Catastrophes, Volatility of Insurance Stocks and Transparency

Proposal for EGRIE 2008

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Abstract: In the first part of our study we use Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to investigate into the question if large catastrophic events that occurred between 1985 and 2006 lead to significant increases in the volatility of insurer stock returns following these catastrophes. We measure these increase and persistence of the increases in volatility. In the second part of our study we test if the increases in volatility can be explained using company specific characteristics. In particular, we test if, controlling for an insurer’s exposure to catastrophe risk, asymmetric information between insurers and investors can explain the observed differences between the corporations.

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Motivation

The transfer of risks is one of the central elements of modern economies. Insurance allows individuals and corporations to cede idiosyncratic and non-standardized risks. Although the first insurance contracts date back to medieval times the insurance industry is currently facing a number of challenges. Challenges stem from large scale risks associated with natural catastrophes, liability and terrorism. These risks, which are too large to be diversified in the insurer’s portfolio alone, must be transferred to the financial markets (insurers listed on stock exchanges) or be borne by the members (mutual insurance corporations). Yet, there exists a long strand of literature (among them Doherty and Schlesinger, 2001, and Jaffee and Russell, 1997, and Cummins, Doherty and Lo, 2002) suggesting that insurance does not work well if losses are correlated or exceed certain thresholds.

Froot (2001) provides evidence that catastrophe reinsurance premiums widely exceed the expected value of claims. More specifically, Froot (2001) observes that premiums for catastrophe reinsurance may be several times higher than the expected value of claims. Further, Froot and O’Connell (2008) estimate that the elasticity of the supply of catastrophe reinsurance is about 7. This means that a 1% increase in the prices for catastrophe reinsurance (above the expected of claims) leads to a 7% increase in the reinsurance capacity supplied. The prices for catastrophe bonds which allow insurers to cede natural catastrophe risk to the financial markets are also found to exhibit similar features. Bantwal and Kunreuther (1999) and Litzenberger et al. (1996) find that these financial instruments which can be triggered by certain easily measurable parameters also demand risk premiums far above the expected value of claims.

In this study we contribute to the literature on catastrophe insurance by analyzing the reaction of financial markets to a number of large catastrophe events. More precisely, we investigate how catastrophes simultaneously influence the riskiness and returns of insurance stocks. By explicitly modelling the trade-off between risk and return for insurance stocks after large catastrophic events we are able to provide new insights into an issue that due to the effects of global climate change and the enduring threats from
terrorism is relevant for insurers in Europe and the United States. We investigate into the post-catastrophe relation between risk and return with Generalized Autoregressive Conditional Heteroskedastic (GARCH) models of insurance stock returns (Engle, 1982, and Bollerslev, 1986).¹ In addition, we test if controlling for catastrophe exposure corporate transparency can help to explain the differences in the volatility of insurer’s stocks.

The study employs daily financial market data on stock prices of insurers in the United States and Europe for the period from 1985-2006. It further uses data on large insured catastrophes from Swiss Re and utilizes company specific data from a number of sources that include AM Best and Compustat and I/B/E/S.

A number of factors contribute to the study’s particular relevance for the insurance industry. Preliminary results indicate that in contrast to a number of studies conducted on broader asset markets or foreign exchange rates (Ederington and Lee, 1993² and Andersen and Bollerslev, 1998) the inflow of information of the occurrence of a large catastrophic event does not lead to immediate sharp increases in insurer’s share price volatility. Although we find that large catastrophic events do indeed result in very significant increases in volatility they occur slowly. It typically takes a number of trading days after occurrence of the loss causing event (i.e. the landfall of Hurricane Andrew in Dade County, FL, or the September 11th attacks) for volatility to increase significantly. Even more days pass before volatility reaches its maximum. Following the maximum, volatility decays slower than would be predicted. Figure 2 (Appendix B) provides graphs of the estimated conditional volatility for four insurers in the aftermath of the attacks of September 11th, 2001.

Together, the slow, yet significant, increase in volatility and the slow decay of volatility add to the importance of the research. Since the upwards drift occurs slowly corporations have time to communicate with markets. Although the popular Capital Asset Pricing

¹ Engle received the 2003 Nobel Prize in Economics "for methods of analyzing economic time series with time-varying volatility (ARCH)". [http://nobelprize.org/nobel_prizes/economics/laureates/2003/]
² Ederington and Lee (1993) write: “We find that the major price adjustment occurs within one minute of the release and the direction of subsequent price adjustments is basically independent of the first minute's price change. Nonetheless, prices continue to be considerably more volatile than normal for roughly fifteen minutes and slightly more volatile for several hours.”
Model (CAPM) suggests that investors cannot demand a premium for bearing idiosyncratic risks there is a considerable strand of literature, among them Goyal and Santa-Clara (2003), that finds a significant and positive connection between idiosyncratic risk and asset return. The long persistence of volatility results in a significant risk premium that corporations have to pay to its shareholders for bearing this risk. Thus, understanding which company specific factors contribute to the size and persistence of the increase volatility can help to optimize a corporation’s cost of risk bearing. By choosing policies that decrease share price volatility following large catastrophic events can create value for corporations. Since European insurers and reinsurers are very active in the market for catastrophe insurance the study’s results are of particular significance for them.

**Literature**

The effects of large catastrophic events and regulatory action on the insurance markets have been in the focus of a number of publications. Extending Lamb’s (1995) study for Hurricane Andrew Cummins and Lewis (2003) (from now: CL) consider the differences between the market return and the returns on insurer stocks after the September 11 attacks, Hurricane Andrew and the Northridge Earthquake. They regress the individual insurer’s returns on the market returns to receive a measurement of a stock’s idiosyncratic risk. CL produce non-value weighted portfolios of insurer stocks to measure the idiosyncratic risk of holding this portfolio in the aftermath of a catastrophe. Using a rolling window approach they arrive at the conclusion that the standard deviation of standardized abnormal returns increased after the September 11th attacks and Hurricane Andrew. Using these results they find that insurers with a better rating fared better than those with an inferior rating.

Using a similar methodology Brown, Cummins, Lewis and Wei (2004) analyze the effect that the inflow of new information about the introduction of the Terrorism Risk Insurance Act had on the stocks from a number of industries. They show that the returns of property

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3 The rolling window approach calculates an equally weighted average of the observations inside the window and disregards the observations outside the window.
and casualty insurers showed a significantly negative reaction to the passage of the bill into law and the signing of the bill by President Bush.

Doherty, Lamm-Tennant and Starks (2003) (from now: DLS) use the concept of transparency to explain the change of insurer’s share prices between 9/10/2001 and (a) 09/17/2001 and (b) 11/16/2001. They measure transparency by looking at firms gross losses (model b) and at firms net losses (models a and b). Net losses are equal to gross losses minus reinsurance recoverables. DLS find that investors react positively to a very timely announcement of net losses (until 09/17/2001, model a) or any announcement of et losses (model b). Yet, they do not find any evidence that the market appreciated the announcement of gross losses. Thus, they failed to find any support for their hypothesis that investors reward insurers for communicating the credit risk involved with the reinsurance coverage.

Although DLS and CL look at the effects of September 11th, Hurricane Andrew (CL) and the Northridge Earthquake (CL) on the stock market and even apply the concept of transparency to explain the rebound of insurer’s stock prices (DLS) they leave a number of questions unanswered. From an investor’s of view it is of great relevance to know how the risk of an individual stock or how a portfolio’s value of risk reacts to catastrophes. Since investors might have a demand for liquidity holding a stock that might eventually rebound is not the same as holding a stock that did never loose a large part of its value. Therefore it is not only important to model the effect of transparency on the returns of a stock. It seems to be equally important to measure the effect of transparency on the riskiness of a stock. As our preliminary findings show that insurance stocks react strongly to catastrophe events these seem to provide for good fit to test if transparency makes insurance stocks less volatile. Knowing if transparency reduces volatility is also interesting from a corporation’s point of view. Although the Capital Asset Pricing Model suggests that idiosyncratic risk should not be relevant for pricing financial assets there is strong evidence that managing risks can be in the interest of a company’s shareholders (Mayers and Smith, 1982 and Goyal and Santa-Clara, 2003). Thus, understanding how to reduce the risk induced by informational asymmetries is likely to create value.

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4 09/17/2001 was the first day of trading after the terrorist attacks of September 11.
A further aspect that has so far been neglected in the insurance literature is the importance of forecasting returns and volatility. A noteworthy exception is the work of Brewer et al. (2007) on interest rate risk and the equity value of life insurance companies. While CL can estimate the performances of insurance stocks relative to the market and produce a measure of the relative average volatility there are some limitations to their methodology. The methodology used in CL does not allow them to forecast neither expected returns nor expected volatility. Yet, forecasts of returns and in particular forecasts of the volatility are central for investors looking to buy/sell insurer’s stocks. We therefore turn to a widely used GARCH time series methodology (Poon and Granger, 2003) to provide new insights to this problem. Figure 1 (Appendix B) presents some preliminary results of this forward looking methodology for the time period around September 11th, 2001. It shows the actual returns and one step ahead forecast of the predicted return’s 95%-confidence interval.

Methodology and Data

Part 1

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are of particular importance for financial assets which tend to exhibit volatility clustering (Mandelbrot, 1963 and Fama, 1965). When volatility is high it tends to stay high. If it is low it has the tendency to remain low. This heteroskedasticity makes forecasting future volatility of returns difficult. Yet, future volatility is of great importance to asset holders who are concerned with the expected return over and the expected variance of returns over the holding period. Thus, a simple approach that ignores heteroskedasticity, approximates the actual variance with its long term average and models the return as a simple autoregressive moving average (ARMA(m,n)) will not satisfy an investor that only plans to hold the asset from period t until t+1.

A simple form of linear stochastic difference equations is the ARMA(m,n) model. A ARMA model for a stationary (return) series can be expressed as:

\[ r_t = a_0 + \sum_{j=1}^{m} a_j r_{t-j} + \sum_{j=1}^{n} b_j (\varepsilon_{t-j})^2 + \varepsilon_t \]
where $r_t$ is the difference of the logs of the price of an asset on days t-1 and t. $\varepsilon_t$ is the predicted residual in period t. $a_0$, $a_1$ and $b_i$ are constants which are to be estimated. Yet, as the variance of asset returns is usually not constant over time the unconditional forecast error is much greater than that of a forecast that considers the current level of volatility. Engle (1982) provides a solution for this problem. He suggests to explicitly model the variance process. His Autoregressive Conditional Heteroskedastic (ARCH) model forecasts the conditional variance of $\varepsilon_t$ as an autoregressive process that uses the information contained in the residuals:

$$
\varepsilon_t = v_t \sqrt{\alpha_0 + \sum_{i=1}^{q} \alpha_i (\varepsilon_{t-i})^2},
$$

where $v_t$ is a white noise process with $\sigma_v^2 = 1$ and $v_t$ and $\varepsilon_{t-i}$ are independent of each other.

Engle’s (1982) formulation was extended by Bollerslev (1986) to also incorporate the forecasted conditional variance $h_t$ in the estimate of future volatility. Bollerslev’s (1986) formulation expresses $\varepsilon_t$ as:

$$
\varepsilon_t = v_t \sqrt{h_t}
$$

where

$$
h_t = v_t \sqrt{\alpha_0 + \sum_{i=1}^{q} \alpha_i (\varepsilon_{t-i})^2 + \sum_{j=1}^{p} \beta_j h_{t-j}}.
$$

The GARCH approach thus allows modeling both the risk $h_t$ and the return $r_t$ of an asset simultaneously.

The study presented here uses this formulation to investigate into the reaction of insurer’s stock prices to large catastrophes. The data that encompasses the time period from January 1985 until December 2006 is collected from the Center for Research in Security Prices (CRSP) database and Datastream. Insurance corporations are among others identified by their Standard Industrial Classification (SIC) number. We restrict our study to insurers that in the datasets for more than 36 consecutive months and that have an average market capitalization of $250$ million or more. This leaves us with more than 110 insurance corporations from the United States and Europe. For each of these insurers we then estimate separate GARCH models. We select the parsimonious models following

$$
\sum_{i=1}^{q} \alpha_i \leq 1
$$

5 Stability of the process demands that $0 \leq \sum_{i=1}^{q} \alpha_i \leq 1$
the outlines suggested by Engle and Patton (2001) and Enders (2004) and conduct a number of diagnostic checks. We adjust equations (1) and (2) and provide for explicit models the mean and the variance. To avoid an over fitting of our models we restrict ourselves to including each a constant and up to two AR-or MA-terms for the model of the mean. For the model of the conditional variance we limit ourselves to using a formulation up to GARCH(2,2). Assuming that an asset’s variance is finite, we restrict the sum of the GARCH-coefficients to be smaller or equal to one \(\alpha_i + \alpha_2 + \beta_1 + \beta_2 \leq 1\). The models are then estimated simultaneously by maximum likelihood. This gives us two equations to be estimated for each of the insurers:

\[
(1a) \quad r_t = a_0 + a_1 r_{t-1} + a_2 r_{t-2} + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \varepsilon_t
\]

and

\[
(2a) \quad h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \lambda^* \left( \varepsilon_{t-1} \right)^2
\]

We check for asymmetry and include, where necessary, a term \(\lambda^*\), which is equal to one \(\lambda^* = 1\) if the residual \(\varepsilon_t < 0\) and equal to zero if \(\varepsilon_t \geq 0\). The term \(\lambda^*\) accounts for the asymmetry of the changes in the volatility (Glosten, Jaganathan and Runkle, 1993). The model, also referred to as threshold-ARCH (TARCH), builds upon the theory that equity returns are not only influenced by the size of the squared innovation but also the type of news. Symmetric models predict that increases in volatility will be followed by higher levels of volatility. Asymmetric models also account for investors’ risk aversion. Risk aversion suggests that an increase of volatility decreases the demand for an asset. As a result the increase in volatility does not only lead to an increase of the predicted volatility but results also in a decrease of asset prices. Table 1 (Appendix A) provides the maximum likelihood estimates of equations (1a) and (2a) for the returns of the insurers ACE, AIG, BERKSHIRE and CHUBB.

Further on, we test if an asset’s return is directly determined by its conditional variance. Engle, Lilien and Robins (1987) propose that the risk premium demanded by investors is increasing function of the conditional variance \(h_t\). To test if the excess return for holding a risky asset is a function of the conditional variance we include the term \(\omega h_t\) in the model of the mean ((G)-ARCH-M). Equation 1a becomes:
(1b) \[ r_t = a_0 + \omega h_t + a_1 r_{t-1} + a_2 r_{t-2} + b_1 (\varepsilon_{t-1})^2 + b_2 (\varepsilon_{t-2})^2 + \varepsilon_t \]

In our next step, we extend equation (1a) to control for market risk \((r_{t,m})^6:\)

(1c) \[ r_t = a_0 + a_1 r_{t-1} + a_2 r_{t-2} + \phi r_{t,m} + b_1 \varepsilon_{t-1} + b_2 \varepsilon_{t-2} + \varepsilon_t \]

We then use (1b/1c) and (2a) to investigate if large catastrophic events lead to increases in volatility. Data on the largest insured losses is obtained from Swiss Re (2008). The inflation corrected losses include a number of natural catastrophes, hurricanes, earthquake and (winter-) storms, and the terrorist attacks of September 11th, 2001. The dates mentioned in Swiss Re (2008) are adjusted with data among others from the National Oceanic and Atmospheric Administration's National Hurricane Center (NOAA, 2008), Southern California Earthquake Data Center SCEDC (2008) and the National Commission on Terrorist Attacks Upon the United States (National Commission, 2004). The adjustment is particularly important for hurricanes, which evolve over a number of days. The adjusted event dates are calculated as the date of the landfall in the county with the largest losses. If this date is a weekend or the event happens at a time late in the trading day in New York (for American Stocks) or Frankfurt (for European Stocks), the adjusted event date is set equal to the next trading day.

Using this methodology we test our hypotheses that large catastrophic events lead to significant increases in volatility. We check if the post-event volatility is significantly greater than the volatility on the last trading day before the event. We define “a significant increase” of volatility as a two standard deviation increase over the predicted volatility for the day before the event. In addition, we record the maximum post-event variance, the increase in volatility relative to its standard deviation and the time elapsed between the event and this extreme value. We illustrate the consequences that these catastrophes have for investors by producing a number of portfolios of financial assets and estimating their Value at Risk. Theory assumes that an asset’s volatility has a high degree of persistence and that it is mean reverting. Yet, it is impossible to know an asset’s real mean volatility. We therefore revert to calculating the persistence of the volatility induced by catastrophic events as the half life of the event induced volatility. Having

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6 We use the returns on the S&P500 index to control for market risk.
calculated the investor’s risk premium per unit of variance $\omega$ and knowing the size and persistence of the volatility shocks induced by the catastrophe (1c and 2a) we are able to calculate the additional event induced risk premium demanded by the financial markets for bearing these risks.

Part 2

In the second part of the paper, we use the values obtained from the first part of our study as dependent variables and test if these can be explained by informational asymmetries between the insurers and their shareholders. Information asymmetry in the capital markets can significantly increase external financing costs and thereby limit firms’ ability to finance their growth opportunities (Froot, Scharfstein and Stein, 1993). Economic theory suggests that greater corporate transparency should lower the information asymmetry component of the firm’s cost of capital (Diamond and Verrecchia, 1991 and Easley and Hvidkjaer and O’Hara, 2002).

Property and liability insurance markets are known to follow a cyclical pattern usually referred to as the underwriting cycle. Gron (1994) and Winter (1988, 1991) provide explanations for this behavior and put forward that shocks to insurer’s capital lead to sharp increases in prices for insurance coverage. Thus, the ability for insurers to access financial markets following catastrophic events is central for exploiting profitable growth opportunities. Yet, if investors are not sure about insurer’s real losses they are likely to demand a high risk premium for supplying capital to corporations that are not transparent or susceptible to opportunistic behavior.

A concept that allows quantifying these informational asymmetries is the notion of corporate transparency. Corporate transparency is defined as the widespread availability of firm-specific information to market participants (Bushman, Piotroshki and Smith, 2004). Bushman, Piotroshki and Smith (2004)’s concept of corporate transparency distinguishes between corporate reporting and the acquisition of private information.

Since it is difficult to measure corporate transparency directly we employ a transparency metric developed by Jin and Myers (2006). This metric builds upon Roll (1988)’s $R^2$ measure of share price synchronicity. According to Roll (1988) the more firm specific
information is incorporated into stock prices the lower the $R^2$ of a firm’s stock.\textsuperscript{7} Besides using share price non-synchronicity we also evaluate corporate transparency by analyzing a number of factors suggested by Bushman, Piotroski and Smith (2004). We measure the quality of corporate reporting by the disclosure intensity, the timeliness of disclosure and the credibility of disclosures. We use the timeliness of the insurer’s post catastrophe loss estimates and the accuracy of these estimates as measures for the quality of corporate reporting. Data on these factors is collected from AM Best’s Bestwire (part of the Lexis Nexis Database) and verified with data from insurer’s annual reports. Following Verrecchia (1982), Bushman, Piotroski and Smith (2004) quantify the acquisition of private information as the average number of analysts following a firm. We extract data on the on the average number of analysts following a firm from the I/B/E/S Database. In addition, we use Best's Insurance Reports - Property/Casualty - United States & Canada (Best, 2007), the Compustat database, the insurer’s annual reports and the reports published by the state regulators to control for the insurers size and its exposure to catastrophic risk.

If controlling for a firm’s exposure to catastrophic risk transparency lowers uncertainty over a corporation’s losses that arise from information asymmetries we hypothesize that transparency creates value for shareholders. However, while transparency may facilitate growth and lower a firm’s costs of risk bearing by lowering financing costs this beneficial aspect is likely to differ according to the heterogeneity of insurer’s financing needs.

\textsuperscript{7} The $R^2$ can be obtained by regressing the firm’s returns on the (relevant) market return.
References


The Impact of Public Information on the Stock Market, The Journal of Finance, Vol. 49,  
No. 3, Papers and Proceedings Fifty-Fourth Annual Meeting of the American Finance  
Association, Boston, Massachusetts, January 3-5, 923-950.  
National Commission on Terrorist Attacks Upon the United States, http://www.9- 
11commission.gov/report/index.htm [Accessed, April, 4, 2008]  
NOAA (2008)  
National Oceanic and Atmospheric Administration's National Hurricane Center,  
http://www.nhc.noaa.gov/ [Accessed, April, 4, 2008]  
Roll, Richard (1987)  
Annual Meeting of the American Finance Association, Chicago, Illinois, December 28- 
SCEDC (2008)  
Southern California Earthquake Data Center, www.scedc.scec.org, [Accessed, April, 4,  
2008]  
Verrecchia, Robert (1982).  
“The Use of Mathematical Models in Financial Accounting, Journal of Accounting  
Research (Supplement, 1982), 1-42.  
Swiss Re (2008)  
“Natural catastrophes and man-made disasters in 2007: high losses in Europe”, Sigma  
1/2008.
Appendix A

Appendix A provides the results of the maximum likelihood estimation of the returns (standard errors in parentheses) on the stocks of ACE, AIG, CHUBB and BERKSHIRE. The models use the specification suggested by Glosten, Jaganathan and Runkle (1993). All series exhibit a significant and positive leverage effect. Table 1 shows some descriptive statistics for the insurers considered in this proposal.

\[ r_t = a_0 + a_1 r_{t-1} + a_2 r_{t-2} + b_1 (\varepsilon_{t-1})^2 + b_2 (\varepsilon_{t-2})^2 + \varepsilon_t \]

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<th>(b_2)</th>
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<td></td>
<td>(9.80E-5)</td>
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<td>CHUBB</td>
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<td>(1.61E-4)</td>
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\[ h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \lambda^* (\varepsilon_{t-1})^2 \]

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Table 1 Descriptive Statistics and Overview over Market Capitalization and Dataset

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<td>2003</td>
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<tr>
<td>AIG</td>
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<td>CHUBB</td>
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Figure 1 Daily Returns of Selected Shares August 15, 2001 until November 14, 2001.

September 11th, 2001


Figure 1 provides the actual returns ($r_t$) on the Shares of AIG, CHUBB; BERKSHIRE and ACE. It also displays the 95 % confidence interval of the one step ahead forecast ($E[r_{t+1}] \pm 2(h_{t+1})^{0.5}$) of the expected return ($E[r_{t+1}]$). The graphs show that the attacks of September 11, 2001 first led to a large negative abnormal returns and that returns did remain volatile for a number of weeks.
Figure 2 Estimates of the conditional variance following the attacks of September 11, 2001

**September 11th, 2001**


Figure 2 displays the estimated volatility ($h_t$) for a number of insurers following September 11, 2001. The graph shows that volatility did neither spike on the first or second day of trading. Rather, volatility increased for a number of days following the reopening of the New York Stock Exchange. The graphs underscore that insurance stocks remained highly volatile for a long time after September 11, 2001. Volatility of Chubb and AIG did not even show any strong signs of decline until after November 14, 2001.