

Making Covariance-Based Portfolio Risk Models Sensitive to the Rate at which Markets Reflect New Information

Dan diBartolomeo
Northfield Information Services, Inc.

Sandy Warrick, CFA
Northeastern University

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Abstract

Multiple factor models of security covariance have been widely adopted by investment practitioners as a means to forecast the volatility of portfolios. In that such models arise from the tradition of Markowitz's Modern Portfolio Theory, they have generally been based on a single period assumption, where future risk levels are presumed to not vary over time. In reality, risk levels do vary substantially and modifications of the underlying assumptions of multiple factor covariance models must change to reflect this fact. Our paper reviews the way new information is absorbed by financial markets and contributes a model of how such information can be reflected more efficiently in estimates of future covariance, through the inclusion of implied volatility information. We conclude with an empirical example regarding market conditions before and after the events of September 11, 2001. Not only does this example illustrate the value of including implied volatility as a component to covariance forecasts, but also suggests that some market participants may have acted in anticipation of the tragedies.

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Introduction

Multiple factor models of security covariance have been widely adopted by investment practitioners as a means to forecast the volatility of portfolios. In that such models arise from the tradition of Markowitz's Modern Portfolio Theory (1952), they have generally been based on a single period assumption, where future risk levels are presumed to not vary over time. In reality, risk levels do vary substantially and modifications of the underlying assumptions of multiple factor covariance models must change to reflect this fact. Our paper reviews the way new information is absorbed by financial markets, and how such information can be reflected more efficiently in estimates of future covariance through the inclusion of implied volatility information.

To the extent that levels of risk within an investment market do vary over time, such changes are due to the arrival of new information. Such new information being absorbed by market participants can be categorized into two types, the first being "news" that is wholly unanticipated, and into "announcements" that are anticipated with respect to time but not with respect content. Conditional heteroskedasticity models (ARCH, GARCH, etc.), as pioneered by Engle and Bollerslev (1986) are often used to model changes in volatility levels. However, we argue that to properly capture the dynamics of announcement data in covariance models, methods incorporating data on implied volatility is necessary, and that use of implied volatility data is also the preferred approach to properly reflecting wholly unanticipated news in such models.

One practitioner model of equity security covariance incorporating implied volatility information has been commercially available for a few years. The model has been used by numerous hedge funds since 1999. We present the estimation process for this model as an example of how such incorporation is possible, and to highlight some of the related difficulties.

Finally, we will turn to an empirical example. We will illustrate how quickly the model was able to adapt to the changes in the apparent risk levels of various US stock market sectors connected with the tragic events of September 11, 2001. A surprising aspect of this example is the emergence of data suggesting that some market participants may have acted in anticipation of these tragedies.

We conclude that both a growing body of finance literature and the practitioner experience support the usage of implied volatility information in the estimation of future portfolio risk levels.

Review

The most widely known common factor model of security covariance is the single-index model. The Capital Asset Pricing Model developed by William Sharpe (1964) is a special case of the single index model. In the usual implementation of the single index model, the common factor is the excess return over the risk free rate on a portfolio consisting of the entire equity market. Typically, time series regression analysis is used to estimate the relationship between the returns on a particular stock and the market return factor. The resultant measure of systematic (pervasive) risk is called β (beta).

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The CAPM is a special case of the index model, where we make the additional assumption that higher long term returns may be expected from stocks with higher levels of β (more systematic risk). It should be noted that while there has been much controversy in recent years in the effectiveness of the CAPM (see Grinold, 1993) as a predictor of expected returns, little if any of the criticism of the CAPM has been directed to the use of β as a measure of risk for well diversified portfolios. Many studies such as Petingill, Sundaram and Mathur (1995) have confirmed the effectiveness of β as a means of risk prediction.

Models with multiple common factors are currently the most popular mechanisms for predicting equity risk. The use of multiple factor models arises from the belief that, while a single factor may describe a large portion of the common aspects of security returns, many other factors may influence some important subset of the universe of equities without having any influence on all securities. As an example, it might seem obvious that the variances and correlation of returns of two gold mining stocks would be influenced by the changes in the price of gold, as well as changes in broad economic conditions that are presumed to affect returns of equity securities in general.

Three types of multiple factor covariance models are currently popular. The first is an exogenous factor model, where the common factors are typically macroeconomic state variables such as interest rates, levels of production, inflation, and energy costs. In essence, each stock is presumed to have several β 's, each with respect to a particular aspect of the economy. If two securities (or portfolios) produce similar returns in response to shifts in the prescribed economic variables, they are presumed to be similar. While the changes in the economic variables may be readily observed, the sensitivity of individual stocks to those changes must be statistically inferred. The β values are usually estimated using time series regression analysis, as in the case of the single index model. As in all factor models, security return variations not explainable through the common factor structure are presumed to be security specific and pair-wise uncorrelated.

Proponents of specified macroeconomic factor models point out that such models typically exhibit stable behavior because they are tied to the real economy through genuinely pervasive factors, as discussed in Chen, Roll, Ross (1986). They also provide the opportunity for portfolio managers to gain a new level of insight into top-down economic effects on their portfolios and allow them to forecast likely performance under different scenario forecasts. The primary criticism of models with exogenously specified factors is that they cannot readily capture risks that are not part of the economic state. For example, such a model would not capture the product liability risks of tobacco companies.

The second (and most widely used) type of covariance model uses observable security characteristics as proxies for factors of commonality. Such proxy factors might include stock fundamentals, such as the price/earnings ratio, dividend yield, market capitalization, balance sheet leverage, and industry participation. Repeated cross-sectional regression analyses are usually used to estimate the returns to the factors in such models. A time series of the vector of the regression coefficients is then used to form a covariance matrix of the factor returns. Prominent related literature includes papers by Hamada (1972) and Rosenberg (1974).

The strength of "fundamental" common factor models is that they use security characteristics that are very familiar to portfolio managers. Such models usually also have higher in-sample explanatory power than exogenously defined models. Another advantage of such models is that,

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since factor exposures can be immediately observed, changes in a company's fundamental makeup, such as a merger, will be immediately incorporated into the model. Similarly, new issues can be analyzed almost immediately. The primary criticism of endogenous common factor models is that there are often so many overlapping effects that it is nearly impossible to correctly sort them all out, making such models less effective at predicting future conditions than they are at explaining the past. Nevertheless, the success of these models at predicting, controlling (optimizing) future portfolio risk has resulted in the popularity of these models with practitioners.

The final type of model in use today is the so-called blind factor model. In such models, the factors are not specified as being any measurable real world phenomena, but rather both the factors and the β 's to those factors are inferred from the security behaviors themselves. In essence, we find those common factors that the security returns suggest must be present, even if we cannot identify the nature of the factors. Such models are estimated from the security returns using techniques such as principal components regression (see Ball and Torous, 1998) or maximum likelihood factor analysis. The resultant sets of spanning factors are usually orthogonal. The primary benefit of such models is that, since the nature of the common factors is derived inferentially, the structure of the common factors can evolve over time to fit new conditions. Unfortunately critics argue this is also the primary detraction. Without any tie to the real world, such models may be unduly influenced by transitory noise in the data, resulting in unstable results.

All of the models described maintain the usual Markowitz assumption of a single future period. No provision is made for forecast levels of portfolio volatility to vary through time. Security returns are presumed to be independently and identically distributed random walks with no serial correlation, despite extensive empirical evidence to the contrary such as the research of Lo and MacKinlay (1988). Of course, not only do we observe persistent departures from the classical random walk, we also observe significant changes in volatility levels through time, as new information is incorporated into the beliefs of market participants.

For our purposes, we will separate the mechanism of new information arrival into two segments. The first is news, that we define as being new information that is wholly unanticipated by market participants. The second mechanism is announcements, information arrivals that are anticipated with respect to time but not within respect to content. Falling in this second category would be scheduled announcements from government commercial and economic agencies and publicized upcoming announcements such as periodic earnings releases by companies. The differing rate at which market participants are able to assimilate new information contained in news and announcements has been the subject of substantial research. Most closely related to our topic is the work of Ederington and Lee (1996), who studied the impact of information releases on changes in levels of market uncertainty. Similarly, Abraham and Taylor (1993) studied the pricing of currency options (a direct corollary to expected volatility) in the context of the two mechanisms of information arrival.

Early literature on the issue of partially anticipated events in stock markets comes from Malatesta and Thompson (1985). Kwag, Shrieves and Wansley (2000) recently studied upcoming dividend announcements in the context of partially anticipated information.

Some researchers have studied the application of conditional heteroskedasticity models (i.e. ARCH, GARCH) to changes in risk levels of financial markets. Among these are Chong,

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Ahmad and Abullah (1999) who apply GARCH procedures to forecasting stock market volatility and Choudhry (1997) who used GARCH procedures to examine data for markets during the periods surrounding World War II.

Numerous studies have considered the usage of option implied volatility as a mechanism for predicting future volatility levels. Bartunek, Chowdhury and Mac (1995) compare GARCH and implied volatility methods. Among the latest works in this area are Ederington and Guan (1998) and Shu, Vasconellas and Kish (2001). Both of these papers attempt to correct for biases in previous studies of the effectiveness of implied volatility as a predictor of future volatility for stock market indices. Both conclude that implied volatility is a very efficient predictor and that historical volatility adds little predictive power to models that already utilize option implied volatility. Ederington and Guan (2000) find that models that average multiple strikes to compute implied volatility can be improved by correcting for the permanent biases that result in the well-known “volatility smile”.

A recent working paper by Malz (2000) deals with how changes in implied volatility may be signaling changes in anticipated levels of skewness or kurtosis in return distributions, as well as expected changes in variances. This paper provides very vivid examples of how small changes in higher moments can be reflected as large changes in implied volatility. Related work includes that of Corrado and Su (1997) who examine the forward return distribution implied by individual stock option prices. Jiltsov (1999) studies the implied state densities arising from option prices. He finds that the implied distributions are relatively stable in shape, suggesting that new information arrives gradually into the market and is absorbed in a smooth fashion.

Discussion

Despite the literature on whether GARCH and implied volatility models are efficient estimators of the future volatility of markets, we found no existing research on how to incorporate such work into models used to estimate portfolio risk over a large range of securities. GARCH processes have been used in to some extent in multiple factor models of security covariance. In particular, the BARRA company has used GARCH processes to improve their estimates of factor variances and asset specific variances in their E2 and E3 models that are widely used by practitioners. The general aspects of the implementation are discussed in Sheik (1994) and Kahn (1994).

In diBartolomeo (2000a) a controversy regarding using a GARCH approach is discussed. Most importantly, a GARCH process is clearly inconsistent with the assumptions of a pure random walk that underlie traditional portfolio theory. It is essentially universal in the investment industry to quote security and portfolio volatility information in annual units (e.g. 30% per year). However, in order to have enough data to practically estimate models, periodicities of sample observations of daily to monthly are always utilized. Once we discard the random walk assumption, we can no longer assume that variances are a simple function of time, and the standard procedure of rescaling daily, weekly or monthly standard deviations into annual units by multiply by the square root of time is no longer valid. While we could try to annualize the higher frequency risk estimates by the explicit time series process embodied in the GARCH model, but we cannot simultaneously assume a GARCH process for estimating the risk forecast and assume a random walk process for rescaling that estimate to annual units.

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A critical problem with GARCH approaches are market microstructure effects having to do with differences in the rates at which markets adjust to unanticipated news as compared to partially anticipated announcements. GARCH processes are designed to model the impact of a shock on a system that is already close to an equilibrium condition. While the impact of unanticipated news may sometimes fit this description, it clearly is not consistent with trading before surrounding announcements.

Market actions around announcement dates often bear specific patterns of liquidity that confound the GARCH process. For example, take the case of an individual stock with an upcoming earnings announcement. Anecdotal evidence from option market makers such as Hull trading indicate that intra-day volatility for individual stocks on earnings announcement days can be as much as nine times as great as non-announcement days. The days before the announcement are apt to be quiet as traders await the news, reducing both trading volume and volatility. As the quiet period continues, a GARCH process will adjust the conditional volatility estimate downward relative to the long-term mean. Unfortunately, volatility will then spike upward dramatically as the actual announcement is made and traders respond. In that the announcement was anticipated, all market participants had time to think through their intended actions, to be promptly implemented once the content of the announcement was revealed. Accordingly, the market adjustment to announcement information is very rapid. Since our process has now badly underestimated volatility on the announcement date, the GARCH process will upwardly adjust the volatility estimate for future days. Again our estimate will prove wrong, as volatility reduces back to normal once the post-announcement flurry of activity is now over. For a good discussion of the issue of liquidity driven effects around events, see Taleb (1997) and Shanken (1987).

An implied volatility approach offers the hope of getting correct adjustments to volatility forecasts with respect to announcements. Option traders anticipate announcements along side other market participants involved in the underlying security. As such, option implied volatilities ought to correctly account for the dynamics of volume and short-term volatility variations around announcement dates, as has generally been reported in the cited literature. Option traders also respond very rapidly to true news in an intelligent rather than mechanical fashion, particularly when that news has wide-ranging implications, again offering an apparent advantage over GARCH approaches.

The Model

Our chosen approach is to condition our estimates of risk in our multiple-factor security covariance model with information derived from changes in the relationship between implied volatility and historic sample volatility. The implied volatility information is used to condition both the factor variances and asset specific variances within the multi-factor model.

Linear factor risk models express the expected covariance matrix of security returns in the form of a factor covariance matrix to which each security is exposed and a security-specific portion. Such models are estimated over historical sample periods. The usual mathematical formulation is:

$$V_p = \sum_{i=1}^n \sum_{j=1}^n e_{p,i} e_{p,j} \mathbf{s}_{f(i)} \mathbf{s}_{f(j)} \mathbf{r}_{i,j} + \sum_{k=1}^m w_k^2 \mathbf{s}_{s(k)}^2 \quad [1]$$

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$$e_{pi} = \sum_{k=1}^m w_k b_{k,i} \quad [2]$$

where:

V_p = variance of portfolio return

n = number of factors in the risk model

m = number of securities in the portfolio

$e_{p,i}$ = exposure of the portfolio to factor i

$\sigma_{f(i)}$ = standard deviation returns attributed to factor i

$\rho_{i,j}$ = correlation between returns to factor i and factor j

w_k = weight of security k in the portfolio

$\sigma_{s(k)}$ = standard deviation of security specific returns for security k

$\beta_{k,i}$ = beta of security k to factor i

For a portfolio of just one security k , this expression simplifies to

$$V_k = \sum_{i=1}^n \sum_{j=1}^n b_{k,i} b_{k,j} \sigma_{f(i)} \sigma_{f(j)} \rho_{i,j} + \sigma_{s(k)}^2 \quad [3]$$

If we have implied volatility information on a given security k , we can separately estimate the value of V_k as the square of the implied volatility. However, implied volatility is often considered an upward biased estimator of expected volatility for markets that do not have extremely high levels of liquidity. This arises because option traders do not use exact delta hedging because:

1. The Black-Scholes (1973) assumption of costless hedging does not hold even weakly for many securities.
2. Return distributions often vary from geometric Brownian motion.

To avoid the bias problem, we choose to condition our model by assuming that changes in implied volatility levels are useful estimators of the changes in expected volatility levels, rather than using the implied volatilities themselves. This also reduces the importance of any other persistent biases in our process to estimate implied volatility values. Accordingly, we introduce V_k^* as our conditional estimate of the future volatility of security k , as normally V_k times an adjustment factor M_k .

$$V_k^* = V_k \times M_k \quad [4]$$

Adding time subscripts to allow us to evaluate our situation at a particular moment, we obtain

$$M_{k,t} = \left(\frac{I_{k,t} / V_{k,t}}{\frac{\sum_{s=t-z}^{t-1} I_{k,s} / V_{k,s}}{z-1}} \right) \quad [5]$$

where:

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$I_{k,t}$ = implied volatility of security k at time t

$V_{k,t}$ = the volatility of security k obtained from the multi-factor risk model before adjustment at time t

z = the number of past periods over which we choose to observe the relation between implied and multiple factor estimates of volatility

Equation 5 should be intuitive. The numerator is the ratio of the current implied volatility to the current value of expected volatility obtained from our multiple factor risk model. The denominator is merely z period moving average of that ratio. Our logic is that changes in the ratio of the two volatility estimates are likely to occur, as new information is reflected in financial markets. In that the option implied values adjust more rapidly than the factor risk model that is estimated over a historic sample period, changes in the ratio will be an efficient estimator changes in future risk levels. Implied volatilities are based on closing bid prices of the average of multiple strikes with the expiration date closest to 45 days. Closing bid prices at or below intrinsic values are removed from the sample (treated as if the stock did not have traded options).

One can easily envision a hypothetical scenario wherein a major event occurs to a single company. Imagine Bill Gates coming from out of his home and being run over by an autobus. As soon as the information comes over the news wires, option prices on Microsoft stock are apt quickly reflect the uncertainty arising from this event. In this contrived example, we would expect the increase in uncertainty to be concentrated in Microsoft alone, although one make an argument for some sort of contagion effect that would impact Microsoft suppliers and customers.

In the real world, we sometimes live through sudden, yet pervasive events such as the tragedies of September 11th, 2001. While we could observe the impact on overall market uncertainty though implied information on index options, we can readily incorporate concurrent changes in the implied volatility of numerous individual securities into our factor covariance matrix. Our approach is to construct our factor model using a variation of principal components analysis, such that our factor covariance matrix is itself diagonal. This simplifies equation 3 to:

$$V_k = \sum_{i=1}^n \sum_{j=1}^n b_{k,i} b_{k,j} s_{f(i)} s_{f(j)} r_{i,j} + s_{s(k)}^2 \quad [6]$$

$$V_k^* = M_k \times \left(\sum_{i=1}^n b_{k,i}^2 s_{f(i)}^2 + s_{s(k)}^2 \right) \quad [7]$$

Rearranging we obtain:

$$V_k^* / M_k - s_{s(k)}^2 = \sum_{i=1}^n b_{k,i}^2 s_{f(i)}^2 \quad [8]$$

If we have expressions like equation 8 for many securities, we can set them up as a set of simultaneous equations and solve for the maximum likelihood values of $\sigma_{f(i)}$ (the factor variances), subject to the condition all values of $\sigma_{f(i)}$ are non-negative. Once we have obtained conditional estimates for the factor variances we can substitute these values back into equation 8 for each security and obtain a new value for the asset specific risk $\sigma_{s(k)}$. Using this two-step

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procedure it is possible that the final resulting estimate of $\sigma_{s(k)}$ is improperly negative. To avoid this possibility we arbitrarily define a limit at which the value of $\sigma_{s(k,t)}$ can decline from prior values. It should be noted that given this ability to condition both factor variances and specific variances, stocks within the model universe, on which no options are traded, are still subject to adjustments in the factor variances.

$$\sigma_{s(k,t)} = \max[\sigma_{s(k,t)}, \sigma_{s(k,t-1)} \times p] \quad 0 < p < 1 \quad [9]$$

We believe this treatment for $\sigma_{s(k,t)}$ is appropriate. While it is easy to envision many circumstances that would cause the rapid increase in the expected volatility of a stock, it is harder to conceive of economic events that would create a dramatic decline in expected volatility from one time period to the next.

The described model has actually been implemented for US equity securities and has been utilized for actual portfolio trading purposes by numerous hedge funds. The principal components based multiple factor model is estimated from a covariance matrix of stock returns representing 250 trading days of returns (corrected for serial correlation and heteroskedasticity) of each stock. The model is freshly estimated at the close of each trading day with a twenty trading day moving average used to estimate the typical bias in implied volatility relative to historic values and the maximum allowable daily decline of asset specific variance set to 25% ($p = .75$).

A Few Examples

The ability of this model to adapt to unusual market conditions surrounding the behavior of Internet stocks has already been examined in diBartolomeo (2000b). This study found that after extensive adjustments specific to the Internet stock phenomenon, an endogenous factor model produced risk estimates of portfolios that were consistent with this model operating in its typical fashion.

The tragedy of September 11th, 2001 provides an example of how rapidly this model can adapt to violent changes in market conditions. As an example we created a capitalization-weighted (as of September 10) portfolio of the forty-two airline stocks within the coverage universe. The risk level of the portfolio was evaluated on September 10th, on September 17th when trading resumed, and on November 30th. The expected volatility of the portfolio was 26%, 54% and 35% respectively.

With the suspension of trading at September 11th, there was no way for a model based solely on backward looking information to have made a substantial adjustment in the estimated risk level by the time that trading resumed. The more than doubling of the risk level of an all airline portfolio was anecdotally consistent with qualitative views of financial institutions that have the model in use.

Given that only a handful of the airline stocks in the portfolio have options traded on them, we wanted to also check an equal-weighted portfolio, where the smaller non-optionable stocks would predominate. For the purposes of comparison, we constructed similar equal-weighted portfolios for three other industries: property and casualty insurance, food production and manufacturing. We estimated risk levels for the four industry portfolios as of August 31, and

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again at September 30th. Our expectation was that the airline and insurance portfolios should show a marked increase in risk, while the foods and manufacturing portfolios should not. These results are presented in Table 1 and are exactly as anticipated.

Table 1: Portfolio Risk Levels at August 31, 2001 and September 30, 2001

Industry	August 31, 2001	September 30,2001	% Change
Airlines	23.77	29.69	+ 24.9
Property and Casualty	13.04	16.87	+ 29.4
Food Production	20.88	19.38	(7.2)
Manufacturing	11.56	11.31	(2.2)

Once we had established that our initial results did not appear to be driven by random noise, we undertook a more detailed examination of the model output for the capitalization weighted airline portfolio in the days surrounding September 11th. The 54% total risk estimate (standard deviation) as of September 17th equates to 2916 units of variance. Of this total, 2755 units arose from factor risks and 161 units were the aggregate asset specific risk of the portfolio. As of September 10th, the total volatility figure was 26% standard deviation, or 676 variance units. Of that total 588 arose from common factor risks and 98 units arose from aggregate asset specific risk. While the vast increase in common factor risk was immediately understandable, the increase of more than 60% in the asset specific portion of the portfolio risk from 98 units to 161 units was less intuitive. As of November 30th, the values were 35% volatility, 1223 units of variance, of which 1145 arose from common factors and 177 arose from asset specific risks.

To further investigate the shift in the perceived level of asset specific risk, we calculated the portfolio asset specific risk for various dates from August 10th to November 30th. This information is portrayed in Chart 1. What is striking about this data is the precipitous decline of approximately 60% in portfolio asset specific risk for the two trading days immediately preceding September 11th. This is extremely counterintuitive. Even if information about the terrorist attacks had somehow leaked into financial markets, we would have expected an increase, rather than a decrease in risk expectations.

As shown in Figure 1, the drop in estimated asset specific risk of the portfolios could be traced to a dramatic decline in the implied volatility of options on Southwest Airlines (LUV) for the two trading days prior to September 11th. For all trading days in 2001 prior to September 7th, the implied volatility for Southwest had a mean value of 45% with a daily standard deviation of 13%. For September 7th, the implied volatility value was 22%, followed by 15% on September 10th. For all trading days from September 17th to November 30th, the mean implied volatility was 54% with a standard deviation of 18%. Of more than 400 stocks analyzed for implied volatility as of September 10th, Southwest options ranked in the bottom 1% (seemingly inconsistent with the normally volatile operations of an airline). As of September 17th, Southwest's rank implied volatility was in the 9th (91st from the bottom) percentile of the universe of stocks with options.

One could draw an inference that the market in LUV options had been subject to transactions, such as call writing that drove down the implied volatility of the options. Examination of volume and open interest data in LUV options did not reveal levels of trading volume on the dates in question that were statistically significantly different from the average of the prior month. We also reviewed news wire reports on LUV for the period prior to September 11th and

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did not find any fundamental information relating to Southwest Airlines that would provide an immediate explanation of the apparent collapse of implied volatility.

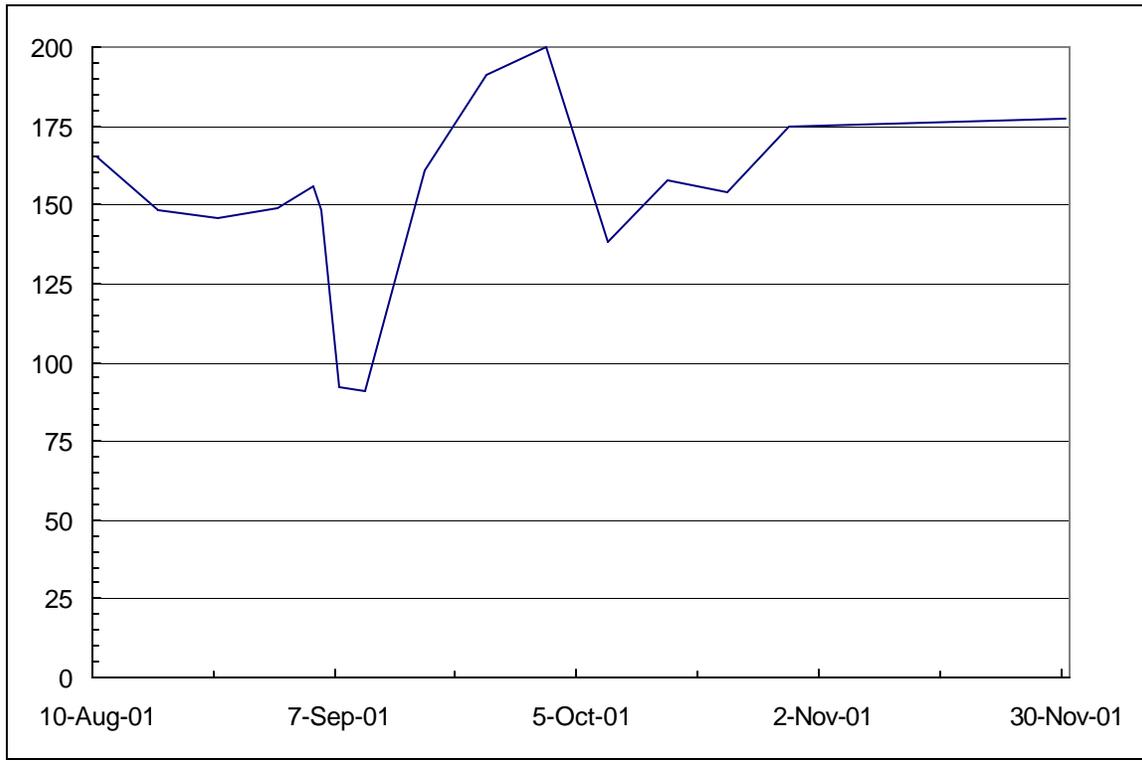


Figure 1: Asset Specific Volatility – Southwest Airlines – August through November 2001

Conclusions

An increasing body of literature supports the use of implied volatility in forecasting financial market risks and their changes in the level of such risk. Analytical methods utilizing implied volatility seem to appropriately capture the dynamics of information release around announcement dates, while time series methods do not.

We have presented a method to incorporate volatility data in a multi-factor security covariance model. Such a model has proven to be of practical value to hedge fund managers and other financial market participants.

The model reacted rapidly and sensibly to the changing financial market circumstances surrounding the September 11, 2001 terrorist attacks. Furthermore, the model provides evidence of a potential anomaly in option pricing that could be construed as weak evidence of irregular market trading in anticipation of the tragedies.

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