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1. INTRODUCTION

Volatility has become a topic of enormous importance to almost anyone who is involved in the financial markets, even as a spectator. To many among the general public, the term is simply synonymous with risk: high volatility is thought of as a symptom of market disruption. To them, volatility means that securities are not being priced fairly and the capital market is not functioning as well as it should. But for those who deal with derivative securities, understanding volatility, forecasting it accurately, and managing the exposure of their investment portfolios to its effects are crucial.

A widely studied and quite useful measure of volatility is the implied volatility index. Although, there is a growing literature on the construction and the properties of implied volatility indices (Fleming et al., 1995, Whaley, 1993, and 2000, Wagner and Szimayer, 2000), to the best of our knowledge there has not yet been constructed and examined an implied volatility index on an individual stock. And this is the purpose of this paper. By construction, **Implied Volatility Indices** are weighted averages of the implied volatilities computed from call and puts near-the-money, nearby and second nearby option contracts on the relevant underlying stock index and they represent the implied volatility of a synthetic option that has constant time to maturity (usually 22 trading days) and fixed strike price (usually at-the-money). In this paper, we construct an implied volatility index on the General Motors U.S. stock (GM), with the methodology of VIX (CBOE VIX white paper, 2003), we call it GMVIX, and then we try to investigate its properties. We are confident that this study will contribute significantly in the relative literature and will be of interest to practitioners as well.

The usual properties that implied volatility indices exhibit, are the "investor's fear gauge" (see Whaley, 2000, Dotsis et. al., 2000), this is a negative relationship between underlying stock index returns and the implied volatility index. The leverage effect[1], which refers to the fact that when stock returns fall, volatility increases. These

[1] The "leverage effect" refers to the negative relationship between stock returns and volatility: volatility increases when the stock prices fall. It is attributed to the effect that a change in the market valuation of

two relationships are quite the same effect seen reverse. We also test whether GMVIX has any predictive power over stock price and the reverse, via Granger causality tests. Then we test whether there is any spillover effect between the original VIX and the constructed GMVIX. This means whether VIX lead or whether it can predict the GMVIX, and the reverse. We should note here that GM is a stock that is included in S&P 500 index from which VIX is constructed. Hence, we expect VIX to be able to predict GMVIX, but the reverse is rather unlikely. Finally, we investigate whether this GMVIX has any predictive power over GM option prices. This seems to be rather unlikely, but we believe that any information content in the implied volatility index would be quite useful, if not for speculation, at least for hedging purposes.

The rest of the paper is organized as follows, in the next of this section we refer to some important issues like implied volatility indices and the related literature. In section 3 we describe the data set. In section 4 we describe the VIX calculation, which is the method that we have also used in order to construct the implied volatility index of General Motors, GMVIX. In section 5 we investigate the properties of GMVIX, investor's fear gauge, leverage effect, Granger-cause and spillover effect. In section 6 we try to test the predictive ability of GMVIX over the GM options. The conclusions drawn are presented in the last section.

a firm's equity has on the degree of leverage in its capital structure. Figlewski and Wang (2000) report that the "leverage effect" is not just the result of changing financial leverage since the effect is different for implied vs. historical volatilities and for falling vs. rising markets.

2. BACKGROUND

2.1 Implied Volatility Indices

Volatility risk is one of the main risks an investor faces and the more difficult to deal with. In the past, many financial institutions have been severely damaged because of their unhedged position in volatility risk. So far, standard options were used in various ways in order to hedge both price and volatility risk. This is inefficient since it insures both type of risk and is also more expensive than a pure bet in volatility. Volatility derivatives are the new products that allow us to hedge efficiently volatility risk. These are futures and options written on some measure of risk, like an implied volatility index. Chicago Board Options Exchange (CBOE) has introduced such instruments (volatility futures and options) in the first quarter of 2004.

The study of the construction and of the properties of implied volatility indices has been primarily motivated by the increasing need to create derivatives on volatility (volatility derivatives, see Brenner and Galai, 1989). These are instruments whose payoffs depend explicitly on some measure of volatility. Hence, they are the natural candidates for speculating and hedging against changes in volatility (volatility risk). Volatility risk has played a major role in several financial disasters in the past 25 years (e.g. Baring Bank, Long-Term-Capital Management). Many traders also profit from the fluctuations in volatility (see Carr and Madan, 1998, for a review on the volatility trading techniques); Guo (2000), and Poon and Pope (2000) find that profiTable volatility trades can be developed in the currency and index option markets, respectively.

Implied volatility is the volatility that is derived from the option’s market prices, by solving the pricing model with respect to volatility. The first pricing model was introduced in 1973 by Black-Scholes-Merton, and has had a huge influence on the way that traders price and hedge options. In 1997, the importance of the model was recognized when Robert Merton and Myron Scholes were awarded the Nobel prize for economics. Sadly, Fischer Black died in 1995, otherwise he too would undoubtedly have been one of the recipients of this prize. It is widely accepted that the Black-Scholes volatility computed from the market price of an option is a good estimate of the "market's" expectation of the volatility of the underlying asset, and that the market's expectation is informationally efficient. In the framework of an option pricing model such as the Black and Scholes (1973) model, the expected volatility of the asset over the life of the option is the volatility embedded in the price of the option. If call or put option prices are available, then the Black and Scholes (1973) pricing formula can be "inverted" such that the expected volatility over the life of the option is computed from the observed market prices of the call or put options. Indeed, when all the other parameters are known, there is a one-to-one relationship between the option prices and underlying (expected) asset volatility. This yields the so called implied volatility.

It is also widely believed that the volatility implied in an option's price is the option market's forecast of the future return volatility over the remaining life of the option. Under a rational expectations assumption, the market uses all the information available to form its expectations about future volatility and hence the market option price reveals the market's true volatility estimate. Furthermore, if the market is efficient, the market's estimate, the implied volatility, is the best possible forecast given the currently available information. That is, all information necessary to explain future realized volatility generated by all other explanatory variables in the market information set should be subsumed in the implied volatility.

Black-Scholes model assumes that volatility is constant throughout the life of the option, but this is not the case in real life, implied volatility is a function of both the strike price and the time to maturity. And since we have many options in the market, both puts and calls, with different expiries and strikes (which means different implied volatilities), we need a measure that will give us something like the weighted-average of all these implied volatilities. And this is the so called implied volatility index.

By construction, **Implied Volatility Indices** are weighted averages of the implied volatilities computed from call and puts near-the-money, nearby and second nearby option contracts on the relevant underlying stock index. The weighting method ensures that the implied volatility index on any given point in time, represents the implied volatility of a synthetic option that has constant time to maturity (usually 22 trading days) and fixed strike price (usually at-the-money). For instance, VIX of CBOE is such an index computed from implied volatilities in S&P 500 index options.

In an efficient market where option prices reflect all available information, the level of the implied volatility index "is the market's best assessment of the expected volatility of the underlying stock index over the remaining life of the option". Note that, by construction, these implied volatility indices take into account early exercise and dividend payment features, and they do not use as inputs market prices from options that are not actively traded (thus avoiding the troublesome problem of stale quotes for deep out-of-the-money or in-the-money options). Thus, implied volatility indices deliver easy-to-use information regarding future volatility and should be less prone to computation errors than previous measures of implied volatility.

Several volatility indices have been developed since 1993. The idea of developing a volatility index was first suggested by Brenner and Galai in 1989. Fleming, Ostdiek and Whaley in 1993 describe the construction of an implied volatility index (the VIX) originally based no S&P 100 options. Currently CBOE disseminates prices for VIX based on S&P500 options, VXO based on S&P100 options. Skiadopoulos (2004) developed a methodology for the construction of GVIX, the Greek market volatility index based on FTSE/ASE-20 option series.

A volatility index serves two primary purposes. First, it is an "investor's fear gauge"[2] as it provides an indicator of the market consensus estimate of the expected future stock market volatility – a measure of stock market risk. The term "fear" arises from the fact that investors are averse to risk and such fears are reflected to stock prices. If a stock market volatility is expected to increase, investors will demand higher rates of return on stocks and so stock prices are going to fall. This is an alternative explanation of the negative relationship between returns and volatility other than the leverage effect. Second, it can serve as the underlying asset to volatility derivatives; it could play the same role as the market index plays for options and futures on the index[3]. A volatility index can also be used for Value-at-Risk purposes (Giot, 2002b), to identify buying/selling opportunities in the stock market (Stendahl,

[2] See Whaley (2000)
[3] A volatility derivative can also be written on an asset that has a payoff closely related to the volatility swings, e.g. a straddle. See Brenner et al. (2002) who propose an option on a straddle.

1994, Whaley, 2000) and to forecast the future market volatility (see Fleming et al., 1995, Giot, 2002b).

In 1993 CBOE introduced the CBOE Volatility Index VIX, an index which tracks the implied volatility from options on S&P100 (OEX) and it became the benchmark for stock market volatility. In the ten years following the launch of VIX, theorists and practitioners have changed the way they think about volatility. On September 2003 CBOE updated the construction methodology of VIX in order to ensure that it remains the premier benchmark of U.S. stock market volatility. The changes reflect the latest advances in financial theory and what has become standard industry practice. As far as the old methodology index is concerned, CBOE continues the calculation and dissemination of original VIX, but under a new ticker symbol – "VXO".

The fundamental features of VIX remain the same. VIX continues to provide a minute-by-minute snapshot of expected stock market volatility over the next 30 calendar days. This volatility is still calculated in real time from stock index option prices and is continuously disseminated throughout each trading day.

The two important changes in the new methodology are the following:

- The most significant change is a new method of calculation. The new VIX estimates expected volatility from the price in stock index options in a wide range of strike prices, not just from at-the-money strikes as in the original VIX. Thus it is more robust because it pools the information from option prices over the whole volatility skew, not just from at-the-money options. Also, the new VIX is not calculated from the Black Scholes option pricing model; the calculation is independent of any model. The new VIX uses a newly developed formula to derive expected volatility by averaging the weighted prices of out-of-the-money puts and calls, taking into account a broader range of strike prices.
- The second noteworthy change is that the new VIX calculation will use options on the S&P 500 (SPX) index rather than the S&P 100. While the two indices are well correlated, the S&P 500 is the primary U.S. stock market benchmark as well as the reference point for performance of many stock funds, with over $800 billion in indexed assets. In addition, the S&P 500 underlies the most active stock index derivatives.

2.2 Related Literature

There is a recently growing literature on the behavior and the interrelations of implied volatilities especially those conveyed by implied volatility indices. These include for example Whaley (1993, 2000), Giot (2002a), Skiadopoulos (2004), Wagner and Szimayer (2004). Giot (2002a) reports a negative and statistically significant relationship for the period 1995-2002 between the levels of S&P100 and NASDAQ100 and their implied volatility indices: positive stock index returns lead to decreased implied volatility levels, while negative returns lead to higher implied volatility levels. He also finds that this relationship is asymmetric in the sense that negative stock index returns yield bigger proportional changes in implied volatility measures than do positive returns. Whaley (2000) observes an asymmetric negative relationship between weekly changes of the old VIX and weekly returns of S&P100 over the period 1995-2000. Skiadopoulos (2004) also reports the existence of an asymmetric leverage effect between returns of GVIX and changes of it's underlying FTSE/ASE-20 and finds a contemporaneous spillover of implied volatility changes between GVIX and VXO/VXN. Gemmill and Kamiyama (2000) examine whether there ate spillovers of implied volatility and implied skewness across time zones, using daily data of the index-option markets of the US, Japan and UK. They find that the level of implied volatility spills across markets but skewness of the volatility smile is a local phenomenon.

Several papers have been written on the information content and the predictive power of implied volatility index prices as a forecast of future realized volatility. Fleming-Ostdiek-Whaley (1995) found that implied volatilities contained substantial information for future volatility. Giot (2002b) found that VIX and VXN provide accurate and meaningful information as to future volatility forecasts. Fleming et al. (1995) concluded that implied volatility (VIX 1986-1992) is an upwardly biased estimator of future volatility even if the magnitude of the bias is not economically significant. They also concluded that implied volatility dominates past volatility as a forecast of future volatility. Malz (2000) found that implied volatility contains information regarding future large-magnitude returns, which is not contained in other risk measures, and this fact can help risk managers posture themselves for stress events. On the other hand, Canina and Figlewski (1993), reported for S&P 100 (1983-

1987) that implied volatilities have little predictive power for future volatility – in fact implied volatility has no correlation with future return volatility – and therefore they are significantly biased forecasts. Figlewski (2004) concluded that even though implied volatility contains significant information about future volatility, it does not pass the test of forecast rationality and is not necessarily a more accurate forecast of future volatility than historical volatility. He also showed that the historic volatility forecasts more accurately for large samples and long rather than short forecasting horizons.

3. THE DATA SET

We use daily data on American style options on the General Motors (GM) from www.ivolatility.com for the period January 1st 2001 – March 20th 2006. This data set contains the following daily information for each option traded: the expiration date, the strike price, the last bid and ask prices, the trading volume, and the GM closing price. In Appendix 1 we represent the data for a single date (11/22/05) and only for the two nearest expiration dates, for the reader to take a clue of the data set form. The average of the bid-ask option price is used as the option's market price. This is a standard approach taken to reduce the impact of measurement errors on the implied volatilities calculated subsequently.

The last trading day of the GM options is the business day (usually a Friday) preceding the expiration date. The expiration date is the Saturday following the third Friday of the expiration month. Up to six near-term months are traded every day. The strike prices are spaced at intervals of five or two and a half stock points. The options are traded from 8:30 a.m.-3:15 p.m. central time (Chicago time).

In addition, we use London Euro-currency interest rates (middle rates) on the US dollar obtained from DataStream to proxy for the risk-free rate. Daily interest rates for 7-days, one-month, three months, six months and one year were used, while those for other maturities were obtained by linear interpolation. These rates where transformed to continuously compounded rates.

3.1 Screening the Data

The raw data is screened for data errors for the purposes of the subsequent analysis. Options with zero trading volume and less than $0.5 premium were discarded. The underlying GM of the options is a dividend-paying asset. Therefore, the dividend yield to be realized over the life of the option is required as an input so as to check the arbitrage bounds for the option prices. Toward this end, we obtained from DataStream the daily dividend yields for General Motors and for the period January 1st 2001 – April 30th 2006. A dividend is counted as occurring during the life of the option if the ex-dividend date is during its life. In some countries, like U.S.A., a small number of ex-dividends dates tend to be used by all companies. In such cases, it is appropriate to assume that stock indices provide a dividend yield at discrete points in time. These dividends can be converted to an equivalent continuous dividend yield by

$$q = \frac{1}{T-t}\ln(1+Q)$$

where $Q = (1+q_1)*(1+q_2)*...*(1+q_n)-1$. $q_1, q_2, ..., q_n$ are the discrete dividends yields expected between time zero and time T-t (time to maturity).

Finally, the standard upper and lower arbitrage bounds for the American option prices (Merton, 1973) were checked using the dividend yield obtained and the options, for which bounds were violated, were discarded.

The upper arbitrage bounds are $C \leq S$ and $\mathrm{P} \leq \mathrm{K}$, for calls and puts respectively, where C is the call price, P is the put price, S is the stock price and K is the strike price.

Also, the American options must satisfy the following inequality

$$S_t * \exp(-q_{t,t} * t) - K \leq C_t - P_t \leq S_t - K * \exp(-r_{t,t} * t)$$

Where $q_{t,t}$ and $r_{t,t}$ is the dividend yield and risk-free rate in the day t and for time to expiry τ.

4. GMVIX CALCULATION

We use the calculation method of CBOE's VIX White Paper (2003) to construct the implied volatility index on the individual U.S. stock General Motors. We will call this index **GMVIX**.

The generalized formula of VIX is **VIX = σ *100**

where σ is the weighted implied volatility as a result of interpolation between the implied volatilities of a series from options. For every option, σ is the square root of

$$s^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K} - 1\right]^2 \qquad (1)$$

T is the time to expiration in minutes

F is the forward index level derived from index option price

K_i is the strike price for the i^{th} out-of-the money option; a call if K_i>F and a put if K_i<F

ΔK_i is the interval between strike prices – half the distance between the strike on either side of K_i: $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$

K_0 is the first strike price below the forward index level F

R is the risk-free interest rate to expiration

$Q(K_i)$ is the midpoint of the bid-ask spread for each option with strike K_i

The options used are put and call options in the two nearest-term expiration months in order to bracket a 30-day calendar period. However, with 8 days left to expiration, the new VIX 'rolls' to the second and third contract months in order to minimize pricing anomalies that might occur close to expiration.

The time of the VIX calculation is assumed to be 8:30 a.m. (Chicago time). The new VIX calculation measures the time to expiration T in minutes rather than days in order to replicate the precision that is commonly used by professional option and volatility traders. The time to expiration is given by the following expression:

$$T = \{M_{Current\ day} + M_{Settlement\ \mathrm{day}} + M_{other\ \mathrm{days}}\} / \text{Minutes in year} \quad (2)$$

where

Mcurrent day is the number of minutes remaining until midnight of the current day

Msettlement day is the number of minutes from midnight until 8:30 a.m. on SPX settlement day

Mother days is the total number of minutes in the days between current day and settlement day

The basic steps in the calculation of (1) are the following:

Step 1: Select the options to be used in the formula. For each contract month:

- Determine the forward index level F, based on at-the-money option prices. The at-the money strike is the strike at which the difference between the call and put prices is smallest. The formula used to calculate the forward index level is F = Strike price + exp(RT)*(Call – Put price)
- Determine K_0, the strike price immediately bellow the forward index level F.
- Sort all of the options in ascending order by strike price. Select call options that have strike prices greater than K0 and a **non-zero** bid-price. After

encountering two consecutive calls with a bid price of zero, do not select any other calls. Next, select put options that have strike prices less than K0 and a **non-zero** bid price. After encountering two consecutive puts with bid price of zero, do not select any other puts. Select **both** the put and call with strike price K0. Then average the quoted bid-ask prices for each option.

Notice that two options are selected at K_0, while a single option, either a call or a put, is used for every other strike price. This is done to center the strip of options around K_0. In order to avoid double counting, however, the put and call prices at K0 are averaged to arrive at a single value.

Step 2: Calculate implied volatility for both near term and next term options by applying the formula (1).

The new VIX is an amalgam of the information reflected in prices off all of the options used. The contribution of a single option to the new VIX value is proportional to the price of that option and inversely proportional to the option's strike price.

Step 3: Interpolate the s_1^2 and s_2^2 to arrive at a single value with a constant maturity of 30 days to expiration. Then take the square root of that value and multiply by 100 to get VIX. If s_1^2 and s_2^2 are the values for near term and next term options respectively, then the interpolation formula is

$$s = \sqrt{\left\{ T_1 s_1^2 \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}} \right] + T_2 s_2^2 \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}} \right] \right\} \times \frac{N_{365}}{N_{30}}} \qquad (3)$$

Where…

N_{T1} = number of minutes to expiration of the near term options

N_{T2} = number of minutes to expiration of the next term options

N_{30} = number of minutes in 30 days (30*1440=43,200)

N_{365} = number of minutes in a 365-day year (365*1440 = 525,600)

One of the most interesting features of VIX, and the reason it has been called "investor fear gauge", is that historically, VIX hits its highest levels during times of financial turmoil and investor fear. VIX is based on real-time option prices, which reflect investors' consensus view of future expected stock market volatility. Historically, during periods of financial stress, which are often accompanied by steep market declines, option prices – and VIX – tend to rise. The greater the fear, the higher the VIX level. As investor fear subsides, option prices tend to decline, which in turn causes VIX to decline. It is important to note, however, that past performance does not necessarily indicate future results.

Another interesting aspect of VIX is that, historically, it tends to move opposite its underlying index (leverage effect). VIX measures market expectation of near term volatility conveyed by stock index option prices.

The VIX is calculated using a wide range of strike prices in order to incorporate information from the volatility skew. It also uses a newly developed formula to derive expected volatility directly from the prices of a weighted strip options.

The VIX calculation reflects the way financial theorists, risk managers and volatility traders think about – and trade – volatility. As such, the VIX calculation more closely conforms to industry practice. It is simple, yet it yields a robust measure of expected volatility. It is robust because it pools information from option prices over a wide range of strike prices thereby capturing the whole volatility skew, rather than just the volatility implied by at-the-money options, which were used in the calculation of the Old VIX. The New VIX is simpler because it uses a formula that derives the market expectation of volatility directly from stock option prices rather than an algorithm that involves backing implied volatilities out of an option-pricing model.

In the next section we report the evolution of the constructed index GMVIX and we try to investigate whether it has all the above discussed properties of VIX, and hence if it can be called "investor's fear gauge".

5. GMVIX PROPERTIES

5.1 Summary Statistics

Figure 1 shows the evolution of GMVIX calculated from the average bid-ask option prices. It also shows the evolution of the General Motors stock over the same period. We can see that in certain periods there seems to be a negative correlation between the changes in the GM and the changes in the volatility index. This has been termed as leverage effect.

In order to study the time series properties of the constructed index formally, we proceed as follows. Table 1 shows the summary statistics (mean, median, maximum, minimum, standard deviation, skewness, kurtosis, and the results from the Jarque-Bera test with it's p-value in the brackets) of the GM stock and the implied volatility index GMVIX. GM and GMVIX have both high mean near 40, but GMVIX has higher std. deviation indicating that it is more volatile than GM stock, and this can be attributed to the jumps that we can observe when GM falls (investor' s fear gauge, see next section). Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as X^2 with 2 degrees of freedom. The reported probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis. Since zero probabilities are reported for all our time series' Jarque-Bera statistics, we are led to the rejection of the null hypothesis of a normal distribution. This means that extreme volatility changes are assigned higher probabilities with regard to those under a normal distribution. This can also be evident from the Q-Q plots reported below (Figure 2). Hence, we can claim that the two series are distributed non-normally.

In order to check our series for unit roots we use the augmented Dickey-Fuller test. This test gives has the null hypothesis that a series has unit root. The p-values we get for the GM and GMVIX are 0.7516 and 0.003*, respectively. This means that we reject the null for a significance level of 1% in the case of GMVIX, but we cannot reject it for GM. Therefore, GM seems to be a random walk and hence a non-stationary process. For that reason, we will thereafter use the (continuously compounded) returns of the GM (R) for our analysis (which are stationary, p-value of augmented Dickey-Fuller test is 0.00*), because if we don’ t our results will be spurious. For the GMVIX series we can use the levels since we have stationarity. But we will use the first differences instead, whenever we want to check a relationship between GM and GMVIX, in order to have comparable sizes.

Table 2 shows the summary statistics of the (continuously compounded) returns of the GM (*R*) and the ***changes*** *ΔGMVIX = GMVIXt – GMVIXt-1* of the index, as well as their cross-correlation. The sample mean for the *ΔGMVIX* and for ***R*** are both zero indicating that there is a zero trend. But still *ΔGMVIX* has higher std. deviation indicating that it is more volatile than GM stock. Both R and the volatility index changes are distributed non-normally; hence extreme movements in the volatility changes and in the stock returns are more probable than under the normal distribution.

The cross-correlation between *ΔGMVIX* and *R* is also reported in Table 2, and it confirms the existence of the leverage effect, even though this is rather weak. The correlation between the GM return and the changes in GMVIX is found to be -0.246.

Finally, regarding the autocorrelation coefficients, the standard 5% significance bound is $2/\sqrt{T} = 2/\sqrt{1301} = 0.05549$. The autocorrelations of GM return and the changes in GMVIX are also reported in Table 2. We can see that the first and third order autocorrelation for measure of ΔGMVIX is statistically significant, and it is negative. This can be interpreted as evidence of mean reversion in the implied volatility index. Alternatively, the negative serial autocorrelation can be interpreted as a signal for the presence of measurement errors in the calculation of implied volatility.

We can see in Figure 3 (Table 3) the autocorrelations and the partial autocorrelations of GM, respectively, and we can see that there seems to be autocorrelation of first order. In reality we have a unit root and not an AR(1). This is why as we have mentioned above we use the GM returns. We can now see in Figure 4 (Table 4) that Returns (R) seem to be uncorrelated. On the other hand GMVIX does not have a unit root as we have mentioned above, but we can see from Figure 5 (Table 5) that it seems to follow an AR(p) model. In Figure 6 (Table 6) we can see that the first differences of GMVIX (ΔGMVIX) still seem to be autocorrelated.

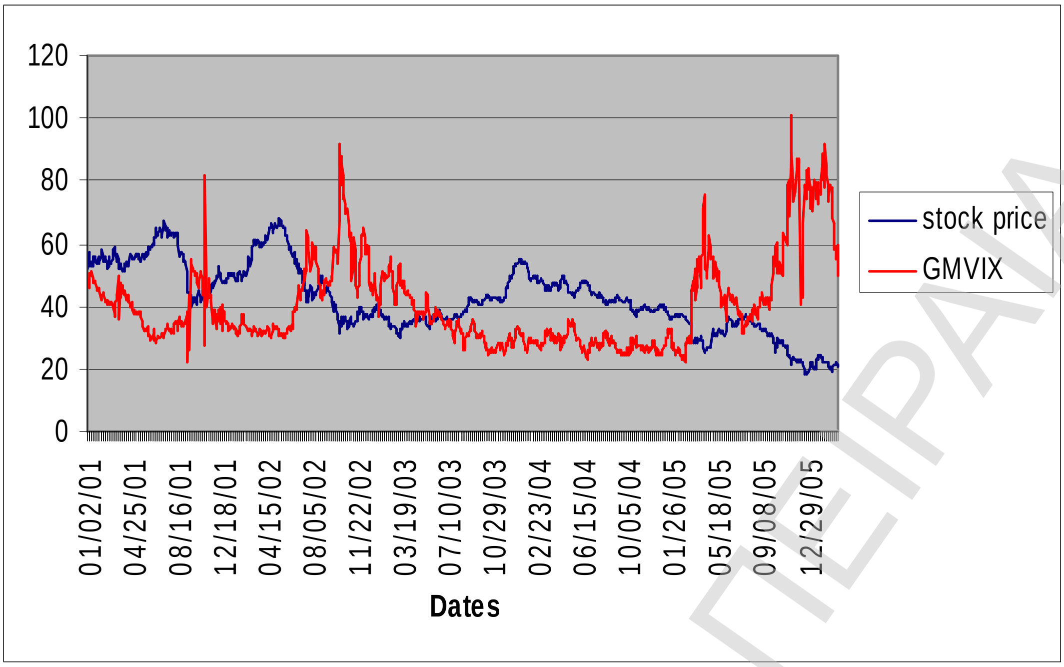


Figure 1. Evolution of implied volatility index GMVIX and GM stock for the period 02/01/2001 – 20/03/2006.

	GM Stock	**GMVIX**
Mean	42.49	40.38
Median	41.74	35.67
Maximum	68.02	101.17
Minimum	18.61	22.12
Std. Dev.	10.90	14.26
Skewness	0.132	1.427
Kurtosis	2.571	4.747
Jarque-Bera	13.75(0.001)	607.46(0.00)

Table 1: Summary Statistics of the GM stock and the implied volatility index GMVIX

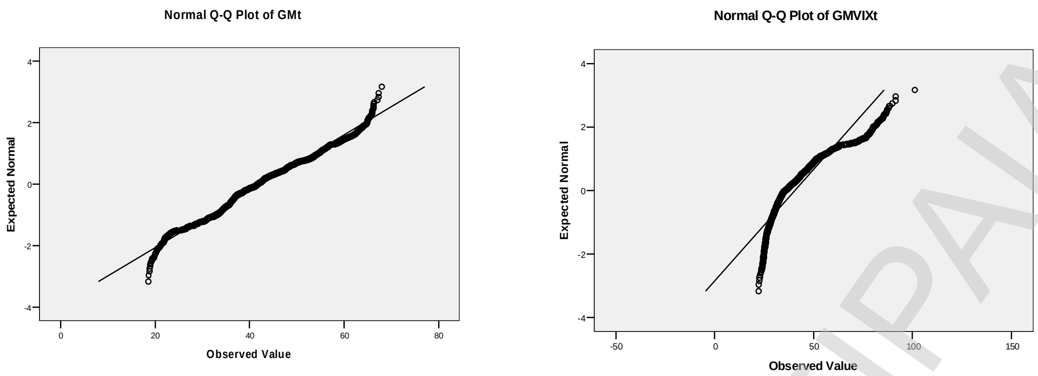


Figure 2. Q-Q plot for the GM stock series (left) and the implied volatility index GMVIX (right).

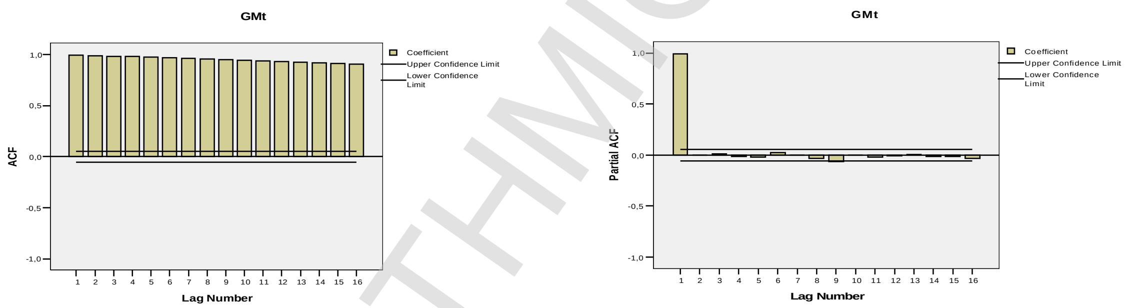


Figure 3. GM autocorrelogram (left) partial autocorrelogram (right)

	GM Return	ΔGMVIX
Mean	0.00	0.00
Median	0.00	-0.089
Maximum	0.16647	53.51
Minimum	-0.15045	-41.49
Std. Dev.	0.022	3.65
Skewness	0.02	1.4926
Kurtosis	9.063	64.22
Jarque-Bera	1991.56(0.00)	203530.5(0.00)
Cross-correlations		
GM Return	1	-0.246
ΔGMVIX	-0.246	1
Autocorrelations		
$\hat{p}(1)$	-0.022	-0.1984*
$\hat{p}(2)$	-0.0166	-0.0302
$\hat{p}(3)$	0.040	-0.0668*

Table 2: Summary Statistics of the returns GM (R) and the changes of the implied volatility index, ΔGMVIX. Cross-Correlations and autocorrelations up to three lags are reported. The asterisk indicates significance of the autocorrelation coefficient at 5% level of significance.

Autocorrelations and Partial Autocorrelations

Series: GMt

Lag	Autocorrelation	Std.Error	Box-Ljung Statistic				
			Value	df	Sig.(b)	Partial Autocorrelation	Std.Error
1	0.995	0.028	1289,942	1	0	.995	.028
2	0.989	0.028	2566,899	2	0	-.002	.028
3	0.984	0.028	3831,41	3	0	.015	.028
4	0.979	0.028	5083,154	4	0	-.016	.028
5	0.973	0.028	6321,75	5	0	-.018	.028
6	0.968	0.028	7548,043	6	0	.025	.028
7	0.963	0.028	8762,074	7	0	-.003	.028
8	0.957	0.028	9963,094	8	0	-.031	.028
9	0.951	0.028	11149,63	9	0	-.061	.028
10	0.945	0.028	12321,8	10	0	-.003	.028
11	0.939	0.028	13479,25	11	0	-.021	.028
12	0.932	0.028	14621,91	12	0	-.006	.028
13	0.926	0.028	15750,04	13	0	.003	.028
14	0.919	0.028	16863,54	14	0	-.013	.028
15	0.913	0.028	17962,12	15	0	-.016	.028
16	0.906	0.028	19045,13	16	0	-.031	.028

a The underlying process assumed is independence (white noise).
b Based on the asymptotic chi-square approximation.

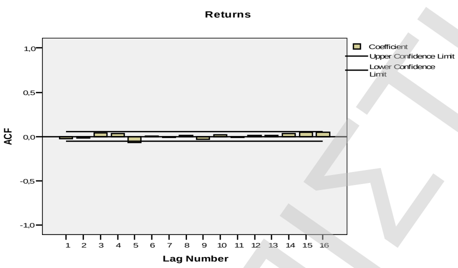
Table 3. GM autocorrelations and partial autocorrelations for up to 16 lags.

Autocorrelations and Partial Autocorrelations

Series: Rt

Lag	Autocorrelation	Std.Error	Box-Ljung Statistic			Partial Autocorrelation	Std.Error
			Value	df	Sig.(b)		
1	-.022	.028	.636	1	.425	-0.022	0.028
2	-.017	.028	.996	2	.608	-0.017	0.028
3	.041	.028	3.140	3	.371	0.04	0.028
4	.035	.028	4.735	4	.316	0.037	0.028
5	-.068	.028	10.799	5	.056	-0.065	0.028
6	.006	.028	10.854	6	.093	0.003	0.028
7	-.008	.028	10.938	7	.141	-0.013	0.028
8	.015	.028	11.223	8	.189	0.019	0.028
9	-.028	.028	12.237	9	.200	-0.023	0.028
10	.017	.028	12.597	10	.247	0.012	0.028
11	-.012	.028	12.778	11	.308	-0.012	0.028
12	.011	.028	12.943	12	.373	0.011	0.028
13	.010	.028	13.065	13	.443	0.013	0.028
14	.033	.028	14.501	14	.413	0.03	0.028
15	.047	.028	17.455	15	.292	0.052	0.028
16	.050	.028	20.811	16	.186	0.05	0.028

Table 4. GM returns autocorrelations and partial for up to 16 lags



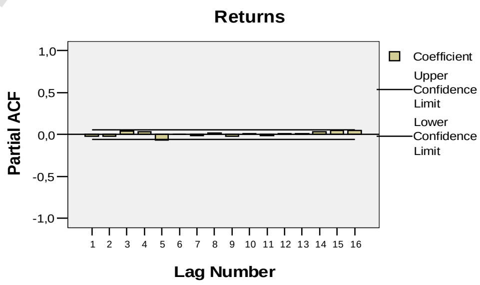


Figure 4. GM returns autocorrelogram (left) partial autocorrelogram (right)

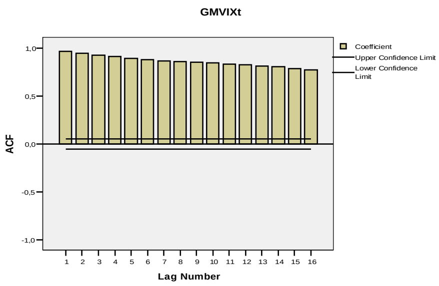
Autocorrelations Partial Autocorrelations

Series: GMVIXt

Lag	Autocorrelation	Std.Error(a)	Box-Ljung Statistic Value	df	Sig.(b)	Partial Autocorrelation	Std.Error
1	0.967	0.028	1219,191	1	0	0.967	0.028
2	0.947	0.028	2388,49	2	0	0.179	0.028
3	0.928	0.028	3514,175	3	0	0.062	0.028
4	0.914	0.028	4607,248	4	0	0.08	0.028
5	0.897	0.028	5659,472	5	0	-0.032	0.028
6	0.883	0.028	6679,374	6	0	0.037	0.028
7	0.87	0.028	7670,251	7	0	0.032	0.028
8	0.863	0.028	8645,995	8	0	0.102	0.028
9	0.855	0.028	9605,143	9	0	0.04	0.028
10	0.846	0.028	10545,56	10	0	0.001	0.028
11	0.835	0.028	11462,47	11	0	-0.027	0.028
12	0.825	0.028	12358,52	12	0	-0.002	0.028
13	0.816	0.028	13235,59	13	0	0.017	0.028
14	0.803	0.028	14085,96	14	0	-0.051	0.028
15	0.789	0.028	14905,75	15	0	-0.047	0.028
16	0.774	0.028	15696,23	16	0	-0.025	0.028

a The underlying process assumed is independence (white noise).
b Based on the asymptotic chi-square approximation.

Table 5. GMVIX autocorrelations and partial autocorrelations for up to 16 lags



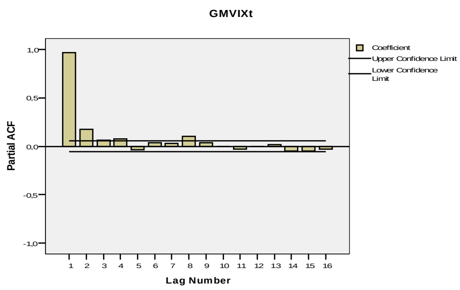


Figure 4. GMVIX autocorrelogram (left) partial autocorrelogram (right)

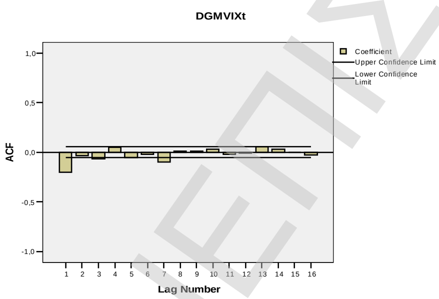
Autocorrelations and Partial Autocorrelations

Series: DGMVIXt

Lag	Autocorrelation	Std.Error(a)	Box-Ljung Statistic Value	df	Sig.(b)	Partial Autocorrelation	Std.Error
1	-0.198	0.028	51.314	1	0	-0.198	0.028
2	-0.03	0.028	52.507	2	0	-0.072	0.028
3	-0.067	0.028	58.333	3	0	-0.092	0.028
4	0.054	0.028	62.088	4	0	0.019	0.028
5	-0.05	0.028	65.415	5	0	-0.046	0.028
6	-0.019	0.028	65.901	6	0	-0.043	0.028
7	-0.096	0.028	77.922	7	0	-0.116	0.028
8	0.01	0.028	78.065	8	0	-0.05	0.028
9	0.014	0.028	78.309	9	0	-0.012	0.028
10	0.033	0.028	79.705	10	0	0.016	0.028
11	-0.018	0.028	80.123	11	0	-0.008	0.028
12	-0.011	0.028	80.273	12	0	-0.025	0.028
13	0.056	0.028	84.453	13	0	0.043	0.028
14	0.031	0.028	85.725	14	0	0.039	0.028
15	-0.003	0.028	85.736	15	0	0.02	0.028
16	-0.026	0.028	86.655	16	0	-0.007	0.028

a The underlying process assumed is independence (white noise).
b Based on the asymptotic chi-square approximation.

Table 6. ΔGMVIX autocorrelations and Partial autocorrelations for up to 16 lags



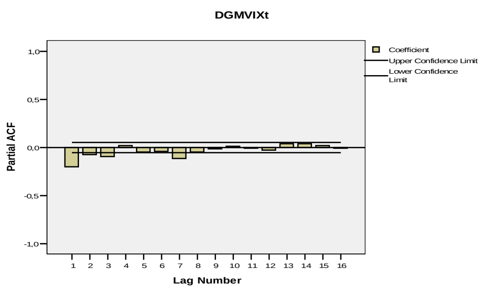


Figure 5. ΔGMVIX autocorrelogram (left) partial autocorrelogram (right)

5.2 Investor's Gauge of Fear

The capital asset pricing model theories predict that the expected return depends on the expected volatility. In addition, within the implied volatility index literature, Whaley (2000) and Giot (2002a) have found a negative relationship between returns and VIX. A possible explanation of this is that the demand for puts increases when the market declines. Increased demand means higher put prices, and hence higher implied volatilities. Furthermore, this relationship is asymmetric: an equal size positive/negative shock on implied volatility does not have the same effect on the index return. Hence, they interpret the VIX as "the investor's fear gauge"; the further VIX increases in value, the more panic is in the market. The further VIX decreases in value, the more complacency there is in the market.

We now turn to investigating whether this interpretation can also be attributed to GMVIX. First let's have a look at Figure 1 which shows the closing values of the GMVIX and the GM over the past five years. We observe that like VIX, GMVIX spikes during periods of market turmoil and hence can be named "investor's fear gauge", just like the VIX. Naturally, such fears are usually reflected in stock prices also. This stands to reason. If expected market volatility increases, investors demand higher rate of return on stock (GM), so stock price falls. The relation is not perfect, however. As Figure 1 show, some spikes in the GMVIX are coincident with spikes in the opposite direction for the GM. In October 2002, for example, GMVIX spiked upward and the GM spiked downward. Similar effects are also seen in months such as November 2001, August 2002, March 2005, and November 2005. At other times, however, there can be a run-up in stock prices as well as volatility. In September 2001, the GMVIX was rising (i.e., investors were becoming more nervous) while the level of GM was rising. Yet, at even other times, there can be a run-up in stock prices with little movement in volatility.

In Figure 6 we can take a first idea of the relationship between ΔGMVIX and R. We can observe a slightly negative relationship which goes nearly at the zero axes. We can still observe some outliers which are only a few exceptions and we believe that they will not influence the robustness of our analysis.

To assess more precisely the relation between GM and the GMVIX, we regress the daily returns R_t of GM on the daily changes ΔGMVIX of the GMVIX.

$$R_t = b_0 + b_1 \Delta GMVIX_t + e_t \qquad (4)$$

In every regression that we will run thereafter we will use OLS to estimate the parameters, the t-statistic and hence the p-values (computed using Newey-West's heteroskedasticity-consistent standard errors). We must also check the residuals, which must follow a White noise in order to have robust results. For that purpose we check the residual plots and the Durbin-Watson (DW) statistic. A DW statistic around 2 indicates the absence of first-order serial correlation in the residuals. If residuals are correlated with their own lagged values, OLS will no longer be efficient among linear estimators and standard errors will be generally understated.

In equation (4) the model's prerequisites (e_t follows a White Noise), were not surely satisfied (DW = 2.13). And hence, we have adjusted an autoregressive model of order p = 1 in the residuals. We have checked various ARMA models and found that AR(1) has the smallest AIK(Akaike Information Criterion). After this adjustment the model's prerequisites (e_t follows a White Noise), were satisfied (DW = 2.0041).

The regression results (p-values in brackets) are

$$R_t = -0.000737 - 0.001636 * \Delta GMVIX_t \qquad (4)$$

p-val. (0.1978) (0.00)

R-square = 0.0648

We can see now that if the implied volatility rises the stock GM is going to fall and vice versa. In order to check whether this relationship is **asymmetric** we regress the daily returns R_t of GM on the daily changes ΔGMVIX of the GMVIX and the change $\Delta GMVIX^+$ of GMVIX when the change is positive i.e. $\Delta GMVIX^+ = \Delta GMVIX$ if $\Delta GMVIX > 0$, and $\Delta GMVIX^+ = 0$, otherwise

$$R_t = b_0 + b_1 \Delta GMVIX_t + b_2 \Delta GMVIX_t^+ + e_t \qquad (5)$$

As above, we adjust an AR(1) model to the residuals and hence the model's prerequisites (e_t follows a White Noise), and were all satisfied (DW = 2.0054).

The regression results (p-values in brackets) are

$$R_t = 0 - 0.0012 * \Delta GMVIX_t - 0.000786 * \Delta GMVIX_t^+ \quad (5)$$

p-val. (0.9448) (0.0) (0.0368)

R-square = 0.0679

The number of observations is 1301 and the R-square is 0.0679. This number is very small indeed, but it gives at least a sense of the relationship of the stock returns and the implied volatility index first differences. At least, we can see that the regression coefficients are all significant different from zero at a significance level of 5%.

We observe that the estimated intercept of the regression is 0 with big probability. This means that if the GMVIX does not change, the GM stock is not expected to change either.

From the perspective of understanding the relation between changes in the GMVIX and the stock returns of GM, however, the two slope coefficients rather than the intercept term tell the story. What they say is that if GMVIX falls by 100 basis points, the GM stock will rise by R_t =-0.0012x (-1.00) = 0.0012%,

while, if the GMVIX rises by 100 basis points, the GM will fall by

R_t =-0.0012(1.00)-0.000786(1.00) = -0.001986%.

Interestingly, the relation between stock returns and changes in the GMVIX is asymmetric. The stock market reacts more negatively to an increase in the GMVIX than it reacts positively when the GMVIX falls, even though this difference is quite small. Put differently, GMVIX is more a barometer of investors' fear of the downside than it is a barometer of investors' excitement (or greed) in a market rally. And these results are in accordance with Whaley (2000), Giot (2002a) and Skiadopoulos (2004). But in contrast with the literature our results indicate a more weaker relationship.

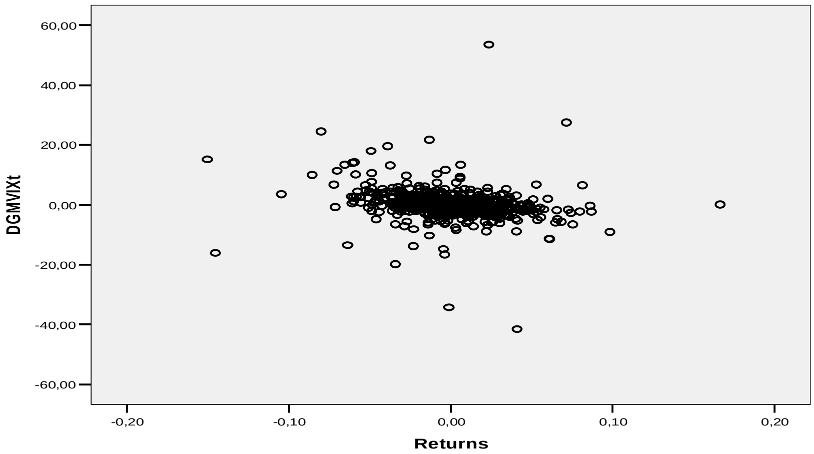


Figure 6. Scatter plot of the returns GM (R) and the changes of the implied volatility index, ΔGMVIX

5.3 Leverage Effect

In this section, we will take a broad look at the "leverage effect", as the term is normally used to describe the relation between the return on an underlying asset and its subsequent volatility. Volatility can mean the standard deviation of realized returns, or it can mean implied volatility in option prices. Leverage effects are commonly found in both, but we are interested in the latter one.

We run the following simple regression:

$$\Delta GMVIX_t = a + b * R_t + e_t \qquad (6)$$

The model's prerequisites (e_t follows a White Noise) ,were checked but were not all satisfied (DW = 2.483), because the first differences of the GMVIX are autocorrelated and in evidence of this we can take a look at the autocorrelation and the partial correlation Figure 5, as well as in the respective Table 6. We can see from Figure 5 and Table 6 that DGMVIX might be autocorrelated. And it seems to be an autoregressive model of order 1 to 3. In order to take into consideration this autocorrelation we will try to model the residuals with some different ARMA(p,q) models so that to eliminate the autocorrelation of DGMVIX. We will choose the ARMA model that has the smallest AIK (Akaike Information Criterion). We have checked the various ARMA models and we have found that the model that best fits the data and has the smallest AIK is the ARMA(2,1). So we run the regression (6) with the residuals following an ARMA(2,1) and we get the following results:

$$\Delta GMVIX_t = -0.018246 - 47.73342 * R_t \qquad (6)$$

p-value 0.4817 0.000

R-square=0.1457

We should note here that after fitting the ARMA model in the residuals all the model's prerequisites were satisfied (DW = 2.00).

The R-square is only 0.1457. This number is small indeed, but it gives at least a sense of the relationship of the stock returns and the implied volatility index first differences. At least, we can see that the regression coefficient is significant different from zero at a significance level of 1%. We observe that the estimated intercept of the regression is -0.018246. This means that if the GM stock does not change, the GMVIX is expected to fall by 0.018246.

From the perspective of understanding the relation between changes in the GMVIX and the stock returns of GM, however, the slope coefficient rather than the intercept term tell the story. What it says is that if GM stock falls by 100 basis points, the GMVIX will rise by $GMVIX_t$ =-0.018246-45.73342x(-1.00) = 45.7151%, and if GM stock rises by 100 basis points, the GMVIX will fall by $GMVIX_t$ =-0.018246-45.73342x (1.00) = -45.7516%.

A fall in the market price for the stock should increase its subsequent volatility, and a price rise of the same magnitude should reduce volatility by a comparable amount. However, the existence of a "leverage effect" is most commonly associated with falling, rather rising, stock prices. This raises the question of whether it may be an asymmetrical phenomenon more closely related to negative returns than to leverage per se. To examine this possibility, we add a Down market dummy variable specification to equation (6):

$$\Delta GMVIX_t = a_0 + b_1 * R_t + b_2 R_t * Down + e_t \quad (7)$$

where Down =1 if R is negative, and 0 otherwise. Now the leverage effect is measured by b_1 in an up market and $b_1 + b_2$ in a down market. A significantly negative value for b_2 will indicate that the effect is stronger when prices are falling.

In regression (7) like in (6) we apply an ARMA (2,1) model in the residuals, which we found that has the smallest AIK and we get the following results:

$$DGMVIX_t = -0.2994 - 26.6994 * R_t - 34.3794 * R_t^- \quad (7)$$

p-value	0.00	0.00	0.00

R-square=0.1541

DW = 1.9926

These results suggest indeed that the "leverage effect" is stronger when prices are falling. We can see that when GM stock falls by 100 basis points, the GMVIX will rise by $GMVIX_t$ = -0.2994 – 26.6994x (-1.00) - 34.3794x(-1.00) = 60.7794%, and when GM stock rises by 100 basis points, the GMVIX will fall by

$GMVIX_t$ = -0.2994-26.6994x (1.00) = -26.9988%. We can now clearly see that when the stock price falls (financial turmoil) the implied volatility rises by a very big amount (60.7794%), but when the stock price rises the implied volatility falls only by roughly the half of that amount (-26.9988%). We should note that all the regression coefficients are significant different from zero for a significance level a = 1%, but still the R-square is quite small and we cannot say that the relationship between DGMVIX and R is very strong. At least we can claim that there is such a relationship, even a weak one, and this gives some useful information. Finally, we should mention that the leverage we have observed above is much bigger than the observed in the literature. Of course, this may be attributed to the fact that we have an implied volatility index of an individual stock, which is much more volatile than an implied volatility index of a market index, like VIX.

5.4 Granger Causality Tests

A time series Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients on the lagged X's are statistically significant. It is important to note that the statement "X Granger causes Y" does not imply that Y is the effect or the result of X. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term (see Hamilton, 1994, for a detailed description of the Granger causality test).

In this section we want to test whether ΔGMVIX (R) helps to predict R (ΔGMVIX). The Granger causality test consists of running bivariate regressions of the form

$$\Delta GMVIX_t = c + \sum_{l=1}^{m} a_l \Delta GVIX_{t-l} + \sum_{l=1}^{m} b_l R_{t-l} + u_t \quad (8)$$

$$R_t = c + \sum_{l=1}^{m} a_l R_{t-l} + \sum_{L=1}^{m} b_l \Delta GMVIX_{t-l} + u_t \quad (9)$$

The null hypothesis is $H_0 : b_1 = ... = b_m = 0$.

The interpretation of the null is that R does not Granger-cause ΔGMVIX in the first regression and that ΔGMVIX does not Granger-cause R in the second regression. If both these events occur there is feedback. The test for causality is based on an F-statistic that is calculated by estimating the above expression in both unconstrained and constrained forms (full and reduced model). The full model is the equation (8) and (9) and the reduced model is the one without the $\sum_{l=1}^{m} b_l R_{t-l}$ term for equation (8) and without the $\sum_{l=1}^{m} b_l \Delta GMVIX_{t-l}$ term for equation (9).

$$F = \frac{(SSE_r - SSE_f)/m}{SSE_f /(T - 2m - 1)}$$

where SSE_r, SSE_f = residual sum of squares of the reduced and full model, respectively,

T = total number of observations,

m = number of lags.

F is (Fisher's) F distributed with m and (T-2m-1) degrees of freedom F~F(m,T-2m-1).

We should note here that for regression (8) (for both m=2 and m=1) and we have adjusted to the residuals an ARMA(2,1) model in order to take into consideration the autocorrelation of ΔGMVIX, like we did in regression (6).

Tables 8 and 9 show the results from the Granger causality test using two (m=2) and one lags (m=1) and the results for the respective regressions.

We can see that, for two lags (m=2), R Granger-causes ΔGMVIX (i.e., rejection of the null (p-value = 0.00)). The reverse is also true but for a higher significance level of 5%. Of course, we cannot claim with big certainty that ΔGMVIX Granger-causes R because as we can observe from Table 8, only coefficient b_1 is statistically significant. As for the one lag (m=1) regressions, R Granger-causes ΔGMVIX (i.e., rejection of the null (p-value = 0.00)) and the reverse is also true (i.e., rejection of the null (p-value = 0.005)). Our findings are of particular importance to an investor who has a position in GM options. They suggest that he can use the returns of the underlying asset in order to forecast the future movement of the implied volatility, and hence the option price. The opposite could also be applied in order to forecast the future returns from the implied volatility. Of course, this forecasting ability should not be misunderstood, since the R-square of all the above regressions are very small. This implies that the relationships are rather weak and hence would not provide much useful information for speculation purposes. They just give some sense of what is going on. Finally, we should report that following a general-to-specific approach, we have run similar regressions with higher order lags, but we have found that these do not have any additional forecasting power. Therefore, the investor can use the information contained in the values of ΔGMVIX and R of the past two or even one periods to develop appropriate strategies for hedging purposes.

Null Hypothesis (m=2)	F-Statistic	Probability
R does not Granger Cause ΔGMVIX	17.93*	0.00
ΔGMVIX does not Granger Cause R	4.426**	0.01213
Regression Results: Equation (5) with m=2, R^2 = 0.083		
Coefficient	**Estimate**	**P-Value**
c	-0.002776	0.5692
a_1	0.7827*	0.00
a_2	0.0445	0.8258
b_1	-20.6320*	0.00
b_2	13.2459*	0.0045
Regression Results: Equation (6) with m=2, R^2 = 0.007725		
c	-0.000815	0.1981
a_1	-0.04282	0.1381
a_2	-0.016387	0.5697
b_1	-0.000477**	0.0101
b_2	0.000148	0.4233

Table 8. Granger causality test between R and ΔGMVIX using two lags (m=2). The results from regressions (8) and (9) with m=2, are also reported. One asterisk denotes significance at a 1% significance level, and two asterisks denote significance at a 5% significance level.

Null Hypothesis (m=1)	F-Statistic	Probability
R does not Granger Cause ΔGMVIX	29.36*	0.00
ΔGMVIX does not Granger Cause R	7.8972*	0.005
Regression Results: Equation (5) with m=1, R^2 = 0.0812		
Coefficient	**Estimate**	**P-Value**
c	-0.008571	0.6518
a_1	0.5819	0.00
b_1	-15.2008	0.00
Regression Results: Equation (5) with m=1, R^2 = 0.0065		
c	-0.000769	0.2244
a_1	-0.04193	0.1418
b_1	-0.000504*	0.005

Table 9. Granger causality test between R and ΔGMVIX using two lags (m=1). The results from regressions (8) and (9) with m=1, are also reported. One asterisk denotes significance at a 1% significance level, and two asterisks denote significance at a 5% significance level.

5.5 Spillover Effect

In this section we examine whether there is a relationship between the VIX of the CBOE and the new implied volatility index, of the individual U.S. stock General Motors, GMVIX, which we have constructed with the methodology of VIX. In Figure 7 we can see the evolution of the VIX and GMVIX indices over the period 2001 – 2005. From this Figure we can observe that the two indices have almost the same evolution over the time period observed, except for the late 2005 where we can see that while VIX follows a descending course, GMVIX is rising and has many spikes. This, approximately same movement, gives us a good reason to believe that the two indices are highly correlated. As for the latest time period, the completely opposite evolution between them may be due to the fact that GM stock is falling (so high implied volatility (GMVIX) is observed, "investor's fear gauge"), while S&P 500 is rising (making implied volatility (VIX) to fall). This may be evident from Figure 8. Usually a stock follows the course of the market index in which it belongs, GM belongs in the S&P 500, and we indeed observe GM to roughly follow the evolution of S&P 500. In contrast, at the very end of our observation period we observe the GM and S&P 500 to move to the opposite directions. And that is how the evolution of the two indices is explained.

In order to check the VIX series for unit root we use the augmented Dickey-Fuller test. This test gives has the null hypothesis that a series has unit root. The p-value we get for VIX is 0.04**. This means that we reject the null for a significance level of 5%, but we cannot reject it for a significance level of 1%. Therefore, we cannot say with certainty that VIX does not have a unit root. For that reason, we will thereafter use the first differences of VIX, ΔVIX, for our analysis (which is stationary, p-value of augmented Dickey-Fuller test is 0.00*).

Table 10 shows the cross-correlation between VIX and GMVIX in their first differences. We can see that this correlation is quite small, only 0.0908. This is in contrast to our first observation

Next, we test whether there is a Granger causality relationship between changes in GMVIX and VIX. We use four, two and one lags. The results are shown in Table 11. As we can see ΔVIX does Granger Cause ΔGMVIX for any m used and it does so in significance level of 1%. Nevertheless, the reverse is not true. We can see that ΔGMVIX does not Granger Cause ΔVIX in any lag used. These results suggest that the changes in the GMVIX cannot forecast the changes in VIX, but the changes in VIX can forecast the changes in the GMVIX.

In Figure 9, we can see the relationship between the VIX and GMVIX first differences. We can observe that there is a slightly upward slope and this is evidence for a positive correlation between the two indices.

Finally, the following unidirectional regressions are performed in order to study further the presence of any spillover effect:

$$\Delta GMVIX_t = c + a * \Delta VIX_t + u_t \quad (10)$$

$$\Delta GMVIX_t = c + b * \Delta VIX_{t-1} + u_t \quad (11)$$

$$\Delta GMVIX_t = c + a * \Delta VIX_t + b * \Delta VIX_{t-1} + u_t \quad (12)$$

In every of the above regressions we have adjusted an ARMA(2,1) model to the residuals. Equation (10) shows whether there is a contemporaneous relationship between ΔGMVIX and ΔVIX. Equation (11) checks whether the VIX index leads the GMVIX volatility index. Equation (12) examines whether there is both a contemporaneous and a lead relationship between the two indices.

Table 12 show the results of the equations 10 to 11, respectively. We can see that in every regression the coefficients are statistically significant in a significance level of 1%. These results suggest that there is both a contemporaneous and a lead relationship between the two indices, although these relationship are rather weak since all the equations of interest have very small R–square. And this seems to be consistent with the earlier Granger causality tests.

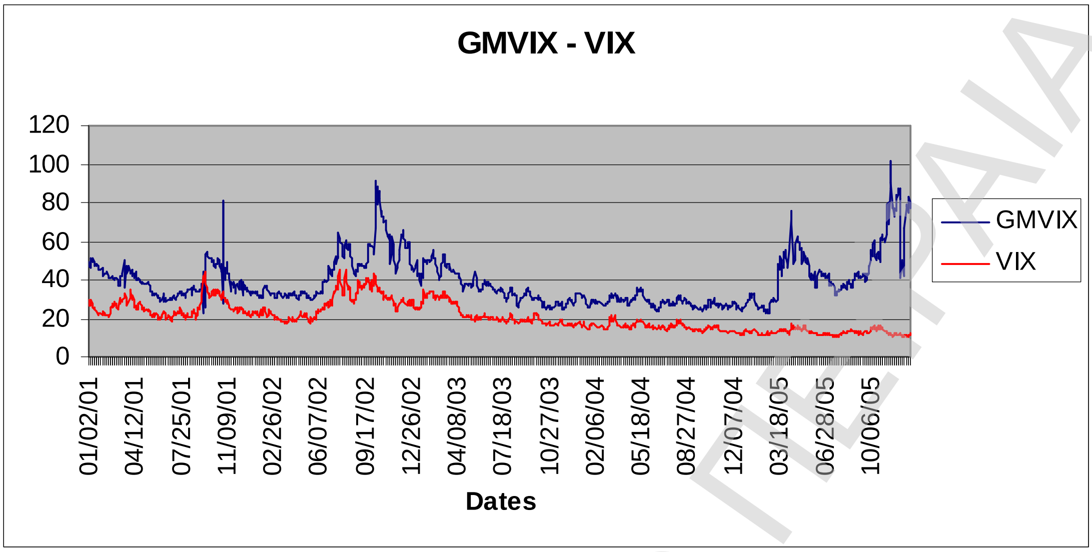


Figure 7. Evolution of VIX and GMVIX for the period 2/01/2001 – 31/12/2005

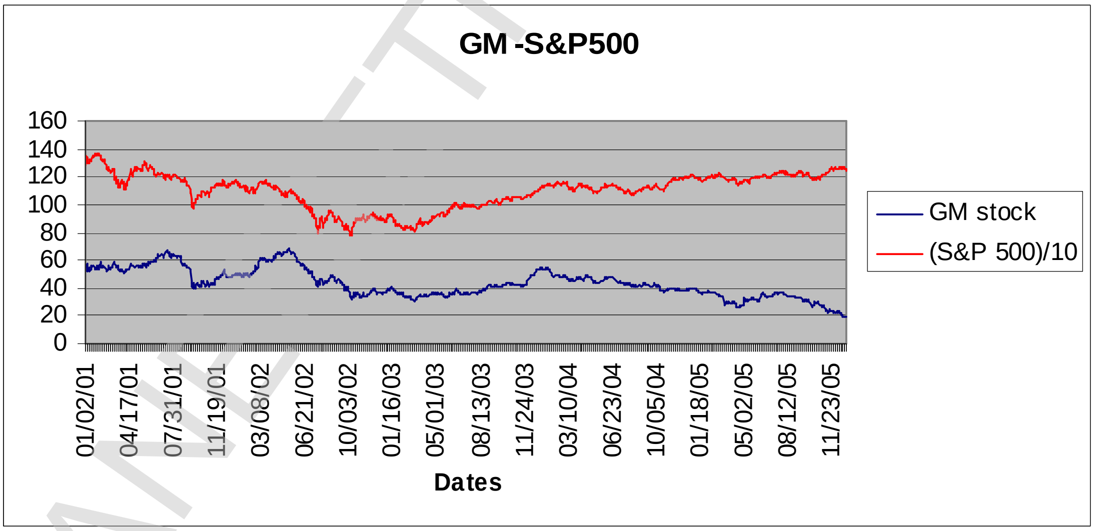


Figure 8. Evolution of GM stock price and S&P 500 index price (divided by 10) for the period 2/01/2001 – 31/12/2005

	ΔVIX	ΔGMVIX
ΔVIX	1	0.0908
ΔGMVIX	0.0908	1

Table 10. Cross-correlation between VIX and GMVIX in the first differences

Null Hypothesis (m=4)	**F-Statistic**	**Probability**
ΔVIX does not Granger Cause ΔGMVIX	6.75*	0.00
ΔGMVIX does not Granger Cause ΔVIX	0.4217	0.793
Null Hypothesis (m=2)	**F-Statistic**	**Probability**
ΔVIX does not Granger Cause ΔGMVIX	12.6212*	0.00
ΔGMVIX does not Granger Cause ΔVIX	0.03	0.97023
Null Hypothesis (m=1)	**F-Statistic**	**Probability**
ΔVIX does not Granger Cause ΔGMVIX	13.7823*	0.00021
ΔGMVIX does not Granger Cause ΔVIX	0.04950	0.8239

Table 11. Granger causality test between R and ΔGMVIX using four, two and one lags (m=4, m=2, m=1). One asterisk denotes significance at a 1% significance level, and two asterisks denote significance at a 5% significance level.

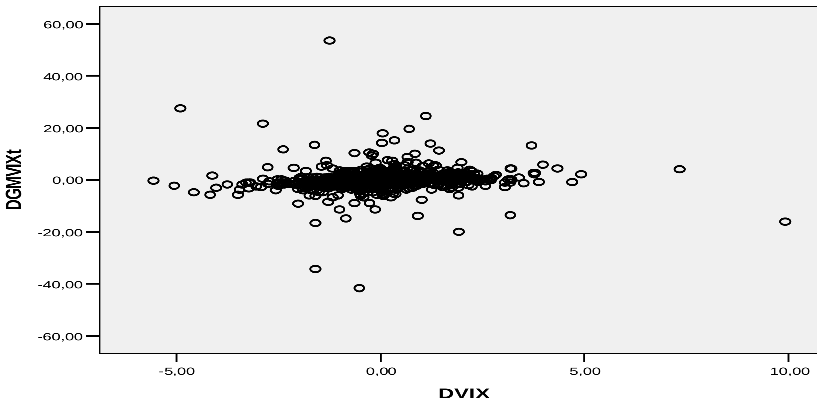


Figure 9. Scatter plot of first differences in VIX and first differences in GMVIX.

Regression Results: Equation (10) with m=1, $R^2 = 0.074$		
Coefficient	**Estimate**	**P-Value**
c	0.0255	0.5637
a	0.3742*	0.00
Regression Results: Equation (11) with m=1, $R^2 = 0.0757$		
c	0.0289	0.5072
b	0.4010*	0.00
Regression Results: Equation (12) with m=1, $R^2 = 0.08597$		
c	0.02866	0.4845
a	0.30466*	0.00
b	0.3332*	0.00

Table 12. The results from regressions (10), (11) and (12) are reported. One asterisk denotes significance at a 1% significance level, and two asterisks denote significance at a 5% significance level.

6. FORECASTING CALLS AND PUTS

6.1 Moneyness and Maturity dimension

In this final section will try to test whether the implied volatility index of GM can be used in order to forecast option prices of GM. In order to do that we have to construct in some way the option series that we want to forecast. For that purpose, we separate the options regarding their moneyness dimension, as follow:

Call options are regarded in-the-money (ITM) when $S/K > 1.02$ (S is the Stock Price and K is the Strike Price), at-the-money (ATM) when $0.98 < S/K < 1.02$ and out-of-the-money (OTM) when $S/K < 0.98$. Put options are regarded ITM when $S/K < 0.98$, ATM when $0.98 < S/K < 1.02$ and OTM when $S/K > 1.02$. For the purposes of our analysis, because there are many such options (ITM, ATM and OTM), we use the first ITM and OTM options (those that are closest to the ATM) and the closest ATM option (the one for which S/K is closest to 1). Hence, we have 3 series of call and 3 series of put options regarding their moneyness.

We also separate the options regarding their maturity dimension, as follows:

We have the shortest to expiry options if their time to maturity is less than 40 days, the second shortest to expiry options if their time to maturity is between 40 and 70 days, and the third shortest to expiry options if their time to maturity is more than 70 days. Therefore, we also separate the options regarding their time to maturity in 3 different classes.

Hence, we get 9 series of call options (ITM, ATM and OTM for every of the three maturity classes) and 9 series of put options (ITM, ATM and OTM for every of the three maturity classes). We symbolize them as *c_itm1, c_itm2, c_itm3, c_atm1, c_atm2, c_atm3, c_otm1, c_otm2, c_otm3, p_itm1, p_itm2, p_itm3, p_atm1, p_atm2, p_atm3,*

p_otm1, p_otm2, p_otm3, respectively. We will also refer to these series as **Real series** because they are real prices that exist in the market.

We will also construct options series with another way. We keep the same means of maturity dimension, but we get the moneyness dimension through interpolation. To make this more concrete, we get the ITM call or put price of moneyness 2% (*S/K = 1.02* for calls and *S/K = 0.98* for puts) via interpolation, even when these calls-puts does not exist. Therefore, we get the price that would more possibly have the option with moneyness 2%, and we find this price by interpolating between the market prices of the options that are above and below this moneyness level. We do the same for ATM options and OTM options. By this way, we also get 9 series of call and 9 series of put prices, which we also symbolize as *c_itm1, c_itm2, c_itm3, c_atm1, c_atm2, c_atm3, c_otm1, c_otm2, c_otm3, p_itm1, p_itm2, p_itm3, p_atm1, p_atm2, p_atm3, p_otm1, p_otm2, p_otm3,* but we will refer to these series as **Interpolated series**, because they are derived via interpolation and they do not represent existing prices in the market.

6.2 Summary Statistics of Option Series

In Table 13 we report the summary statistics for the Real series of calls and puts. And in Tables 14 we report the summary statistics for the respective Interpolated series. We can see that in general the mean price of all options increases as the time to maturity increases and this of course is expected since there is more time (higher probability) for the option to become in-the-money. Since zero probabilities are reported for all our time series' Jarque-Bera statistics, we are led to the rejection of the null hypothesis of a normal distribution. This means that extreme volatility changes are assigned higher probabilities with regard to those under a normal distribution.

We can observe that ATM and OTM call and put Real series have smaller mean than those of the Interpolated series. On the other hand, ITM call and put Real series have higher mean than those of the Interpolated series. We can also observe that ATM and ITM Real call and put series have higher maximums and higher standard deviations than the respective ATM and ITM Interpolated call and put series. Contrary, OTM Real call and put series have smaller maximums and smaller standard deviations than the respective OTM Interpolated call and put series. These results give us a good reason to believe that the Real and Interpolated series are quite different and forecasting them will be a different matter.

Finally, from Figures 10 (autocorrelogram and Partial autocorrelogram of c_atm2), we can observe that the ATM Real shortest call series are autocorrelated. The same patterns have also been observed in every other series, both Real and Interpolated, and hence we can say that every series is autocorrelated.

Real series	**Mean**	**Median**	**Max**	**Min**	**Std. Dev.**	**Skew.**	**Kurtos.**	**Jarque-Bera P-value**
c_atm1	1.19	1	20.3	0.0	1.204	6.97	86.86	0.00
c_atm2	1.98	1.85	5.65	0.0	0.837	0.85	3.69	0.00
c_atm3	2.91	2.70	6.45	1.00	1.065	0.71	2.98	0.00
c_itm1	2.81	2.52	13.0	0.0	1.30	1.46	6.99	0.00
c_itm2	3.50	3.25	7.25	1.52	1.21	0.88	3.13	0.00
c_itm3	4.39	4.05	20.0	2.00	1.54	2.15	16.76	0.00
c_otm1	0.36	0.30	4.20	0.0	0.35	2.34	15.72	0.00
c_otm2	1.00	0.92	3.15	0.0	0.54	0.82	3.58	0.00
c_otm3	1.85	1.75	5.75	0.32	0.817	0.67	3.32	0.00
p_atm1	1.25	1.10	17.6	0.00	0.91	5.54	87.29	0.00
p_atm2	2.20	2.10	9.05	0.42	0.86	1.44	8.89	0.00
p_atm3	3.30	3.20	27.0	0.7	1.20	6.12	117.06	0.00
p_itm1	2.95	2.70	17.6	0.62	1.37	2.17	17.22	0.00
p_itm2	3.73	3.40	22.4	1.40	1.44	3.36	34.64	0.00
p_itm3	4.74	4.40	27.0	2.05	1.52	3.05	37.79	0.00
p_otm1	0.45	0.38	2.52	0.00	0.37	1.44	5.98	0.00
p_otm2	1.22	1.13	3.85	0.20	0.56	0.99	4.31	0.00
p_otm3	2.21	2.10	5.90	0.22	0.81	0.61	3.38	0.00

Table 13. Summary Statistics for Real call and put Series

Interpo-lated series	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Jarque-Bera P-value
c_atm1	1.23	1.09	13.0	0.0	0.74	5.13	62.27	0.00
c_atm2	2.03	1.86	4.60	0.0	0.65	0.60	2.78	0.00
c_atm3	2.95	2.73	6.13	1.46	0.92	0.65	2.70	0.00
c_itm1	1.68	1.50	13.0	0.0	0.80	4.66	49.99	0.00
c_itm2	2.47	2.25	5.26	0.0	0.71	0.56	2.72	0.00
c_itm3	3.37	3.10	6.66	1.67	0.97	0.68	2.62	0.00
c_otm1	0.85	0.73	13.0	0.0	0.71	6.41	85.42	0.00
c_otm2	1.60	1.47	3.85	0.0	0.58	0.63	2.89	0.00
c_otm3	2.52	2.31	5.78	1.02	0.86	0.63	2.84	0.00
p_atm1	1.31	1.22	17.6	0.04	0.77	8.61	107.15	0.00
p_atm2	2.23	2.10	9.05	0.75	0.70	1.68	12.35	0.00
p_atm3	3.32	3.22	27.0	1.54	1.10	7.74	163.15	0.00
p_itm1	1.81	1.69	17.6	0.17	0.79	7.14	130.26	0.00
p_itm2	2.71	2.54	9.05	1.12	0.77	1.46	9.48	0.00
p_itm3	3.80	3.67	27.0	1.55	1.14	6.61	130.17	0.00
p_otm1	0.98	0.88	17.6	0.0	0.75	9.78	191.71	0.00
p_otm2	1.87	1.77	9.05	0.58	0.70	2.27	17.31	0.00
p_otm3	2.95	2.86	27.0	1.25	1.08	8.48	183.5	0.00

Table 14. Summary Statistics for Interpolated call and put series

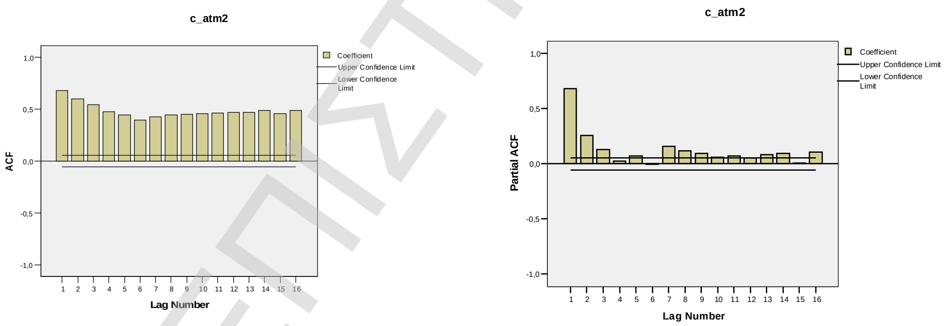


Figure 10. Autocorrelogram and Partial autocorrelogram of Real ATM call of shortest expiry.

6.3 Forecasting options

In order to test the forecasting ability of GMVIX in the option prices, we run the following regressions:

$$calls_t = c + b * GMVIX_{t-1} + e_t \quad (13)$$

$$puts_t = c + b * GMVIX_{t-1} + e_t \quad (14)$$

$$\Delta calls_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t \quad (15)$$

$$\Delta puts_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t \quad (16)$$

where Δcalls are the daily first differences of the call prices and Δputs the daily first differences of the put prices. Alternatively, we could insert in regressions (13) and (14) as an independent variable the stock price GM

$$(calls_t = c + b_1 * GMVIX_{t-1} + b_2 * GM_{t-1} + e_t),$$

but this would overestimate the coefficients and the R-square and general give spurious results, since GM is non-stationary. This is the reason that we have decided not to include GM in regressions (13) and (14). Contrary, in equations (15) and (16) we have taken the returns of GM (R) and so there is no problem with non-stationarity. Because every option series is autocorrelated and this makes the residuals autocorrelated we have fitted an ARMA model to the residuals.

We run the above regressions for both Real option series and Interpolated series, and the results are reported (p-values in brackets) in Tables 15 and 17 for Real series and equations (13) to (16), and in Tables 16 and 18 for Interpolated series, respectively.

We can see in Table 15 that some coefficients are statistically significant in 1%, in 5% and some are not at all. More specifically, for call options we can see that ITM options can not be predicted (insignificant coefficient b), ATM options are better predicted as the time to maturity is heightened, and OTM options can generally be predicted, with *c_otm2* be more significant than the other c_otm. In general R-squares are satisfactory high. The better predicted Real call series is the ATM calls for second-shortest expiry, *c_atm2*, because it has a statistically significant coefficient in 1% level and has the highest R-square comparable with the other statistically significant coefficients in 1% level.

On the other hand, from Table 16 we can see that GMVIX does not have any forecasting ability in the Interpolated series. R-squares are higher from those of Table 15, but this fact is insignificant to the forecasting ability of GMVIX since all coefficients are statistically insignificant. This might be attributed to the fact that the Interpolated series are not true option prices but hypothetical.

In Table 15 for the Put series, we can see that some coefficients are statistically significant in 1%, in 5% and some are not at all. More specifically, we can see that ITM options can be better predicted for second-shortest expiry, ATM options can be predicted only for shortest expiry, and OTM options can be predicted for shortest and second-shortest expiry. In general R-squares are good enough. The better predicted Real put series is the OTM puts for second-shortest expiry, p_otm2, because it has a statistically significant coefficient in 1% level and has the highest R-square comparable with the other statistically significant coefficients in 1% level.

On the other hand, from Table 16 we can see that only p_atm1 is significant in 5%, p_itm2 in 10% and p_otm1 in 10%. R-squares are higher from those of Table 15, but this does not mean that GMVIX predicts better the Interpolated than the Real series, since the coefficients significance is what matters. Hence, we can claim that in the case of puts, as with calls, GMVIX can better predict the Real series. This might be attributed to the fact that the Interpolated series are not true option prices but hypothetical.

$calls_t = c + b * GMVIX_{t-1} + e_t$ (13) (***Real call series)***

Real series	c	b	R-square
c_atm1	0.99 (0.00)*	0.004814 (0.1293)	0.30
c_atm2	1.1828 (0.0013)*	0.01014 (0.00)*	0.54
c_atm3	2.4453 (0.00)*	0.009206 (0.0148)**	0.71
c_itm1	2.67678 (0.00)*	-0.005675 (0.3727)	0.50
c_itm2	2.7887 (0.00)*	0.004687 (0.1688)	0.68
c_itm3	3.814 (0.00)*	0.006544 (0.1002)	0.65
c_otm1	0.2133 (0.00)*	0.003741 (0.0235)**	0.42
c_otm2	0.652119 (0.00)*	0.007164 (0.0068)*	0.53
c_otm3	1.5393 (0.00)*	0.007032 (0.0373)**	0.68
$puts_t = c + b * GMVIX_{t-1} + e_t$ (14)		(***Real put series)***	
p_atm1	0.1957 (0.7340)	0.007622 (0.0086)*	0.18
p_atm2	2.3114 (0.00)*	-0.004252 (0.6646)	0.47
p_atm3	3.088 (0.00)*	0.00329 (0.6163)	0.41
p_itm1	2.7496 (0.00)*	-0.00889 (0.0183)**	0.37
p_itm2	2.2861 (0.0013)*	0.01344 (0.0029)*	0.43
p_itm3	4.2385 (0.00)*	0.006284 (0.2834)	0.53
p_otm1	0.2527 (0.00)*	0.04939 (0.0051)*	0.49
p_otm2	0.7408 (0.00)*	0.01063 (0.0011)*	0.64
p_otm3	1.8566 (0.00)*	0.008467 (0.1231)	0.72

Table 15. Results from regressions (13) and (14) for Real call and put series. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

$calls_t = c + b * GMVIX_{t-1} + e_t$ (13) (***Interpolated call series)***

Real series	c	b	R-square
c_atm1	1.4130 (0.00)*	-0.0045 (0.4314)	0.4889
c_atm2	1.7177 (0.00)*	0.001089 (0.5383)	0.8565
c_atm3	2.8394 (0.00)*	0.000163 (0.9456)	0.9335
c_itm1	0.8959 (0.3699)	0.005719 (0.3411)	0.4954
c_itm2	2.073 (0.00)*	0.0000796 (0.9647)	0.8621
c_itm3	3.2285 (0.00)*	0.00104 (0.9623)	0.933
c_otm1	0.8737 (0.00)*	-0.00603 (0.9032)	0.4441
c_otm2	1.3181 (0.00)*	0.002272 (0.1594)	0.8594
c_otm3	2.4099 (0.00)*	0.000653 (0.7859)	0.9379
$puts_t = c + b * GMVIX_{t-1} + e_t$ (14)		(***Interpolated put series)***	
p_atm1	0.3641 (0.5856)	0.005916 (0.0265)**	0.27011
p_atm2	1.9022 (0.00)*	0.0037 (0.4153)	0.7839
p_atm3	3.155 (0.00)*	0.002839 (0.6311)	0.5232
p_itm1	1.1709 (0.0433)**	0.000483 (0.8619)	0.3602
p_itm2	2.1936 (0.00)*	0.006537 (0.0563)***	0.7606
p_itm3	3.635 (0.00)*	0.002168 (0.7192)	0.56467
p_otm1	0.7887 (0.00)*	0.004645 (0.0814)***	0.2022
p_otm2	1.5937 (0.00)*	0.003834 (0.4792)	0.7451
p_otm3	2.7797 (0.00)*	0.003427 (0.5819)	0.4988

Table 16. Results from regressions (13) and (14) for Interpolated call and put series. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

Now, in Table 17 (Panel A) we can see the results from equation (15). We can see that in most cases ΔGMVIX is statistically significant at least in 10%, but R in most cases is not. In the cases where ***R*** is not statistically significant we have reported the results of the equation (15) without R. We can also see that all R-squares are near 0.20 and 0.30, which implies a good relationship between the variables, but not a very strong for the purpose of forecasting. Hence, we can say that the first differences of GMVIX and the returns of GM can give us a clue about the movement of the future call price, but not a perfect tool for forecasting. The better series forecasted are the ITM calls of second and third expiry.

As for the Interpolated series, the results of equation (15) can be seen in Table 18 (Panel A). In contrast with the Real series we can see that ΔGMVIX is statistically insignificant in every case but for Δc_itm1. We can also see that in some cases R is statistically significant (which is rather unrealistic), but the R-squares are quite small and so we can not claim about any forecasting ability. We can also see here that we can better forecast the Real series than the Interpolated series.

Finally, in Table 17 (Panel B) we report the results from equation (16) for Real series. We observe that ΔGMVIX is statistically significant only in the cases of atm1, itm2, itm3 and otm2, and R is statistically significant only in the cases of itm1, itm2, itm3 and otm1. We can see that the better results are for Δp_itm2 and Δp_itm3 which have significant coefficients in 1% level and also high enough R-squares near 0.40.

In Table 18 (Panel B), we can see that in some cases ΔGMVIX is statistically significant but only for 5% or 10% significance level. R-squares are worse than the ones of the Real put series and we can again say that Real series can be better predicted from Interpolated series.

To conclude this final section, we can say that in general Real series can better be predicted than Interpolated series and this may be due to the fact that Interpolated option series are not real option prices which are observed in the market, but they are constructed and hence hypothetical market prices. In general, we have observed that using GMVIX levels, equations (13) and (14), OTM options are better forecasted than ATM and ITM options, and this may be attributed to the fact that GMVIX is indeed constructed from OTM options. But, when we use the first differences of GMVIX and the returns of GM, equations (15) and (16), we observe that we can better forecast the ITM options and more precisely the second and third expiry ITM options. In general it seems that OTM and ITM options can more easily be forecasted. This is rational, since ATM options have strike price equal to the stock price and hence they can easily become OTM or ITM, with big probability. So, their prices may easily change, making them hard to forecast. On the other hand, stock price must move quite rapidly for OTM and ITM option prices to make big movements, and that's why we can more easily forecast them.

We can finally say that Stock returns have little information regarding the future option prices. This was expected, since tomorrow's option prices depend on tomorrow's stock price and not yesterday's stock price. On the contrast, we can claim that the implied volatility index GMVIX, both in levels and in first differences, has some information regarding the future option prices, though this information is just elementary and does not constitute an artificial device for speculation purposes. But, it could instead be used for delta hedging purposes.

Panel A: $\Delta calls_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t$ (15) (***Real call series)***

Real series	c	b_1	b_2	R-square
Δc_atm1	-0.001203 (0.0033)*	0.009817 (0.0613)***	0.1457 (0.69)	0.2869
Δc_atm1	-0.001284 (0.00)*	0.008409 (0.0138)**	--	0.2868
Δc_atm2	-0.000923 (0.2636)	0.013225 (0.0003)*	0.4078 (0.2611)	0.2869
Δc_atm2	-0.001162 (0.1946)	0.010387 (0.0013)**	--	0.2863
Δc_atm3	-0.000954 (0.5934)	0.014573 (0.00)*	1.0408 (0.0436)**	0.2486
Δc_atm3	-0.001579 (0.4398)	0.009613 (0.0077)**	--	0.2458
Δc_itm1	-0.000719 (0.4899)	0.009381 (0.3683)	1.9863 (0.0146)**	0.2958
Δc_itm1	-0.000918 (0.4682)	--	1.4481 (0.0031)*	0.2947
Δc_itm2	-0.000933 (0.4910)	0.017092 (0.00)*	2.0967 (0.00)*	0.2849
Δc_itm3	-0.000985 (0.4455)	0.025616 (0.00)*	2.7839 (0.00)*	0.3461
Δc_otm1	-0.000404 (0.00)*	0.004364 (0.0538)***	-0.1802 (0.2467)	0.2391
Δc_otm1	-0.000313 (0.00)*	0.0058 (0.00)*	--	0.2382
Δc_otm2	-0.00077 (0.4608)	0.006549 (0.0377)**	-0.2787 (0.3985)	0.2978
Δc_otm2	-0.000599 (0.8432)	0.007941 (0.0041)*	--	0.2972
Δc_otm3	-0.000599 (0.8432)	0.008638 (0.0350)**	0.4896 (0.3138)	0.2624
Δc_otm3	-0.000920 (0.7681)	0.006981 (0.0627)***	--	0.2617

Table 17, Panel A. Results from regression (15) for Real call. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

Panel B: $\Delta puts_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t$ (16) (***Real put series)***

Real series	c	b_1	b_2	R-square
Δp_atm1	-0.000637 (0.0043)*	0.011596 (0.0128)**	0.3821 (0.3263)	0.3728
Δp_atm1	-0.000829 (0.00)*	0.008091 (0.0172)**	--	0.3720
Δp_atm2	-0.001377 (0.3254)	0.001313 (0.9067)	-0.3543 (0.6689)	0.3161
Δp_atm3	-0.001169 (0.6480)	0.008598 (0.3187)	0.5236 (0.4687)	0.3372
Δp_itm1	-0.000655 (0.4850)	0.006443 (0.2025)	1.8515 (0.00)*	0.3833
Δp_itm1	-0.000766 (0.426)	--	1.5014 (0.00)*	0.3828
Δp_itm2	-0.000967 (0.2434)	0.0306 (0.00)*	2.3639 (0.00)*	0.409
Δp_itm3	-0.000935 (0.7778)	0.01809 (0.0049)*	2.284 (0.00)*	0.399
Δp_otm1	-0.000393 (0.2502)	0.0022 (0.3869)	-0.3233 (0.1073)	0.1917
Δp_otm1	-0.000427 (0.2694)	--	-0.4349 (0.0267)**	0.1911
Δp_otm2	-0.000686 (0.5365)	0.009591 (0.0113)**	-0.3550 (0.2808)	0.2309
Δp_otm2	-0.00045 (0.6943)	0.011019 (0.0012)*	--	0.2299
Δp_otm3	-0.0000888 (0.9821)	0.008354 (0.1947)	0.4397 (0.4964)	0.1980
Δp_otm3	-0.000934 (0.9208)	0.007159 (0.2185)	--	0.1975

Table 17, Panel B. Results from regression (16) for Real put series. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

Panel A: $\Delta calls_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t$ (15) ***(Interpolated call series)***

Interpolated series	c	b_1	b_2	R-square
Δc_atm1	-0.000945 (0.0373)**	-0.00454 (0.64159)	-0.3293 (0.5663)	0.2059
Δc_atm2	-0.001238 (0.2679)	0.000218 (0.9131)	-0.2845 (0.2944)	0.1271
Δc_atm3	-0.001357 (0.3571)	0.001884 (0.4438)	0.4385 (0.0389)**	0.0729
Δc_itm1	-0.000291 (0.6603)	0.01217 (0.0259)**	0.8698 (0.0389)**	0.2268
Δc_itm2	-0.00128 (0.2408)	0.000205 (0.9204)	-0.010925 (0.9680)	0.1251
Δc_itm3	-0.001208 (0.7588)	0.00112 (0.6894)	0.4998 (0.2115)	0.08
Δc_otm1	-0.000966 (0.0199)	-0.004392 (0.6395)	-0.6378 (0.2541)	0.2211
Δc_otm2	-0.00119 (0.2590)	0.000657 (0.7256)	-0.5178 (0.0464)**	0.1305
Δc_otm2	-0.001201 (0.2583)	--	-0.5490 (0.0158)**	0.1304
Δc_otm3	-0.00128 (0.3642)	0.001756 (0.5111)	0.2273 (0.4720)	0.055

Table 18, Panel A. Results from regression (15) for Interpolated call series. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

Panel B: $\Delta puts_t = c + b_1 * \Delta GMVIX_{t-1} + b_2 * R_{t-1} + e_t$ (16) (***Interpolated put series)***

Interpolated series	c	b_1	b_2	R-square
Δp_atm1	-0.000675 (0.0017)*	0.01048 (0.0139)**	0.388 (0.1604)	0.3659
Δp_atm1	-0.000849 (0.0021)	0.006386 (0.0263)**	--	0.3650
Δp_atm2	-0.001177 (0.3739)	0.004215 (0.4676)	-0.06626 (0.8992)	0.1448
Δp_atm3	-0.001085 (0.8339)	0.004968 (0.3969)	0.2139 (0.7619)	0.3866
Δp_itm1	-0.000612 (0.0123)**	0.009966 (0.0146)**	0.8922 (0.0008)*	0.366
Δp_itm2	-0.001276 (0.3099)	0.009374 (0.0591)***	0.3964 (0.4266)	0.2032
Δp_itm2	-0.00154 (0.2416)	0.007409 (0.0304)**	--	0.2023
Δp_itm3	-0.0001015 (0.8406)	0.007265 (0.1744)	0.7252 (0.2881)	0.4013
Δp_otm1	-0.000717 (0.0044)*	0.008941 (0.0464)**	0.01189 (0.9695)	0.3766
Δp_otm1	-0.000722 (0.0013)*	0.008815 (0.0035)*	--	0.3765
Δp_otm2	-0.001225 (0.3694)	0.002853 (0.6671)	-0.479 (0.4073)	0.1511
Δp_otm3	-0.001178 (0.8268)	0.003801 (0.5346)	-0.2588 (0.7349)	0.3921

Table 18, Panel B. Results from regressions (16) for Interpolated put series. One asterisk denotes significance at a 1% significance level, two asterisks denote significance at a 5% significance level and three asterisks denote significance at 10%.

7. CONCLUSION

We have constructed an implied volatility index on an individual stock price, General Motors. We have used the new VIX methodology to construct it and we called it GMVIX. Next, the properties of GMVIX have been examined. In line with Whaley (2000) and Giot (2002a), we have found that the index can be used as a gauge of the investor's fear. We also found that leverage effect is true and it is also asymmetric, "leverage effect" is stronger when prices are falling. Moreover, the results from Granger causality tests imply that the investor can use the information contained in the values of GM of the past two or one periods to forecast the future GMVIX and hence to develop a profitable option strategy. GMVIX can also forecast the future GM returns but the relationship is weaker. We have also observed a spillover effect between GMVIX and VIX, VIX can forecast GMVIX but the opposite is not true. This was rather expected since GM is included in S&P 500.

Finally, we have taken ATM, ITM and OTM, with maturities near, second near and third near to maturity, call and put series. We constructed Interpolated series and Real series and we test whether GMVIX and GM have any predictive power over these options. We have found that in general GMVIX has some predictive power but GM has not. This predictive power is weaker and almost non-existent in the case of the Interpolated series. Furthermore, OTM options seem to be easier predicted by GMVIX, since GMVIX is constructed by OTM option prices. Despite these results, the reader should not be confused. Our results do not indicate any speculative device, but can just provide some useful information regarding future option movements. Hence information content in GMVIX could be used for hedging purposes.

Future research should investigate whether GMVIX can forecast the future market volatility. This can be done by means of statistical analysis or under a more practical metric such as Value-at-Risk by performing the appropriate Backtesting.

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APPENDIX 1

We represent here a sample Data set of a day's (11/22/05) option series and only for the two nearest expiration dates

symbol	date	expiration	strike	call/put	ask	bid	volume	stock price
GM	11/22/05	12/17/05	5	C	18.4	18.1	40	23.27
GM	11/22/05	12/17/05	5	P	0.05	0	0	23.27
GM	11/22/05	12/17/05	7.5	C	15.9	15.6	0	23.27
GM	11/22/05	12/17/05	7.5	P	0.05	0	0	23.27
GM	11/22/05	12/17/05	10	C	13.4	13.2	100	23.27
GM	11/22/05	12/17/05	10	P	0.05	0	0	23.27
GM	11/22/05	12/17/05	12.5	C	10.9	10.7	0	23.27
GM	11/22/05	12/17/05	12.5	P	0.1	0.05	594	23.27
GM	11/22/05	12/17/05	15	C	8.5	8.3	10	23.27
GM	11/22/05	12/17/05	15	P	0.2	0.1	403	23.27
GM	11/22/05	12/17/05	17.5	C	6.1	5.9	27	23.27
GM	11/22/05	12/17/05	17.5	P	0.3	0.25	993	23.27
GM	11/22/05	12/17/05	20	C	3.8	3.7	400	23.27
GM	11/22/05	12/17/05	20	P	0.5	0.45	7211	23.27
GM	11/22/05	12/17/05	22.5	C	1.9	1.8	5126	23.27
GM	11/22/05	12/17/05	22.5	P	1.1	1.05	8731	23.27
GM	11/22/05	12/17/05	25	C	0.75	0.65	6311	23.27
GM	11/22/05	12/17/05	25	P	2.5	2.35	2429	23.27
GM	11/22/05	12/17/05	27.5	C	0.25	0.2	1852	23.27
GM	11/22/05	12/17/05	27.5	P	4.5	4.4	107	23.27
GM	11/22/05	12/17/05	30	C	0.1	0.05	715	23.27
GM	11/22/05	12/17/05	30	P	6.9	6.6	1503	23.27
GM	11/22/05	12/17/05	32.5	C	0.05	0	136	23.27
GM	11/22/05	12/17/05	32.5	P	9.4	9.1	650	23.27
GM	11/22/05	12/17/05	35	C	0.05	0	16	23.27
GM	11/22/05	12/17/05	35	P	11.9	11.6	19	23.27
GM	11/22/05	12/17/05	37.5	C	0.05	0	3	23.27
GM	11/22/05	12/17/05	37.5	P	14.4	14.1	10	23.27
GM	11/22/05	12/17/05	40	C	0.05	0	6	23.27
GM	11/22/05	12/17/05	40	P	16.9	16.6	0	23.27
GM	11/22/05	12/17/05	42.5	C	0.05	0	0	23.27
GM	11/22/05	12/17/05	42.5	P	19.4	19.1	0	23.27
GM	11/22/05	12/17/05	45	C	0.05	0	0	23.27
GM	11/22/05	12/17/05	45	P	21.9	21.6	0	23.27
GM	11/22/05	01/21/06	2.5	C	20.9	20.6	0	23.27
GM	11/22/05	01/21/06	2.5	P	0.05	0	0	23.27
GM	11/22/05	01/21/06	5	C	18.4	18.1	70	23.27
GM	11/22/05	01/21/06	5	P	0.05	0	70	23.27
GM	11/22/05	01/21/06	7.5	C	16	15.7	50	23.27
GM	11/22/05	01/21/06	7.5	P	0.1	0.05	20	23.27

GM	11/22/05	01/21/06	10	C	13.6	13.4	78	23.27
GM	11/22/05	01/21/06	10	P	0.2	0.2	2510	23.27
GM	11/22/05	01/21/06	12.5	C	11.2	11	0	23.27
GM	11/22/05	01/21/06	12.5	P	0.4	0.3	980	23.27
GM	11/22/05	01/21/06	15	C	8.9	8.7	10	23.27
GM	11/22/05	01/21/06	15	P	0.55	0.45	955	23.27
GM	11/22/05	01/21/06	17.5	C	6.8	6.5	0	23.27
GM	11/22/05	01/21/06	17.5	P	0.9	0.8	621	23.27
GM	11/22/05	01/21/06	20	C	4.7	4.6	273	23.27
GM	11/22/05	01/21/06	20	P	1.4	1.3	3359	23.27
GM	11/22/05	01/21/06	22.5	C	3	2.9	3125	23.27
GM	11/22/05	01/21/06	22.5	P	2.2	2.1	7204	23.27
GM	11/22/05	01/21/06	25	C	1.75	1.6	2935	23.27
GM	11/22/05	01/21/06	25	P	3.5	3.4	1849	23.27
GM	11/22/05	01/21/06	27.5	C	0.9	0.85	2151	23.27
GM	11/22/05	01/21/06	27.5	P	5.1	4.9	168	23.27
GM	11/22/05	01/21/06	30	C	0.45	0.35	372	23.27
GM	11/22/05	01/21/06	30	P	7.1	6.9	287	23.27
GM	11/22/05	01/21/06	32.5	C	0.2	0.1	31	23.27
GM	11/22/05	01/21/06	32.5	P	9.4	9.2	569	23.27
GM	11/22/05	01/21/06	35	C	0.1	0.05	30	23.27
GM	11/22/05	01/21/06	35	P	11.9	11.6	102	23.27
GM	11/22/05	01/21/06	37.5	C	0.1	0.05	186	23.27
GM	11/22/05	01/21/06	37.5	P	14.4	14.1	15	23.27
GM	11/22/05	01/21/06	40	C	0.05	0	59	23.27
GM	11/22/05	01/21/06	40	P	16.9	16.6	2	23.27
GM	11/22/05	01/21/06	45	C	0.05	0	1	23.27
GM	11/22/05	01/21/06	45	P	21.9	21.6	0	23.27
GM	11/22/05	01/21/06	50	C	0.05	0	0	23.27
GM	11/22/05	01/21/06	50	P	26.9	26.6	0	23.27
GM	11/22/05	01/21/06	55	C	0.05	0	0	23.27
GM	11/22/05	01/21/06	55	P	31.9	31.6	0	23.27
GM	11/22/05	01/21/06	60	C	0.05	0	5	23.27
GM	11/22/05	01/21/06	60	P	36.9	36.6	0	23.27
GM	11/22/05	01/21/06	65	C	0.05	0	0	23.27
GM	11/22/05	01/21/06	65	P	41.9	41.6	0	23.27
GM	11/22/05	01/21/06	70	C	0.05	0	0	23.27
GM	11/22/05	01/21/06	70	P	46.9	46.6	0	23.27