we proxy the WTC-attack losses with the change in earnings per share (EPS) between fiscal year 2001 and 2000. Panel B shows that the mean difference of SFRs/SAFRs between firms whose EPS changes are above the median change (low loss firms) and firms whose EPS changes are below the median change (high loss firms) is 3.6/5.3 percent, significant at the one percent level. Consistently, the difference in medians of SFRs/SAFRs between the above two groups is 1.8/2.3 percent, also significant at the one percent level. Our forecast revision measures are standardized by stock price. Multiplying the difference in forecast revisions by sample firms' average stock price ($33) provides us a

[9] Swiss Re (2002) provides a list of P&L insurers that have paid most losses for the WTC attack. We also confirm that firms in that list experienced large declines in earnings.

rough dollar measure of 60 cents difference in median forecasted earning between these two groups.

If SFR and SAFR measure the claim effect alone, they shall bear little or no relationship with the growth opportunity of the firm. In panel C of Table 2, we group our sample into high-q insurers and low-q insurers based on the sample median of Tobin's q. The difference between forecast revisions (SFR and SAFR) of these subsamples is indeed insignificant. Furthermore, we confirm our results reported in Panels B and C with regression analyses. In summary, we find a significantly positive association between short-run forecast revisions and changes in EPS, while the relationship between short-run forecast revisions and Tobin's q remains insignificant.[10] In addition, tests using SFR and SAFR provide similar results while test statistics of SAFR (both t statistic and z statistic) are lower than those of SFR. As SAFR controls for the forecast bias by measuring abnormal changes in forecast earnings, we focus our analysis on abnormal forecast revisions in following tests.[11]

Table 3 examines how forecast revisions vary among different types of insurance firms and firms operating in different geographical areas. As P&L firms experienced more losses in the WTC attack than non P&L firms, financial analysts should lower their year 2001 earnings forecasts more for P&L firms than for non-P&L firms. Panel A confirms this conjecture. The average SAFRs of P/L firms are negative 2.9 percent while SAFRs of non P/L firms are negative 0.2 percent, and the difference is significant at the five percent level.[12] Our results clearly demonstrate the claim effect is much stronger for the P&L group.

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[10] Regressions results are available upon request.

[11] SFR and SAFR are highly correlated (the correlation is 0.94) in our sample. Our analyses using SFR and SAFR yield similar results. In addition analyses using LFR and LAFR also provide consistent results.

[12] We also test whether the difference in forecast revisions between these two groups had already been present before the WTC attack. We test whether abnormal forecast revisions for P&L insurers differ from those of non-P&L insurers over a two-year period prior to the WTC attack (September 1999-August 2001). The mean difference between abnormal forecast revisions for P&L insurers and non-P&L insurers over the two-year period is insignificantly different from zero. Among the 24 months used in the test, abnormal forecast revision is significantly different between two groups only in one month. Therefore, the observed difference in forecast revision between P&L and non-P&L insurers can be attributed to the WTC attack.

In Panel B of Table 3, we further separate the P&L sample into two groups: firms specializing in commercial lines and firms specializing in personal lines. The mean SAFRs of commercial P&L insurers is negative 5.5 percent while that of personal P&L firms is about zero. The difference between these two groups is significant at the one percent level. The univariate comparison of median SAFRs yields similar results. Our results indicate a significant difference in claim effects between these two groups.

In panel C, we separate the P&L sample into firms with operation in the New York State and firms without operation in New York. We expect forecast revisions for firms operating in the New York state to be more negative. However, as shown in Panel 3, the difference is insignificant. This might be due to the fact that our data only classify firms that operate in New York State rather than the New York City. In addition, insurance firms typically reinsure a large proportion of their underwritten risk exposure. Thus losses suffered from the WTC attack could be easily spread to reinsurance firms underwriting similar risks in other states. The effect of reinsurance may explain why we observe a significant difference using specialization classification but insignificant results using location classification.

In addition, we also examine the event-period cumulative abnormal stock returns (CARs) and its relationship with the short-run abnormal forecast revisions (SAFRs). Event period CAR is computed using the market model as described in Brown & Warner (1980, 1985). We construct the test statistic following the standard abnormal return method described in Patell (1976). Since WTC attack may increase the variance of stock returns following September 11th, we employ the standardized cross-sectional procedure (Boehmer et al, 1991) to test the significance of abnormal returns. Consistent with previous studies on natural catastrophes and on the WTC attack (Cummins and Lewis, 2002), Panel A of Table 4 suggests a negative mean event-period return after the WTC attack.

In Panel B we compare the mean difference between CARs of P/L firms and non P/L firms. Although our results shows the mean CARs for P&L firms is lower than those of non P&L

firms, the difference is insignificant (t statistic is 0.38). This suggests that event- period abnormal returns capture both the claim effect and the growth effect, and it may not distinguish the performance among different types of insurers. Finally, we regress SAFR on CAR and find that SAFR and CAR are highly correlated. As shown below, the coefficient is positive and significant at 1% level.

$$CAR = -0.029 + \underset{(t = 7.46)}{0.78 * SAFR} + \varepsilon \qquad (7)$$

4.2 Analysis of the Growth Effect

To analyze the growth effect, we examine the following issues: (1) which group of insurers has better growth potential as measured by long-run forecast revisions? (2) What is the relationship between long run forecast revisions and other known proxies of growth opportunities, such as Tobin's q and sales growth.

Panel A of table 5 shows that full sample LAFRs in different time intervals around the WTC attack are insignificantly different from zero. This result is not unexpected. As insurers' future growths are jointly determined by the change in supply and increase in demand, the growth effect hypothesis gives no prediction about LAFRs for full-sample analysis. Moreover, the WTC attack significantly increases information asymmetric of firms' quality and leads to less accurate estimate by analysts.[13]

The growth effect hypothesis suggests that the long-run growth rate for firms specializing in P&L, especially in commercial lines are greater than that of insurers specializing in non-P&L business. Therefore, we compare the long run forecast revisions between P&L insurers and non P&L insurers. Unlike our findings in claim effect analysis, Panel B of Table 5 shows that P&L insurers are expected to have higher growth rates than non-P&L insurers. P&L firms have higher

[13] We examine the dispersion of earnings forecasts using standard deviation of earnings forecasts by different analysts for three months before September 2001 and three months after September 2001. We find that dispersion in long-run growth forecast of the post-attack period is significantly higher.

average abnormal long run forecast revisions than non-P&L firms. The mean and median differences are significant at the 5 percent level.

Furthermore, Panel C reports the difference of long run forecast revisions between two groups of P&L insurers: commercial-line insurers and personal-line insurers. Mean (median) of LAFR of insurers specializing in commercial-line business is 1.7 (0.8) percent greater than that of insurers specializing in personal-line insurers. As the claim effect of the WTC attack concentrates mainly on insurers specializing in commercial-line business, risk updating is also expected to occur in commercial lines. We see that panel B in Table 3 and panels C in Table 5 jointly support the above statement. Finally, we use changes in earnings per share (EPS) between years 2001 and 2002 to measure insurers' losses in the WTC attack. We compare the difference in LAFRs between firms whose EPS changes are above the median change and firms whose EPS changes are below the median change. Panel D shows that differences in LAFRs are negative. Although mean difference is insignificant, median difference is significant at the one-percent level using Wilcoxon z-statistic suggesting that firms with more losses (more reduction in EPS) from the WTC attack have better long-run forecast revisions.

Table 6 explores the relationship between long-run forecast revisions and firms' future growth potential. we measure growth potential by Tobin's q and change in firms' annual sales between 2001 and 2000. Panel A shows that growth potential, measured by either Tobin's q or sales growth, is significantly higher for P&L insurers. Post-attack sales growth for P&L firms is 12.3 percent higher than that of non P&L firms. In panel B, we report that LAFR for high-q firms is larger than LAFR of low-q firms. Furthermore, in panel C, we show that LAFR is significantly greater for firms experiencing greater increase in sales. Our results confirm that LAFR properly measure a firm's growth opportunity.

In summary, our results in Tables 5 and 6 are consistent with many press articles that suggest stocks of P&L insurance firms outperform the general stock market and those of other insurers (for example, Hartwig, 2002). We also compute the long-run stock performance and find consistent results with our earnings forecast analysis. Using the size and book-to-market matching approach suggested in Fama and French (1992, 1993) and Barber and Lyon (1997), stocks of insurers outperform the value-weighted market index by 5 percent while stocks of P&L firms outperform stocks of non P&L firms by 27 percent in the 18-month period following the WTC attack.

5 Robustness Checks

5.1 More Restrictive Sample for P&L Firms

Our original sample of P&L insurers includes 9 firms specializing in title, mortgage and surety insurance. Since these lines are not viewed as traditional P&L business, we exclude them to check test robustness. The first two panels of Table 7 show that our results for short-run forecast revisions remain unchanged after we remove these firms. The difference in the mean SAFRs between P/L firms and non-P/L firms is negative 3 percent, and the difference in SAFRs between commercial P&L insurers and personal P&L insurers is negative 5 percent. Therefore, consistent with our results in Table 3, firms with more exposure in the attack-affected lines experience larger declines in short-run analysts' earnings forecasts.

The last two panels of Table 7 report our long-run earnings forecast results after removing the 9 non-traditional P&L firms. The difference in the mean LAFRs between P&L firms and non-P&L firms is positive 3.6 percent. Moreover, the difference in the mean LAFRs between commercial P&L insurers and personal P&L insurers is 1.7 percent and significant at the five percent level. Our results on claim and growth effects are not sensitive to whether title insurance, mortgage insurance, and surety insurance are included in the analyses.

5.2 Empirical p-values of Test Statistics

Conventional parametric and non-parametric tests assume independence between comparison groups. If an event study involves industry clustering and event-date clustering, t-statistic and z-statistic used in two-sample comparisons could be mis-specified (see, e.g., Brown and Warner, 1980 and 1985). Our study examines the impact of the WTC attack on the insurance industry alone and it deals with a single event date of September 11, 2001. It is necessary to investigate whether our results using conventional t- and z- statistics are robust. To achieve this goal, we compute empirical p values of our test statistics reported in prior sections. Specifically, we calculate t-statistic and z-statistic of two-sample comparisons between P&L insurers and non P&L insurers for every month included in the IBES database. The rank of actual t-statistic/z-statistic is used to calculate empirical p values. Details of empirical p-value analysis are provided in the Appendix.

Table 8 presents the empirical p-values of test statistic. First, we calculate empirical p-value of test statistics for the difference in forecast revisions between P&L insurers and non P&L insurers. The first two rows report empirical p values for actual t-statistic and z-statistic for mean difference in short-run forecast revision measures (SAFRs reported in Panel A of Table 3). The p value of t-statistic of the mean SFR difference is 7.63 percent while that of t-statistic of the mean SAFR difference is 1.53 percent, suggesting the difference in short run forecast revisions remains significant. Similar to the results reported in Section 4, p values of z-statistics are quite high. Rows 3 and 4 report empirical p values for test statistics of mean difference in long-run forecast revision measures (LFRs and LAFRs). The results are similar to those reported in Panel B of Table 5. In sum, our findings are robust after we control for possible misspecifications in test statistics due to event-date clustering and industry clustering.

6. Conclusion

We examine the short-run claim effect and the long-run growth effect after the WTC attack on the insurance industry. Using short-run and long-run earnings forecast revisions as proxies for the claim effect and the growth effect respectively, we show that the WTC attack has dual impacts on P&L insurance firms. On one hand, commercial P&L insurers suffer a substantial claim effect in the short-run. On the other hand, P&L insurers (especially commercial P&L insurers) experience a higher expected growth rate than non P&L insurers in the long-run. Short-run forecast revisions are closely related to measures of claim cost, but not to proxies of growth opportunities. However, long-run forecast revisions are significantly associated with firms' q ratios and sales growth, but not to short-run claim loss.

Our results complement the analysis of Cummins, Doherty and Lo (2002). Although the WTC attack significantly disrupted insurance firms' short-run earnings as shown in the claim effect, the potential growth opportunities may revive insurance firms in the long run. We show that some insurers could benefit from a catastrophic event in the long run as the market updates future catastrophic risks. By clearly identifying claim and growth effects, our study illustrates the interaction between changes in assets in place and in growth opportunities after the WTC attack. Our analysis motivates future research to investigate whether the claim versus growth effect argument holds for other major catastrophic events, and it sheds light on the general impact of unfavorable external shocks on asset valuation as well.

Our analysis has regulatory and investment implications. Major catastrophic events are typically accompanied by large drops in stock prices of insurance firms (see, e.g., Lamb, 1992 and Cummins and Lewis, 2002). Is this market response rational? Should investors sell their holdings of insurance stocks after a major catastrophic event? Should insurance rating agencies change ratings of those P&L firms having large exposure to catastrophic risks? Our results indicate that a careful analysis on both short run claim impact and long run growth effect is essential to answer these questions.

Appendix: Description of the Empirical p-value

To control for potential biases caused by industry clustering and event-date clustering in our sample, we find empirical p-value of the studentized t-statistic and Wilcoxon rank-sums z-statistic for the difference in means of forecast revisions between P&L and non P&L firms. Our analysis includes the following steps.

(1) Calculate t-statistic and z-statistic for the difference in mean of P&L and non P&L firms for every month included in the IBES database for the period between January 1985 and December 2002.

$$t = \frac{\bar{x}_{p\&l} - \bar{x}_{non\_p\&l}}{\sqrt{s_p^{\,2}(1/m + 1/n)}} \qquad \text{(A.1)}$$

where $\bar{x}_{P\&L}$ and $\bar{x}_{non\_P\&L}$ are the mean forecast revisions for P&L sample and non P&L sample respectively. m and n are the number of P&L firms and non P&L firms. In addition,

$s_p^2 = \dfrac{(m-1)s_{p\&l}^2 + (n-1)s_{non\_p\&l}^2}{m+n-2}$, where $s_{P\&L}{}^2$ and $s_{non\_P\&L}{}^2$ are the sample variance for P&L sample and non P&L sample.

$$z = \frac{W - \{n(m+n+1)/2\}}{\sqrt{mn(m+n+1)/12}} \qquad \text{(A.2)}$$

where W is the sum of the ranks assigned to the non P&L firms.

(2) Rank the above time series t-statistics and z-statistics.

(3) Compute p-value by fitting the actual t-statistic and z-statistic of the difference in alternative forecast revision measures into the ranked series of t-statistics and z-statistics.

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Figure 1. Capacity Constraint Framework

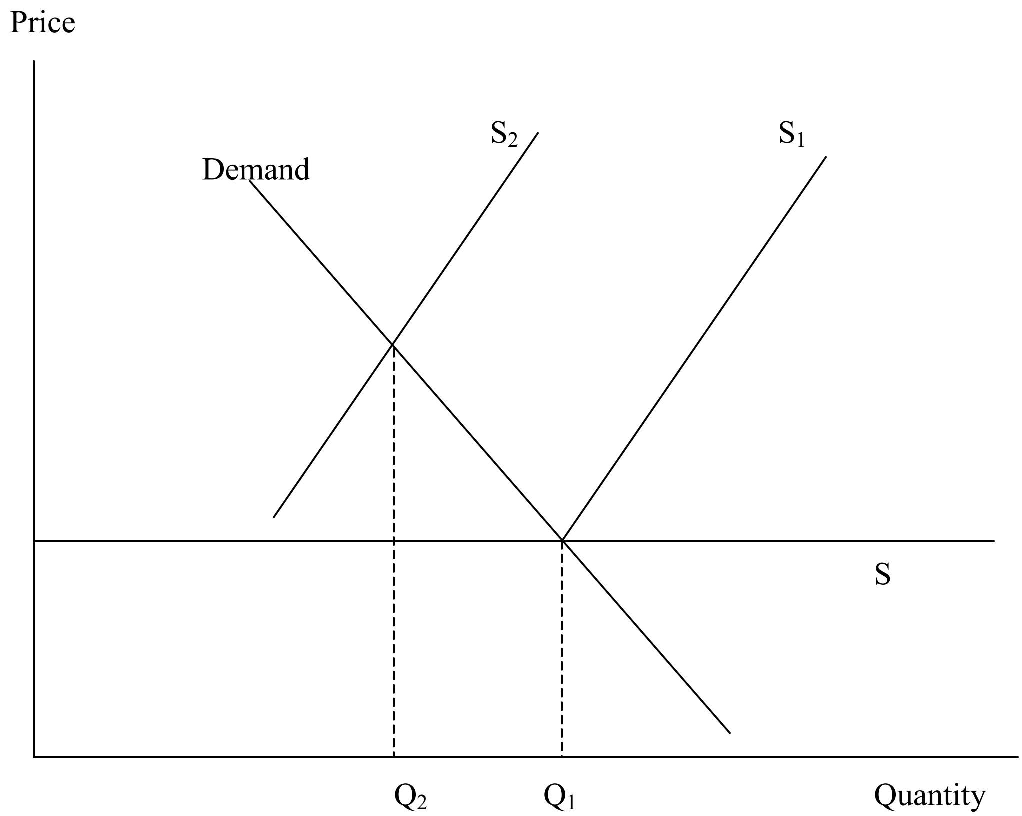


Figure 1 shows the relationship between short-run insurance supply and equilibrium price and quantity within the capacity constraint framework. S_1 and S_2 are the pre-constraint and post-constraint short-run supply curve, respectively. S is the long-run supply curve and D is the demand curve.

Figure 2. Claim Effect

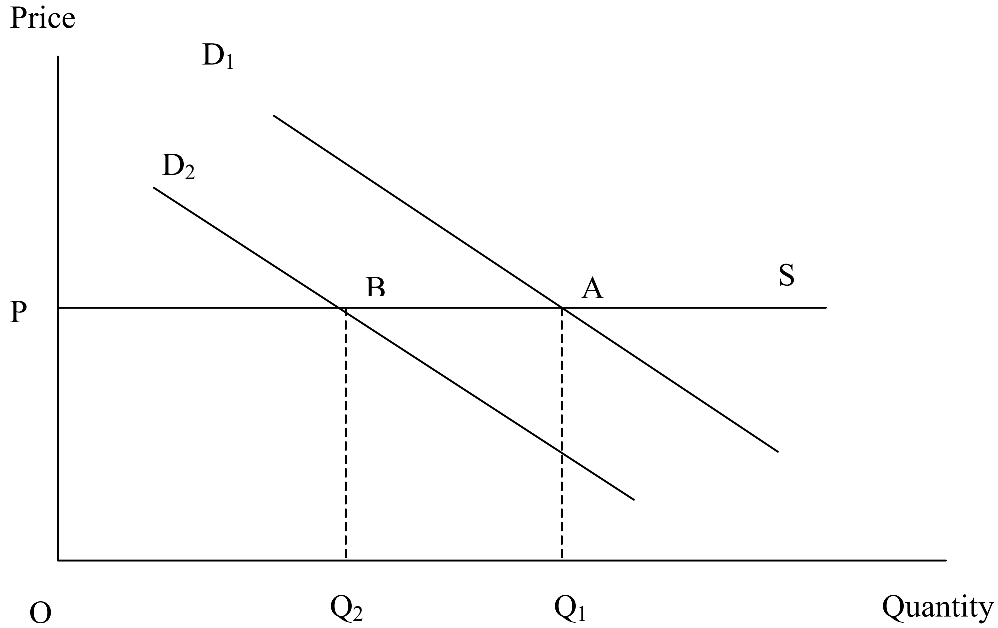


Figure 2 shows the impact of the unexpected loss on insurance firms' short-run profitability. S is the hypothetical short-run supply curve of terrorism insurance had insurance firms known the possibility of terrorism attack. D_1/D_2 is the demand curve for terrorism insurance either supplied by insurers with more/less specialization in underwriting terrorism risks, or demanded by firms exposing high/low level of terrorist attacks.

Figure 3: Growth Effect

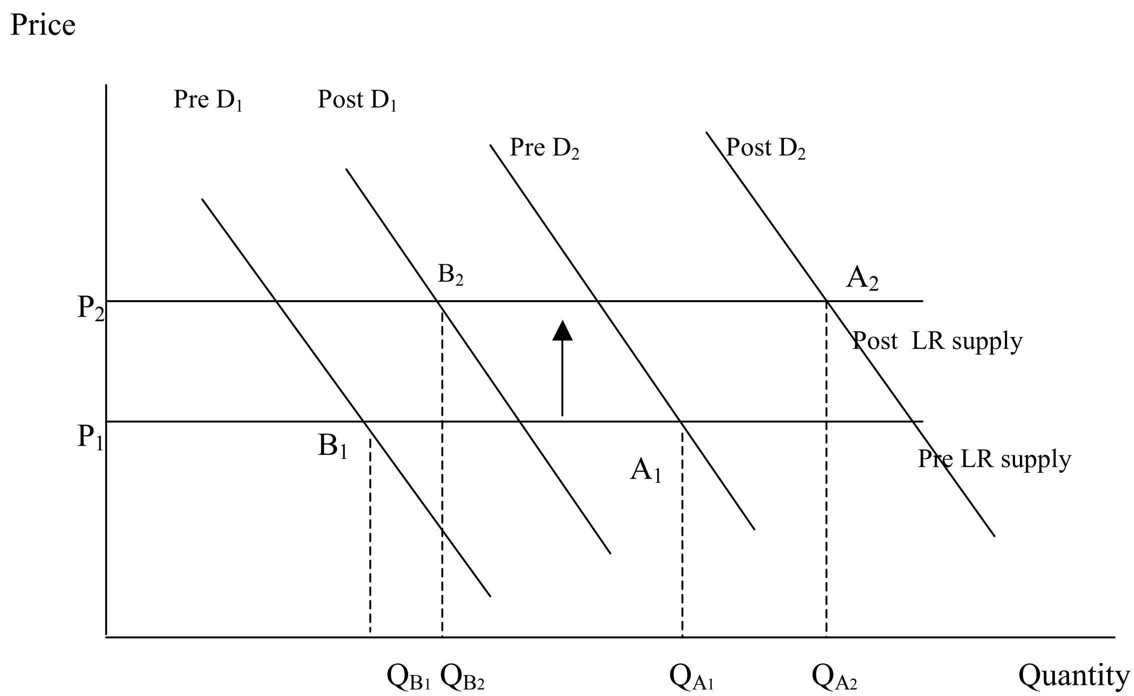
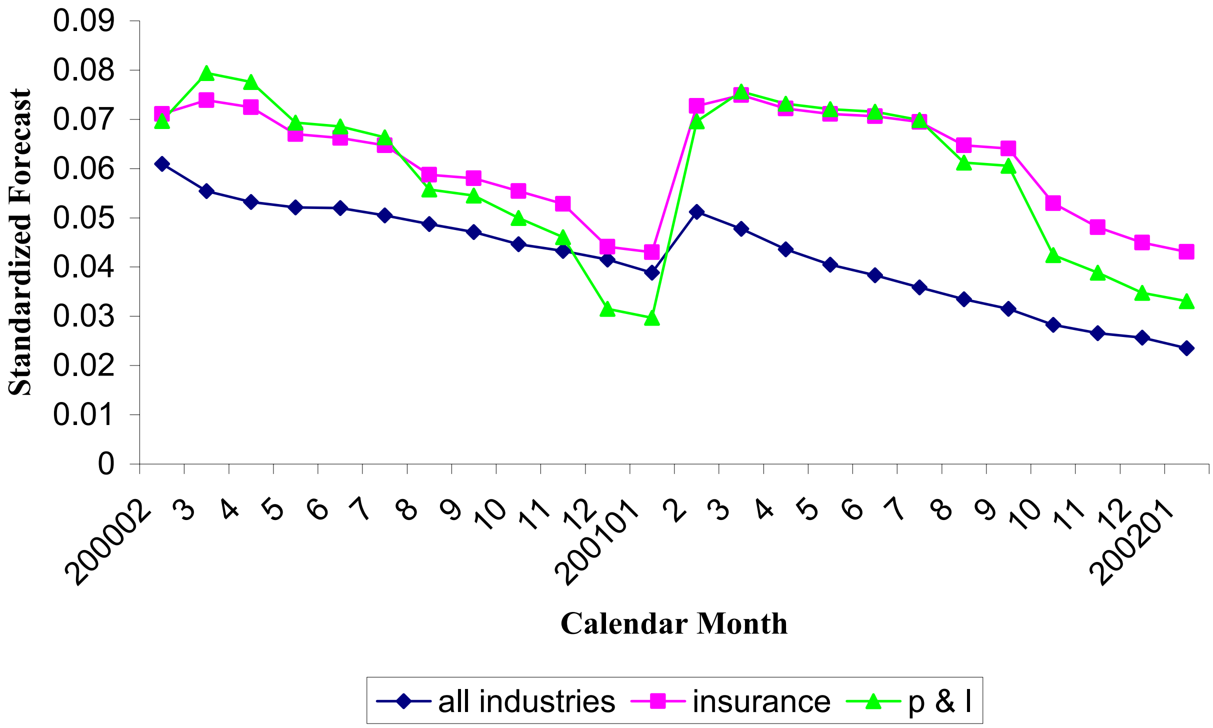


Figure 3 shows the joint impact of greater demand due to risk updating and higher price due to more rigorous underwriting standard. A_1B_1 is the pre-attack long run supply curve and A_2B_2 is the post long run supply curve. Pre D_1 is the pre-attack demand curve of P&L coverage from insurers with no specialty in underwriting P&L risk. Post D_1 is the post-attack demand curve of P&L coverage from insurers with no specialty in underwriting P&L risk. Pre D_2 is pre-attack demand curve of P&L coverage from insurers with no specialty in underwriting P&L risk. Post D_2 is the post-attack demand curve of P&L coverage from insurers with no specialty in underwriting P&L risk.

Figure 4: Patten in Standardized Monthly Forecasts of Annual EPS for Year 2000 and 2001



Standardized forecasts are computed as the median summary earnings forecast divided by the firm's price. Monthly forecasts of 2000 annual EPS are calculated from February 2000 to January 2001. Monthly forecasts of 2001 annual EPS are calculated from February 2001 to January 2002.

Table 1: Lists of Property-Liability Insurance and Non Property-Liability Insurance Firms

Property-Liability Insurance Firms		Non P&L Insurance Firms
1ST AMERN FINL	MARKEL CORP	AEGON NV
21ST CENTURY	MERCURY GEN CP	AFLAC INC
ACE LTD	MIDLAND CO	AMERN NATL INS
ALFA CP	NAVIGATORS GROUP	AMERUS GROUP CO
ALLMERICA FINCL	NYMAGIC	ANNUITY&LIFE RE
ALLSTATE CP	OHIO CASUALTY	AXA SA
AMERN FINL GP	OLD REP INTL	CIGNA CORP
AMERN INTL GROUP	PARTNERRE LTD	CONSECO INC
AMRN SAFETY INS	PENN-AMERICA GRP	DELPHI FINL GROU
ARGONAUT GROUP	PHILA CONSOL HLD	FBL FINL GP - A
BALDWIN & LYONS	PMA CAPITAL CORP	ING GROEP N.V.
BERKLEY W R CP	PMI GRP	INSWEB CORP.
BERKSHIRE HATHWAY CHUBB CP	PROASSURANCE	JEFFERSON-PILOT
CHUBB CP	PROGRESSIVE OHIO	JOHN HANCOCK
CINN FINANCIAL	PXRE GROUP LTD	KANSAS CITY LIFE
CNA FINL CP	RADIAN GROUP INC	LEUCADIA NATL
CNA SURETY CP	RELIANCE GROUP H	LINCOLN NATL
COMMERCE GROUP	RENAISSANCERE HL	METLIFE INC
DONEGAL GROUP	RLI CP	MIIX GROUP INC.
ERIE INDEMNITY	SAFECO CP	MONY GROUP INC.
EVEREST RE GRP	SCPIE HOLDINGS	MUTUAL RISK MGMT
FIDELITY NATL FI	SELECTIVE INS.	NATIONWIDE FINL
FPIC INSURANCE	ST PAUL COS INC	PRESIDENT'L LIFE
FREMONT GEN CP	STATE AUTO FINL	PROTECTIVE LIFE
HARLEYSVILLE GRO	STEWARD INFOR SVC	PRUDENTIAL PLC
HARTFORD FIN SVC	TRANSATLANTIC HL	REINSURANCE GRP
HCC INS HLDGS IN	TRENWICK GRP LMT	SCOTTISH ANNUITY
HORACE MANN EDUC	TRIAD GUARANTY	STANCORP FINL
INVESTORS TITLE	VESTA INSURANCE	TORCHMARK CP
IPC HOLDINGS LTD	XL CAP LIMITED	UICI
LANDAMERICA FIN	WESCO FINANCIAL CORP	UNITRIN INC
LOEWS CP	ZENITH NATL INS	UNUMPROVIDENT

Table 2: Short-run Analysts Forecast Revisions and Claim Effect

SFR and SAFR are the raw and abnormal forecast revision from August 2001 to December 2001. The event month (month 0) is September 2001. High ΔEPS refers to firms whose change in earnings per share (EPS) between fiscal year 2001 and 2000 is at or above the median, otherwise the firms are classified as low ΔEPS firms. High q refers to firms whose Tobin's q is at or above the median, otherwise the firms are classified as low q firms. Tobin's q ratio is the ratio of a firm's market value of assets to its book value of assets. One-sample t-statistic is used to test whether SFR and SAFR are different from zero. The two-sample t-statistic is from the t-test of difference between means. The z-statistic is from the Wilcoxon rank sum test for difference between the respective distributions.

Panel A: Short-run Earnings Forecast Revisions: Full Sample

Relative Month Window	*SFR*	*SAFR*	*N*
(-1, +1)	-0.009	-0.0086	83
	(-3.02)***	(-2.19)**	
(-1, +2)	-0.01	-0.0087	92
	(-2.15)**	(-1.47)	
(-1, +3)	-0.019	-0.02	94
	(-4.28)***	(-2.87)***	

Panel B: Short-run Earnings Forecast Revisions: High ΔEPS Firms vs. Low ΔEPS Firms

	SFR		*SAFR*		*N*
	Mean	Median	Mean	Median	
High ΔEPS	-0.002	-0.001	0.0055	0	46
Low ΔEPS	-0.037	-0.019	-0.047	-0.023	46
Difference in mean	0.036		0.053		
t-statistic	(4.17)***		(3.89)***		
Difference in median		0.018		0.023	
z-statistic		(5.21)***		(4.63)***	

Panel C: Short-run Earnings Forecast Revisions: High q Firms vs. Low q Firms

	SFR		*SAFR*		*N*
	Mean	Median	Mean	Median	
High q	-0.022	-0.002	-0.026	-0.005	47
Low q	-0.017	-0.006	-0.014	-0.003	47
Difference in mean	-0.0046		-0.0121		
t-statistic	(-0.50)		(-0.85)		
Difference in median		0.004		-0.002	
z-statistic		(0.12)		(-1.04)	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3: Short-run Analysts Forecast Revisions: By-group Comparisons

SFR and SAFR are the raw and abnormal forecast revisions from August 2001 to December 2001. One-sample t-statistic is used to test whether SFR and SAFR are different from zero. The two-sample t-statistic is from the t-test of difference between means. The z-statistic is from the Wilcoxon rank sum test for difference between the respective distributions.

Panel A: Short-run Forecast Revisions: P&L vs. non P&L Firms

	SAFR		
	Mean	Median	N
P&L	-0.029	-0.009	63
Non P&L	-0.002	-0.003	31
Difference in mean	-0.024		
t-statistic	(-2.29)**		
Difference in median		-0.005	
z-statistic		(0.61)	

Panel B: Short-run Forecast Revisions: Commercial vs. Personal P&L Firms

	SAFR		
	Mean	Median	N
Commercial P&L	-0.055	-0.021	37
Personal P&L	-0.0002	-0.003	17
Difference in mean	-0.055		
t-statistic	(-3.43)***		
Difference in median		-0.018	
z-statistic		(-2.12)**	

Panel C: Short-run Forecast Revisions: New York vs. non-New York P&L Firms

	SAFR		
	Mean	Median	N
New York P&L	-0.041	-0.01	19
Non New York P&L	-0.024	-0.009	32
Difference in mean	-0.017		
t-statistic	(0.77)		
Difference in median		-0.001	
z-statistic		(0.3)	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 4: Cumulative Average Abnormal Stock Returns

Panel A: Cumulative Abnormal Returns (CARs)

Abnormal stock return is calculated using a market model with the equally weighted index. We use different tests for the null hypothesis that two days and five days abnormal stock return equals zero. The Patell (1976) Z-test examines whether abnormal stock return equals zero assuming cross-sectional independence. The SCS Z-test introduced by Boehmer, Musumeci and Poulsen (1991) is also used to adjust the event-induced variance. Both tests use a 1-tail test.

Days	*Cumulative Abnormal Return (CAR)*	*Patell Z-test*	*SCS Z-test*	*N*
(0, +1)	-4.09%	-12.64***	-5.93***	88
(0, +5)	-6.77%	-11.41***	-6.41***	88

Panel B: Cumulative Abnormal Returns (CARs) for P&L firms vs. non P&L firms

The abnormal stock return used here is the cumulative abnormal stock return for event window (0, 1). The significance of mean abnormal stock return and the difference-in-means is measured using t-statistics. The difference in median is tested using the non-parametric Wilcoxon signed-rank test for medians.

	CAR	*N*
P&L	-0.043	57
Non P&L	-0.037	31
Difference in means	-0.006	
t-statistic	(0.38)	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 5: Long-run Analysts Forecast Revisions: Full Sample and By-group Analyses

LFR and LAFR are the raw and abnormal forecast revisions from August 2001 to December 2001. High ΔEPS refers to firms whose change in earnings per share (EPS) between fiscal year 2001 and 2000 is at or above the median, otherwise the firms are classified as low ΔEPS firms. One-sample t-statistic is used to test whether LFR and LAFR are different from zero. The two-sample t-statistic is from the t-test of difference between means. The z-statistic is from the Wilcoxon rank sum test for difference between the respective distributions.

Panel A: Long-run Earnings growth Forecast Revisions

Relative Month Window	*LFR*	*LAFR*	*N*
(-1, +1)	0.0135	0.017	71
	(1.38)	(1.69)*	
(-1, +2)	-0.005	-0.001	71
	(-0.84)	(-0.17)	
(-1, +3)	-0.0078	-0.004	72
	(-1.34)	(-0.61)	

Panel B: Long-run Forecast Revisions: P&L vs. non P&L Firms

	LAFR		
	Mean	Median	N
P&L	0.0052	0.008	52
Non P&L	-0.028	0.004	20
Difference in mean	0.033		
t-statistic	(1.96)**		
Difference in median		0.004	
z-statistic		(1.82)**	

Panel C: Long-run Forecast Revisions: Commercial vs. Personal P&L Firms

	LAFR		
	Mean	Median	N
Commercial P&L	0.0149	0.009	29
Personal P&L	-0.002	0.001	15
Difference in mean	0.017		
t-statistic	(2.09)**		
Difference in median		0.008	
z-statistic		(2.01)**	

Panel D: Long-run Forecast Revisions: High ΔEPS Firms vs. low ΔEPS Firms

	LAFR		
	Mean	Median	N
High ΔEPS	-0.011	0.006	34
Low ΔEPS	0.0058	0.009	36
Difference in mean	-0.0173		
t-statistic	(-1.34)		
Difference in median		-0.003	
z-statistic		(-2.29)***	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 6: Long-run Forecast Revisions and Growth Opportunities

LFR and LAFR are the raw and abnormal forecast revisions from August 2001 to December 2001. Sales growth is the difference in net sales between fiscal year 2002 and 2001 standardized by net sales in 2001. High q refers to firms whose Tobin's q is at or above the median, otherwise the firms are classified as low q firms. Tobin's q ratio is the ratio of a firm's market value of assets to its book value of assets. High Δsale refers to firms whose sales growth is at or above the median, otherwise the firms are classified as low Δsale firms. One-sample t-statistic is used to test whether LFR and LAFR are different from zero. The two-sample t-statistic is from the t-test of difference between means. The z-statistic is from the Wilcoxon rank sum test for difference between the respective distributions.

Panel A: Growth Potential: P&L vs. non P&L Firms

	Tobin's q			*Sales Growth*		
	Median	*Mean*	*N*	*Median*	*Mean*	*N*
P&L	1.105	1.164	51	0.143	0.178	50
Non P&L	1.036	1.056	20	0.069	0.055	17
Difference in mean		0.108			0.123	
t-statistic		(3.37)***			(2.36)**	
Difference in median	0.069			0.074		
z-statistic	(1.81)**			(1.87)**		

Panel B: Long-run Forecast Revisions: High-q Firms vs. Low-q Firms

	LAFR		
	Mean	Median	N
High q	0.005	0.009	36
Low q	-0.013	0.001	35
Difference in mean	0.018		
t-statistic	(1.41)		
Difference in median		0.008	
z-statistic		(1.32)*	

Panel C: Long-run Forecast Revisions: High Sales-Growth Firms vs. Low Sales-Growth Firms

	LAFR		
	Mean	Median	N
High Δsale	0.0112	0.009	34
Low Δsale	-0.013	0.005	33
Difference in mean	0.024		
t-statistic	(2.18)**		
Difference in median		0.004	
z-statistic		(2.07)**	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. .

Table 7: Analyses with More Restrictive P&L Sample

SFR and SAFR are the raw and abnormal forecast revisions from August 2001 to December 2001. LFR and LAFR are the raw and abnormal forecast revisions from August 2001 to December 2001. One-sample t-statistic is used to test whether means are different from zero. The two-sample t-statistic is from the t-test of difference between means. The z-statistic is from the Wilcoxon rank sum test for difference between the respective distributions.

Panel A: Short-run Forecast Revisions: P&L vs. non P&L Firms

	SAFR Mean	Median	N
P&L	-0.034	-0.014	52
Non P&L	-0.002	-0.003	31
Difference in mean	-0.0316		
t-statistic	(-2.79)***		
Difference in median		-0.016	
z-statistic		(-1.54)*	

Panel B: Short-run Forecast Revisions: Commercial vs. Personal P&L Firms

	SAFR Mean	Median	N
Commercial P&L	-0.061	-0.029	34
Personal P&L	-0.001	-0.005	15
Difference in mean	-0.06		
t-statistic	(-3.49)***		
Difference in median		-0.024	
z-statistic		(-2.25)***	

Panel C: Long-run Forecast Revisions: P&L vs. non P&L Firms

	LAFR Mean	Median	N
P&L	0.008	0.008	43
Non P&L	-0.028	0.004	20
Difference in mean	0.036		
t-statistic	(2.12)**		
Difference in median		0.004	
z-statistic		(1.94)**	

Panel D: Long-run Forecast Revisions: Commercial vs. Personal P&L Firms

	LAFR Mean	Median	N
Commercial P&L	0.0181	0.009	27
Personal P&L	0.0007	0.005	13
Difference in mean	0.017		
t-statistic	(2.19)**		
Difference in median		0.004	
z-statistic		(1.6)*	

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 8: Empirical P value of test statistics of Forecast Revisions for P&L vs. non P&L Firms

Calculate t-statistic and z-statistic for the difference in mean of P&L and non P&L firms for every month included in the IBES database for the period between January 1985 and December 2002. Rank the time series t-statistics and z-statistics. Compute p-value by fitting the actual t-statistic and z-statistic of difference between means into the ranked series of t-statistics and z-statistics.

	Empirical p value	
	t-statistic	z-statistic
Difference in SFR	7.63%	62.5%
Difference in SAFR	1.53%	72.7%
Difference in LFR	3.18%	0.45%
Difference in LAFR	0.91%	0.91%