How Bad is Bad News; How Good is Good News?

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EXECUTIVE SUMMARY

The stock market is driven by news. Good news lifts the market. Bad news dampens growth. Good news does not lift the market as much as bad news depresses it. Also, bad news during a bear market has a bigger negative impact than bad news during a bull market. To illustrate these two asymmetries in stock market, GARCH volatility models are estimated.

Because volatility is unobserved, models for volatility are particularly difficult to validate. Our models are re-cast in terms of how they react to news. By applying news scenarios, the adequacy of the models can be assessed.
How Bad is Bad News; How Good is Good News?

1. Introduction

The stock market is driven by news. Good news, on a good day, lifts the market. Bad news, on a good day, dampens growth. The effect is not symmetric. Good news does not lift the market as much as bad news depresses it. Also, bad news during a bear market has a bigger negative impact than bad news during a bull market. It is important for risk management purposes to ensure that a model of volatility can produce sensible estimates no matter how the market is feeling. To illustrate this, two volatility models are estimated to reflect the intuition that good news and bad news affect the market differently and that the news in a bull market is different from that in a bear market. This paper quantifies these two asymmetries in stock market: (1) the asymmetric impact of good and bad news on the stock market; (2) the asymmetric response to news in a bear and bull market.

Models for volatility are particularly difficult to validate. Volatility is unobserved. Scenarios can be used to aid in managing the model risk of volatility models. Some volatility models can be re-cast in terms of how they react to news. By applying news scenarios, the adequacy of volatility models can be assessed and we can choose between competing models.

Volatility is a crucial input into several risk management activities such as: asset management, portfolio selection, hedging, and pricing. According to finance theory, the valuation of assets, or the expected returns, is related to their volatility, or risk. For derivatives markets, volatility is an even more explicit input into the pricing models used. Stochastic stock return volatility has been suggested as a source of pricing biases in the Black-Scholes option pricing formula. Volatility modeling is also important in trading strategies.

Implied volatilities from traditional models suggest that simple options pricing models are not adequate. The Black-Scholes model gives rise to implied volatility smiles in options markets. Similarly, for any given strike price, there is a term structure of implied volatility. These patterns in Black-Scholes implied volatility, as a function of strike price should not arise if volatility were constant.

In addition to time-varying volatility, traders with experience notice a curious anthropomorphic characteristic to financial markets that bad news during a bear market has a bigger negative impact than bad news during a bull market. Traders seem to know this and they adjust to the market’s moods. Volatility is higher when the market is on the way down and lower following upward market movements. This is well documented in the literature as the asymmetric impact of good and bad news. Anecdotally, we also observe that during a bear market, news, good, or bad is more eagerly anticipated than in a bull market. Bear markets salivate at the expectation of news, digest it voraciously, and react more violently than bull markets.

This paper suggests a volatility model that accounts for two types of asymmetric market response to news. While good and bad news are allowed to have different impact on the volatility, we incorporate bull and bear market effects to test if a bull market reacts to news differently than a
bear market. There is also a lesson regarding model risk and the key role scenarios can play in evaluating volatility models for risk management purposes.

2. Validating Models of Volatility and Managing Model Risk Using Scenarios

Many financial institutions have, in the last few years, adopted models of volatility that better reflect market realities. Proprietary pricing models abound to reflect these realities as perceived by trading desks. Two models are estimated here to reflect:

1. Asymmetry - bad news has a greater impact than good news; and
2. Market dependency - bear markets react more violently to new than bull markets.

As important as these example models is how to validate competing models when volatility itself is unobserved. Risk management teams, responsible for vetting any new pricing models, want a model for pricing that will generate reasonable volatility estimates in bull, bear, sideways, and extreme markets.

As a result, to demonstrate how scenarios can be used in model selection this paper estimates two asymmetric volatility models, one known as and exponential generalized autoregressive conditional heteroskedastic, or EGARCH, model, and one a threshold autoregressive conditional heteroskedastic, or TARCH, model. Built into these models is a framework that switches depending on whether there is a bull or a bear market.

Validating these models is a tall order. How would the risk managers know which model was sensible? Scenarios provide the solution. Volatility models are a good example of how scenarios can be used for model selection. These models are usually complicated mathematical abstractions that are often difficult to interpret. Often parameters restrictions are required to get sensible estimates, although even theoretical restrictions do not always guarantee model performance under all possible market conditions.

Scenarios therefore have a key role to play in evaluating models. Some volatility models can be recast in terms of how they react to news. By exposing proposed models to various plausible and extreme scenarios for news, a risk manager can manage model risk by ensuring that a volatility model performs in calm and turbulent markets.

3. News in Financial Markets

News in the financial markets has a more specific definition than elsewhere. Normally, news is either a report of recent events, or previously unknown information. In financial markets, news falls more into the latter definition. But because financial markets have a tendency to anticipate announcements, financial market news also has the element of being a surprise or a deviation from what was expected. If the Fed cuts interest rates by 25 basis points and this is what markets were expecting then there is no news as the cut has already been assessed, digested, and built into
financial prices. Should the market expect 25 basis points and the Fed announce a 50 basis points cut the market reacts quickly to this news as any arbitrage opportunities are eliminated.

Two types of news need to be defined: good and bad news. Good news usually is defined as upward market movements and bad news is defined as downward market movements. We usually say good news is observed if last period’s stock return is positive and bad news if negative. This implicitly assumes zero-mean market return. This may true over a matter of days but does not hold if a longer period is considered, for example during either a bull or bear market. As can be shown easily bear and bull markets have significant non-zero means. So we can define good news and bad news with respect to either bull or bear markets.

We use an accepted definition of a bull (bear) market in which any market in which prices exhibit an increasing (declining) trend for a prolonged period, usually rising (falling) by 20% or more. One knows, using this definition, whether one is in a bull or bear market as soon as one collects data on the market. This is because the definition uses the last peak or trough as a fixed value from which the growth or decline to today’s level is calculated. To define news we take the daily return and subtracting the mean return for bull markets or the mean return for bear markets depending on which was appropriate.

We use a long history of 22,619 observations for the Dow Jones Industrial Average (DJIA) from January 5, 1915 to October 24, 2001 to cover as many bull and bear regimes as possible. We find the average daily return in bull markets was 0.09% and in bear markets it was -0.17%. These average returns were found to be statistically different from each other. The average volatility of bull markets is 0.99% (16% annually) whereas bear volatility is 37% (22% annually).

With respect to bull and bear markets, news, $u_t$, then can be defined, with $Bull = 1$ if it is a bull market (and $Bull = 0$ if t is a bear market) and $Bear = 1$ otherwise ($Bear = 0$ in a bull market), as:

$$u_t = (\Delta \ln(DJIA_t) \times 100 - 0.09 \times Bull + 0.17 \times Bear)$$

where $\Delta \ln(DJIA_t) \times 100$ is the return of DJIA at time $t$. Positive values of $u_t$ means good news and negative value means bad news. The distribution of news then has a zero mean with a maximum value of 14.2 and a minimum of -25.7. The historical minimum occurs on the day of the October 1987 stock market crash. The other ten negative news days occurred during the 1929-1933 period of stock market crash and depression period, and one more day from the October 1987 crash. The re-opening of the market after the September 11, 2001 terrorist attack on the U.S. ranked number 11 in terms of extreme bad news days.

4. Asymmetric Market Responses to News

News drives the market. Good news lifts the market. Bad news dampens growth. The effect, however, is not symmetric: good news does not lift the market as much as bad news depresses it; good (bad) news does not lift (depress) a bull market as much as a bear market.
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(1) Asymmetric impact of good and bad news

Positive and negative stock return innovations have different impact on the volatility, as found in the literature by many researchers, for example Campbell and Hentschel (1992) and Engle and Ng (1993). Volatility following bad news is found to be higher than following good news. This is the well documented predictive asymmetry effect in stock market, which is sometimes called the leverage effect.

(2) Asymmetric effect of bear and bull market

Besides that good and bad news influences volatility differently, good news in a bull market may not lift up the market as much as in a bear market or vice versa. Intuitively, given a continuous downward market movement, bad news may drag down the market more than if there has been upward market movement. In other words, in a bear market, the market is waiting for bad news and bad news shakes market confidence more than if it has been a bull market. Although some volatility models, mainly in the regime switching context, have allowed for a bull and bear market effect, for example the switching regime GARCH models by Hamilton and Susmel (1994) and Cai (1994), the literature so far has not considered the asymmetric impact of good and bad news in bull and bear markets, which is found to be significant in this study.

- GARCH(1,1)

Volatility tends to be clustered together, that is there are periods of volatility storms and calms, in which, large returns tend to be followed by large returns, and small by small as shown in Figure 1.
Figure 1: Historical Unconditional Variance, or Squared Returns, for the DJIA with the October 1987 Crash Indicated
The GARCH(1,1) model has been shown to be able to capture those features, see Bollerslev et al. (1992),

\[ r_t = \mu + u_t \]  \hspace{1cm} (2)

\[ u_t = z_t \sqrt{h_t} \]  \hspace{1cm} (3)

where \( \mu \) is the conditional mean of the stock returns\(^1\) and \( z_t \) is independently and identically distributed as a normal distribution with mean zero and standard deviation of one, or \( i.i.d. N(0,1) \). The current conditional variance is assumed to be a weighted average of lagged squared innovations in returns and lagged conditional variances:

\[ h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1} \]  \hspace{1cm} (4)

where \( \omega > 0 \), \( \alpha, \beta \geq 0 \), and \( \alpha + \beta < 1 \). Since only squared return shocks are allowed, negative and positive return shocks of the same size are treated the same.

- **TARCH and EGARCH**

We can see that the GARCH(1,1) model cannot capture the important asymmetric impact of news on volatility. This asymmetry is now a well-known feature of financial markets: bad news causes higher volatility than good news of the same magnitude. To allow good and bad news have a different impact on volatility, a few asymmetric GARCH models have been developed in the literature. See Engle and Ng (1993) for a number of asymmetric GARCH models. Here we consider the two most popular asymmetric GARCH models: the Threshold GARCH (TARCH) model by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993)\(^2\) and the exponential GARCH (EGARCH) model by Nelson (1991). In these asymmetric GARCH models, the news component is handled differently depending on whether the news is good, that is a positive surprise, or bad, a negative surprise.

In a TARCH(1,1) model, the conditional volatility follows:

\[ h_t = \omega + \alpha u_{t-1}^2 + \gamma u_{t-1}D_t + \beta h_{t-1} \]  \hspace{1cm} (5)

where \( \omega > 0 \), \( \alpha, \beta \geq 0 \) and \( \alpha + \beta < 1 \) and \( D_t = 1 \) if \( u_t < 0 \) and \( D_t = 0 \) otherwise. If \( \gamma > 0 \), then a leverage effect exists, that is negative news has a bigger impact on volatility than positive news. If \( \gamma \neq 0 \), the news impact is asymmetric. The leverage effect is often described as a falling equity price which leads to an increase in a firm’s debt to equity ratio which increases the volatility of returns to equity holders. The leverage effect is also sometimes explained as the risk premium effect whereby news of increasing volatility reduces the demand for a stock because investors are risk

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\(^1\) We simplify the conditional mean equation and assume \( \mu \) is 0 in the models without bull and bear market effect.

\(^2\) The TARCH model is called the GJR model in Engle and Ng (1993).
averse and the decline in the equity’s price is followed by increased volatility as predicted by the news.

The EGARCH model eliminates the non-negativity constraints of the GARCH models by formulating the conditional variance equation in logarithmic terms:

$$\log h_t = \omega + \gamma \frac{u_{t-1}}{h_{t-1}} + \alpha \left( \frac{|u_{t-1}|}{h_{t-1}} - \frac{1}{\sqrt{\pi}} \right) + \beta \log h_{t-1}$$

(6)

where $\gamma$ and $\alpha$ are unknown parameters. Since $\gamma$ is typically found to be negative, negative return shocks generate greater volatility than positive return shocks.

Engle and Ng (1993) have suggested, for these conditional volatility models, a standard measure of how news influences stock volatility, a news impact curve. Given information up to current time, the news impact curve examines the relationship between the news and future volatility. The news impact curve plots news scenarios, that is a range of bad and good news, on the horizontal axis, against the resulting volatility.

In a standard GARCH model this curve is a quadratic function centered at zero, which has the same slope at both sides. For the TARCH model, the curve is centered at $u_{t-1} = 0$ but has different slopes for positive and negative news. The news impact curve of the EGARCH model is centered at zero, but also different slopes for the effect of good and bad news. Putting the TARCH model and EGARCH model alongside the symmetric GARCH model reveals the differences between these models in terms of the news impact curves:
Figure 2: News Impact Curves For Daily Volatility of the Dow Jones Industrial Average (DJIA) 1915-2001.

The equation for the GARCH(1,1) news impact curve is:

$$ h_t = \omega + \beta u_{t-1}^2 $$

where $A = \omega + \beta \sigma^2$. The equations for the EGARCH(1,1) news impact curve are:

$$ h_t = A^E \exp \left( \frac{\gamma + \alpha}{\sigma} u_{t-1} \right) \quad \text{for} \quad u_{t-1} > 0 \quad \text{and} \quad h_t = A^E \exp \left( \frac{\gamma - \alpha}{\sigma} u_{t-1} \right) \quad \text{when} \quad u_{t-1} < 0 $$

when $u_{t-1} < 0$, where $A^E = \sigma^2 \exp \left( \omega - \alpha \sqrt{2/\pi} \right)$. The equations for the TARCH(1,1) are:

$$ h_t = A^T + \alpha u_{t-1}^2 $$

for $u_{t-1} > 0$ and $h_t = A^T + (\alpha + \gamma) u_{t-1}^2$ when $u_{t-1} < 0$ where $A^T = \omega + \beta \sigma^2$. 
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Figure 2 shows the general characteristics of news impact curves, that GARCH model is symmetric around zero, whereas TARCH and EGARCH are asymmetric, with different slopes.

An alternative to the differing slopes of the EGARCH and TARCH models is the asymmetric GARCH (AGARCH) model by Engle (1990)\(^3\).

In an AGARCH\((1,1)\) model, the conditional volatility follows:

\[
 h_t = \omega + \alpha (u_{t-1} - \delta)^2 + \beta h_{t-1}
\]

where \(\omega > 0\), \(\alpha > 0\) and \(\alpha + \beta < 1\). The asymmetric impact of good and bad news implies that in this model \(\delta > 0\). The news impact curve for an AGARCH model is \( h_t = A^2 + \alpha (u_{t-1} + \gamma)^2 \), where \(A^2 = \omega + \beta \sigma^2\) and is centered at \(u_{t-1} = \delta\).

As shown in Engle and Ng (1993), the existing asymmetric GARCH models capture the asymmetry either by allowing the slope of the two sides of the news impact curve to differ (as EGARCH) or by allowing the centre of the curve to locate at a point right to zero (as AGARCH). Investigation into the AGARCH model suggested that the EGARCH and TARCH models gave more plausible volatility estimates. The following volatility model we propose will be able to allow two types of asymmetry in one model by allowing for differing slopes of the news impact curve depending on whether the news is good or bad, and whether the market is a bull or bear.

- **The Doubly Asymmetric GARCH model**

It is now well known that bad news causes higher volatility than good news of the same magnitude. Besides, bad news in a bear market seems to generate more volatility than in a bull market. Thus it is interesting to see if bad (or good) news has different impact on volatility in bear and bull markets. To test this hypothesis we estimated an EGARCH model using the Dow Jones Industrial Average. The estimated model was an EGARCH\((1,1)\) model but with parameters that were different in bull and bear markets. For later reference, we call this model the doubly asymmetric GARCH (DAGARCH) model since it captures both the asymmetric impact of good and bad news and the asymmetric effect of bull and bear market. In our DAGARCH model, the conditional mean equation is now:

\[
 r_t = \mu_{\text{bear}} + u_t \text{ if } t = \text{ bear market} \tag{8}
\]

\[
 r_t = \mu_{\text{bull}} + u_t \text{ if } t = \text{ bull market} \tag{9}
\]

For the EGARCH version of DAGARCH, the model was calibrated to the historical data using a maximum likelihood method using random starting values for the parameters. For all parameters expected to be positive a random starting value was chosen from the \((0,1)\) interval. For negative parameters they we assigned a random value from the \((0,-1)\) interval.

\(^3\) The AGARCH model is called Quadratic GARCH in Campbell and Hentschel (1992).
All of the parameters of the model were highly significant; the parameter restrictions required by the GARCH family of models to get well-behaved, strictly positive, volatilities were satisfied; the bull and bear parameters were different; but even more satisfying, the model accorded with our intuition:
### Table 1: EGARCH Model With Bull And Bear Switching (DAGARCH) Estimation Results

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{Bull}$</td>
<td>0.0827</td>
<td>0.0091</td>
<td>9.11</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\omega_{Bull}$</td>
<td>0.0038</td>
<td>0.0008</td>
<td>4.57</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\alpha_{Bull}$</td>
<td>0.1368</td>
<td>0.0052</td>
<td>26.34</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\gamma_{Bull}$</td>
<td>-0.028</td>
<td>0.0040</td>
<td>-6.97</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\beta_{Bull}$</td>
<td>-0.1370</td>
<td>0.0160</td>
<td>-8.56</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\mu_{Bear}$</td>
<td>0.9905</td>
<td>0.0008</td>
<td>1200.66</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\omega_{Bear}$</td>
<td>0.0192</td>
<td>0.0019</td>
<td>10.27</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\alpha_{Bear}$</td>
<td>0.1181</td>
<td>0.0076</td>
<td>15.64</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\gamma_{Bear}$</td>
<td>-0.1196</td>
<td>0.0049</td>
<td>-24.26</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\beta_{Bear}$</td>
<td>0.9816</td>
<td>0.0014</td>
<td>726.40</td>
<td>0.0000</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-29,324.1</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
We also estimated a TARCH version of the DAGARCH model using the Dow Jones Industrial Average with parameters that are different in bear and bull markets since EGARCH produces extreme conditional variance estimates sometimes. See Engle and Ng (1993). The conditional mean equation is as above (equations 8 and 9), and the conditional variance equation is:

\[
\begin{align*}
    h_t &= \omega_{bear} + \alpha_{bear} u_{t-1}^2 + \gamma_{bear} u_{t-1}^2 i D_t + \beta_{bear} h_{t-1} \quad \text{if } t = \text{bear market} \\
    h_t &= \omega_{bull} + \alpha_{bull} u_{t-1}^2 + \gamma_{bull} u_{t-1}^2 i D_t + \beta_{bull} h_{t-1} \quad \text{if } t = \text{bull market}
\end{align*}
\]

As with the EGARCH model, all of the parameters of the model were highly significant; the parameter restrictions required by the GARCH family of models to get well-behaved, strictly positive, volatilities were satisfied; the bull and bear parameters were different; and, the model accords with intuition:
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<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{Bull}$</td>
<td>0.0963</td>
<td>0.0092</td>
<td>10.50</td>
<td>0.00</td>
</tr>
<tr>
<td>$\omega_{Bull}$</td>
<td>0.0097</td>
<td>0.0009</td>
<td>10.75</td>
<td>0.00</td>
</tr>
<tr>
<td>$\alpha_{Bull}$</td>
<td>0.0495</td>
<td>0.0043</td>
<td>11.54</td>
<td>0.00</td>
</tr>
<tr>
<td>$\gamma_{Bull}$</td>
<td>0.0383</td>
<td>0.0054</td>
<td>7.03</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{Bull}$</td>
<td>0.9218</td>
<td>0.0035</td>
<td>261.26</td>
<td>0.00</td>
</tr>
<tr>
<td>$\mu_{Bear}$</td>
<td>-0.1671</td>
<td>0.0203</td>
<td>-8.23</td>
<td>0.00</td>
</tr>
<tr>
<td>$\omega_{Bear}$</td>
<td>0.0186</td>
<td>0.00239</td>
<td>7.79</td>
<td>0.00</td>
</tr>
<tr>
<td>$\alpha_{Bear}$</td>
<td>0.0523</td>
<td>0.0064</td>
<td>8.13</td>
<td>0.00</td>
</tr>
<tr>
<td>$\gamma_{Bear}$</td>
<td>0.0912</td>
<td>0.0097</td>
<td>9.36</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{Bear}$</td>
<td>0.9003</td>
<td>0.0044</td>
<td>204.21</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Log Likelihood: -29,227.9

Table 2: TARCH Model With Bull And Bear Switching (DAGARCH) Estimation Results
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The asymmetric impact of good and bad news is found to be significant in both bull and bear markets, with $\delta_{Bull}$ and $\delta_{Bear}$ both being positive. Bad news is found to dampen the market more if it is in a bear market than if in a bull market. This is supported by two observations: $\gamma_{Bear} > \gamma_{Bull}$ and $\alpha_{Bear} > \alpha_{Bull}$ which means the slope of the curve for the bear market is greater than the slope of the bull market curve. This means that the news impact curve left-side (or bad news side) slope is higher for the bear market and the right-side (good-news side) slope is also higher for the bear market. This confirms that both bad and good news generates higher volatility in bear market than in bull market, besides that bad news causes more volatility than good news of the same magnitude. The results also shows that long-run bear market volatility is higher than bull market volatility, $\omega_{Bear} > \omega_{Bull}$. This suggests the importance of taking into account of bull and bear market effect when modeling the time-varying nature of volatility.

5. Stress Testing and Model Risk

To verify a model of volatility, which is unobservable, is a difficult process. To understand which version of the DAGARCH model, the EGARCH or TARCH version, to trust we put them through a bench test that exposed them to various stress scenarios.

Model risk includes a host of risks associated with: the choice of a model; the inputs into the model; uncertainty about the chosen model; the testing and maintenance of the model; and the management, oversight, and audit issues associated with these activities. For liquid securities, validation is easy. A risk management group simply checks that the prices coming out of the model corresponded with externally quoted market prices. For illiquid derivatives things are more complex. The EGARCH model that switched depending on whether there was a bull or a bear market was a model that was meant to capture an intuition. The output was however, not easily checked. Implied volatility is a matter of opinion.

The question is not as simple as “is the model correct?” The EGARCH model is an abstraction from the real world. The question was more “is this a useful abstraction?” The proposed model was bench tested by applying scenarios for extreme good and bad news. Applying news scenarios to the model revealed some shortcomings that were not evident from the estimation results shown in Table 1. For example, a scenario, the size of the post September 11, 2001 shock, gave a conditional volatility number that was many times greater than the unconditional variance, or squared return number for this day. Figure 1 shows the historical squared return series and indicates the largest squared return, that for the October 1987 crash. The EGARCH estimate for the September 11, 2001 conditional volatility is 100,000 times greater than the 1987 crash value of 657.
Worse, for positive shocks of the same size, which had been observed in the historical data, the daily conditional volatility exploded even more ridiculously. By applying news scenarios from history it became clear that under “normal” scenarios for news the model performed well, under extremes the exponential function embedded in the EGARCH functional form kicked in and gave ridiculous results. Table 3 summarizes the results:
### Table 3: Historical News Scenarios and Resulting EGARCH Conditional Volatility Compared to Squared Returns

<table>
<thead>
<tr>
<th>Historical Scenario Date</th>
<th>% Best News</th>
<th>EGARCH-Bear</th>
<th>EGARCH-Bull</th>
<th>Squared Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>9/17/01</td>
<td>0.1%</td>
<td>0.0007</td>
<td>6.80 x10^7</td>
<td>54.70</td>
</tr>
<tr>
<td>6/22/33</td>
<td>1.0%</td>
<td>0.0008</td>
<td>74.22</td>
<td>9.96</td>
</tr>
<tr>
<td>8/29/66</td>
<td>5.0%</td>
<td>0.0009</td>
<td>0.23</td>
<td>3.06</td>
</tr>
<tr>
<td>12/6/94</td>
<td>50.0%</td>
<td>0.0011</td>
<td>0.0010</td>
<td>0.01</td>
</tr>
<tr>
<td>12/19/46</td>
<td>95.0%</td>
<td>1.25 x10^2</td>
<td>3.41</td>
<td>1.94</td>
</tr>
<tr>
<td>5/28/70</td>
<td>99.0%</td>
<td>7.33 x10^6</td>
<td>6.89 x10^3</td>
<td>9.67</td>
</tr>
<tr>
<td>10/7/29</td>
<td>99.9%</td>
<td>4.21 x10^17</td>
<td>1.97 x10^11</td>
<td>37.55</td>
</tr>
</tbody>
</table>
How Bad is Bad News; How Good is Good News?

The squared returns are shown for comparison. It should be noted that although squared returns are used as a benchmark of reasonableness, they are a noisy estimate of unobserved volatility. An EGARCH model estimated with bull and bear switching did not perform as well. While it had, like the DAGARCH model, highly significant coefficients, it gave unrealistically high estimates of volatility.

The EGARCH model results highlight the problem with models that while they may give reasonable results for traders in normal markets may not be appropriate for risk management purposes. Traders want a model to reflect market realities. The risk management team, responsible for vetting any new pricing models, should be more discerning, they should demand a model that can generate reasonable volatility estimates in bull, bear, sideways, and extreme markets.

Running news scenarios through the model from -10 to 10, which corresponded to about a 99.6% coverage of history, gives a reasonable news impact curve for the TARCH version of the DAGARCH model:
How Bad is Bad News; How Good is Good News?

Figure 3: GARCH, TARCH and DAGARCH (TARCH – Bull and TARCH – Bear) News Impact Curves For Daily Volatility of the DJIA 1915-2001

The equations for the DAGARCH(1,1) news impact curves are:

\[ h_t = A_i^T + \alpha_i u_{t-1}^2 \]  for \( u_{t-1} > 0 \) and
\[ h_t = A_i^T + (\alpha_i + \gamma_i) u_{t-1}^2 \]  when \( u_{t-1} < 0 \) where \( A_i^T = \omega_i + \beta_i \sigma_i^2 \) and \( i = \text{Bull or Bear} \).
How Bad is Bad News; How Good is Good News?

Figure 3 highlights the differences between news impact curves of the symmetric GARCH, the asymmetric TARCH and the doubly asymmetric DAGARCH by showing extreme news events. Zooming in on the less extreme news events highlights how the models behave in more normal markets.
How Bad is Bad News; How Good is Good News?

**Figure 4:** Detail from Figure 3 - GARCH, TARCH and DAGARCH (TARCH – Bull and TARCH – Bear) News Impact Curves For Daily Volatility of the DJIA 1915-2001
Figure 4 shows that the DAGRACH model, that is the combination of the TARCH - Bull, with TARCH - Bear, yields a minimum volatility estimate close to the symmetric GARCH model and that this is lower than the TARCH estimate. The bull and bear minimum volatility estimates are virtually identical (although the bear market minimum is actually slightly less than the bull market minimum). Also, it is only when good news becomes really good news that the difference is noticeable, however, even slightly bad news gives different volatility estimates in bull and bear markets.

Figures 3 and 4 show the extra flexibility afforded by the DAGARCH model. It allows for differing good and bad news effects and for this news to have a different effect in good and bad markets.

The DAGARCH model has all of the desired characteristics: bigger volatility resulting from bad news, and bigger volatility still in bear markets. Also, the TARCH version of the model stands-up to the bench test and performs well under stress news scenarios. For example, the September 11, 2001 shock, where the size of the news variable was -7.23, the model predicted a conditional volatility of 6.5 or 104% annually. Because the market also switched from a bull to a bear market on this date, the volatility estimate was 59% higher than for the same shock in a bull market. The volatility was also 105% higher than that predicted by their GARCH model.

The news scenarios applied to the TARCH version of the DAGARCH model are shown below:
### How Bad is Bad News; How Good is Good News?

<table>
<thead>
<tr>
<th>Historical Scenario Date</th>
<th>% Best News</th>
<th>TARCH-Bear</th>
<th>TARCH-Bull</th>
<th>Squared Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>9/17/01</td>
<td>0.1%</td>
<td>6.47</td>
<td>4.06</td>
<td>54.70</td>
</tr>
<tr>
<td>6/22/33</td>
<td>1.0%</td>
<td>1.81</td>
<td>1.33</td>
<td>9.96</td>
</tr>
<tr>
<td>8/29/66</td>
<td>5.0%</td>
<td>0.91</td>
<td>0.80</td>
<td>3.06</td>
</tr>
<tr>
<td>12/6/94</td>
<td>50.0%</td>
<td>0.63</td>
<td>0.63</td>
<td>0.01</td>
</tr>
<tr>
<td>12/19/46</td>
<td>95.0%</td>
<td>0.71</td>
<td>0.71</td>
<td>1.94</td>
</tr>
<tr>
<td>5/28/70</td>
<td>99.0%</td>
<td>0.95</td>
<td>0.94</td>
<td>9.67</td>
</tr>
<tr>
<td>10/7/29</td>
<td>99.9%</td>
<td>2.03</td>
<td>1.96</td>
<td>37.55</td>
</tr>
</tbody>
</table>

**Table 4:** Historical News Scenarios and Resulting TARCH Conditional Volatility Compared to Squared Returns
6. Conclusion

A Doubly Asymmetric GARCH (DAGARCH) model shows that the market reacts differently to news, that is the news impact curve shifts, in bull and bear markets. Not only do good and bad news have different effects on volatility, but whether the market was on a tear or in the doldrums matters too.

Despite the fact that the results from the EGARCH version of the DAGARCH model were excellent, and it performed intuitively in normal market conditions, applying stress scenarios to it revealed that it could be explosive just when someone needed it most, when news rocked the market. To manage the model risk associated with models with unobservable volatilities risk managers must delve further. Experimentation with news scenarios and the TARCH version of the DAGARCH model shows that only it can stand up to stress news scenarios.

REFERENCES


