THE ECONOMIC VALUE OF TRADING WITH REALIZED VOLATILITY IN THE S&P 500 INDEX OPTIONS MARKET

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Abstract:
We investigate the information content in the S&P 500 index options market by using the "realized" volatility approach. We model realized volatility as an ARFIMA process to capture its long memory. We use encompassing regressions to analyze the forecast efficiency and information content of different volatility measures. We find that realized volatility has incremental value over implied volatility in forecasting future volatility. We evaluate the economic benefits of volatility timing by examining whether realized volatility forecasts can be used to formulate profitable out-of-sample trading strategies in the S&P500 index options market. We find that volatility timing using realized volatility has significant abnormal returns of 2.78% per day. Our findings are robust to trading costs and filters.

Key Words: realized volatility, implied volatility, volatility timing, option trading strategies

JEL Classification: G10, G14

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1. Introduction

Recent studies on volatility modeling have focused on estimating volatility from high-frequency data. In this approach, volatility is estimated by summing the squares of intra-day returns over very short intervals. This measure is called realized volatility. The idea was originally proposed by Merton (1980), who showed that precise estimates of volatility can be obtained over fixed time intervals as the sampling interval approaches zero. In the limit, unobservable volatility becomes observable.

Recent work using realized volatility includes Andersen, Bollerslev, Diebold and Labys (2001b). These authors argue that this estimation is model-free and theoretically free from measurement error. Andersen, Bollerslev, Diebold and Ebens (2001a) use this approach in their study of the Dow Jones Industrial Average and find that realized volatility is lognormally distributed. They also find that daily returns standardized by realized volatility are approximately normal. Finally, they show that realized volatility is best described by a long-memory process such as a fractionally integrated autoregressive process. These findings are consistent across asset classes (for exchange rates, see Andersen et al. 2001b and for the Dow Jones Index, see Ebens, 1999). In a recent paper, Andersen, Bollerslev, Diebold and Labys (2003) show that the volatility forecasts using realized volatility dominate the GARCH models. Overall, the realized volatility approach has much to recommend it based on its theoretical soundness, ease in implementation, nice estimation properties, and easy extension to a multivariate setting.

Bai, Russell and Tiao (2002) present a dissenting note. They contend that the sampling interval cannot practically go to zero. More importantly, at high frequency they argue that the geometric Brownian motion assumption does not hold. They examine intra-day exchange rate data and find that the data are characterized by clustering, kurtosis and long memory. They conclude that these features reduce the precision of the volatility estimates using realized volatility. They point out that since the kurtosis and persistence increase with sampling frequency, choosing an optimal frequency is critical. Consistent with these findings, Pong, Shackleton, Taylor and Xu (2002) show that out-of-sample tests are sensitive to the sampling frequency used to construct the realized volatility.

Given these contradictions, the interesting question is whether the realized volatility approach would be useful in financial decisions such as investment management, risk management, asset pricing etc. Blair, Poon, and Taylor (2001) examine short term volatility forecasting using the S&P 100 index options and find that implied volatility (IV) is more informative than realized volatility about future volatility. Poteshman (2000) finds that approximately half the forecasting bias in the S&P500 index options market is eliminated by constructing measures of realized volatility from five-minute observations on S&P 500 futures rather than the index. More importantly he finds that the bias is nearly eliminated when the Heston option-pricing model is used instead of the Black-Scholes option-pricing model. In a recent study, Fleming, Kirby and Ostdiek (2003) find that volatility timing using realized volatility has economic value both for short and long horizons when trading stocks.

In this paper, we undertake a comprehensive examination of the economic value of realized volatility in index option markets. We address the following issues:

- Does the historical realized volatility have incremental value to the Black and Scholes implied volatility in forecasting future realized volatility in index markets?
- Can realized volatility be used to trade profitably in option markets?

We answer the first question by examining if realized volatility has incremental value to the Black-Scholes implied volatility in forecasting future realized volatility in index markets by studying at-the-money (ATM) S&P 500 index options with short maturity. We model realized volatility as a long-memory process. We use encompassing regressions to analyze the forecast efficiency and information content of different volatility measures.

To answer the second question, we evaluate the economic benefits of volatility timing to an options trading strategy by examining whether realized volatility forecasts can be used to formulate profitable out-of-sample trading strategies in the S&P500 index options market. We use the framework proposed by Noh, Engle, and Kane (1994) to estimate the profits from the options trading strategies. Noh et al. (1994) show that simple GARCH models outperform implied volatility models for investors trading in ATM straddles, after accounting for transaction costs. We find that volatility timing using realized volatility has significant abnormal returns of 2.78% per day. Our findings are robust to trading costs and filters.

Following prior research, we adopt a research design that minimizes potential measurement errors. We use high frequency index returns and a long-memory specification to obtain a more accurate estimate of realized volatility. We estimate the implied volatility using the Whaley (1982) approach by using all ATM options around a ten-minute window around the stock market close. This procedure minimize the problems related to bid-ask bounce, non-continuous option prices, infrequent trading and non-simultaneity of prices of options and the underlying index. To avoid the telescoping error problem that arises in overlapping data, we perform the tests using the generalized method of moments (GMM) approach (Fleming, 1998). We also perform sensitivity tests; first we use instrumental variables and second we use forecasts for fixed horizons.

Finally, since the research question is a joint test of market efficiency as well as accuracy of the forecasting procedure, the option pricing model used is important. Bakshi, Cao and Chen (1997) find that for ATM options, the Black Scholes model does as well as stochastic volatility based pricing models. Hence, we use the Black-Scholes model (adjusted for dividends) to price the S&P 500 index options, which are European in nature.

We find that realized volatility has incremental value over implied volatility in forecasting future volatility. We find that option trading strategies using realized volatility are profitable. The overall value of volatility timing in these strategies is 2.78.% per day net of transaction costs. Our findings are robust to trading costs, and filters.

The remainder of the paper is organized as follows. Section 2 provides the motivation and research design. Section 3 describes the data. Section 4 discusses the results from the encompassing regressions and presents the results of our sensitivity tests. Section 5 presents the results from the option trading strategies. Section 6 concludes.

2. Research Design

Next we describe the research methodology that we adopt to explore the research questions.

B. Does realized volatility have incremental value to the Black-Scholes implied volatility in forecasting future realized volatility in index markets?

We follow the approach adopted by Fleming (1998). The paper develops a relation between the implied volatility and the true time-varying volatility as follows. Consider the Hull and White (1987) model where the asset price and volatility are uncorrelated and the volatility risk premium is zero. At time t, the value of an option expiring at T is

$$f_t = E\left[BS\left(\sigma_{t;T}\right) | \Phi_t\right], \tag{1}$$

which is the expected Black-Scholes value evaluated at the average instantaneous volatility over the option's life, $\sigma_{t;T} = \sqrt{\frac{1}{T-1}\int_t^T \sigma_x^2 dx}$, given the information set Φ_t.

For short-maturity ATM options,

$$E\left[BS\left(\sigma_{t;T}\right) | \Phi_t\right] \approx BS\left(E\left[\sigma_{t;T} | \Phi_t\right]\right) \tag{2}$$

Hence,

$$f_t \approx BS\left(E\left[\sigma_{t;T} | \Phi_t\right]\right) \tag{3}$$

For an exact approximation, the implied volatility is $\sigma_{t;T}^{IV} = BS^{-1}(f_t)$

Hence,

$$\sigma_{t;T}^{IV} \approx E\left[\sigma_{t;T} | \Phi_t\right] \tag{4}$$

This implies that IV should represent an unbiased forecast of average volatility over the life of the option and its forecast error should be orthogonal to information at time t.

Following prior research (Christen and Prabhala, 1998 and Jiang and Tian, 2003), we use both univariate and encompassing regression to analyze the unbiasedness and information content of the volatility forecasts. The forecasts are used from a historical volatility (HV) model (20-day moving average of realized volatility), a long-memory model (ARFIMA), a GARCH(1,1) model and an ARFIMA (leverage) model. To avoid the telescoping error problem that arises in overlapping data, we perform the tests using the generalized method of moments (GMM) approach (Fleming, 1998).

Univariate regression:

We use the following specifications:

$$\sigma_{t,T}^{realized} = a + b_1 \sigma_{t,T}^{IV} + \varepsilon_{1t,T}\,, \tag{5a}$$

$$\sigma_{t,T}^{realized} = a + b_1 \sigma_{t,T}^{HV} + \varepsilon_{2t,T}\,, \tag{5b}$$

$$\sigma_{t,T}^{realized} = a + b_1 \sigma_{t,T}^{ARFIMA} + \varepsilon_{3t,T}\,, \tag{5c}$$

$$\sigma_{t,T}^{realized} = a + b_1 \sigma_{t,T}^{GARCH} + \varepsilon_{4t,T}\,, \tag{5d}$$

$$\sigma_{t,T}^{realized} = a + b_1 \sigma_{t,T}^{ARFIMA\_LEV} + \varepsilon_{5t,T}\,, \tag{5e}$$

Information content hypothesis:

In the above specifications if the volatility forecast has no information regarding future realized volatility, the testable hypothesis is H0: $b_1 = 0$.

Unbiasedness hypothesis:

If the volatility forecast is an unbiased estimate of future realized volatility, the testable hypothesis is H0: $a = 0$ and $b_1 = 1$.

Encompassing regression

We use the following specifications:

$$\sigma_{t,T}^{realized} = a + b_1\sigma_{t,T}^{IV} + b_2\sigma_{t,T}^{FV} + \varepsilon_{t,T} , \quad (5g)$$

where $\sigma_{t;T}^{FV}$ is forecasted volatility and includes one of the following models: the historical volatility model, the ARFIMA model, a GARCH(1,1) model and an ARFIMA (leverage) model.

Information content hypothesis:

If the information content in the forecasted volatility model is subsumed in the implied volatility forecast, the testable hypothesis is H0: $b_2 = 0$.

Unbiasedness hypothesis:

If the implied volatility forecast is an unbiased estimate of future realized volatility, the testable hypothesis is H0: $b_1 = 1$ and $b_2 = 0$.

B. Can realized volatility be used to formulate profitable out-of-sample trading strategies in the options market?

We use realized volatility forecasts to trade in ATM delta-neutral straddles. All our trading strategies are based on out-of-sample forecasts. We provide the details of the straddle trading strategy in Appendix 1. We apply the bid-ask spread and transaction cost filters for all the trades, as described in steps 6 and 7 of Appendix 1. As the trading strategies are delta neutral, the returns do not need risk adjustment for minor stock price movements and represent abnormal returns. We compare the profits net of transaction costs and bid-ask spreads.

3. Data and Summary Statistics

We use high frequency tick-by-tick S & P 500 data for the 7-year period: 01/1996 to 12/ 2002 for a total of 1,738 trading days. The intraday realized volatility for day *t* is obtained by the sum of squared returns at finely sampled intervals over a day.

We choose the S&P 500 index ATM options because they are widely traded. The SPX intra-day option data is obtained from the Chicago Mercantile Exchange for the same sample period. We assume that the S&P 500 daily dividend yield interpolated to match the maturity of the option contract is a reasonable proxy for the dividends paid on each option contract. We use the three-month Treasury-bill rate as a proxy for the risk-free rate in the Black-Scholes valuation model.

Options with moneyness (strike price/index level) in the range 0.97 to 1.03 are deemed as ATM options. We exclude options with maturities below 15 days and above 180 days. We only retain options with daily volumes greater than 100. For a given exercise price and maturity, options that have both put and call prices are retained. Options that violate the put-call parity relationship are excluded. Based on these criteria, our sample consists of 1,027 call-put options pairs on 1,738 trading days.

Figure 1 shows the volatility signature plot for realized volatility obtained over a range of sampling intervals. From the graph, we observe that the realized volatility shows no trend at and after the 15-minute intervals. Hence, we use the realized volatility obtained by the sum of squared returns at 15-minute intervals over a day. The summary statistics for the realized volatility and implied volatility are given in Table 1. The realized volatility specified as standard deviation and variance are positively skewed and leptokurtic. However the logarithmic standard deviation is approximately Gaussian. The autocorrelations for the FIGARCH process die out quickly as shown in Figure 2. This implies that realized volatility has a long memory that is captured by a fractionally integrated process (ARFIMA).

Figure 3 suggests the asymmetric volatility effects are present in the data. In Figure 4, we see that the ARFIMA process is an improvement over the GARCH process since it captures the long memory characteristic of realized volatility. We observe that the ARFIMA dies out quickly after a shock and does not persist as GARCH process. The realized volatility process unlike GARCH seems to be very sensitive to shocks over time and shows periods of very high volatility too often. Figure 5 plots the implied volatilities from the options market. The IVS from calls and puts look similar and broadly share the features of the volatilities from time-series models.

4. Results

4.1 Unbiasedness tests:

The results for the unbiasedness tests for S&P500 call options are provided in Table 2. The models are estimated using the GMM approach proposed by Fleming (1998). In Panel A, we use the standard deviation as the specification for the realized volatility. Models 1 to 5 are the univariate specifications. The null hypothesis that the volatility forecast is an unbiased forecast of future realized volatility is rejected for all five models by the Wald test measure. The R^2 measure indicates that the ARFIMA-Leverage forecast is the most informative volatility forecast. These results hold in panels B and C as well where realized volatility is specified as variance and logarithmic standard deviation.

Models 6 to 9 are the encompassing regression results. The results suggest that implied volatility does not subsume the information contained in the other volatility forecast measures. Notice that the coefficient for the implied volatility forecast is lower in the encompassing regression compared to the univariate regression. The R^2 for the encompassing regressions are larger than the univariate regressions. Furthermore, the R^2 for the ARFIMA-Lev forecast is the largest indicating that the forecasts have the highest additional information content. Table 3 presents the results for put options and all the above results hold as well for puts. The findings from the univariate specifications and encompassing regressions are consistent with Christensen and Prabhala (1998) and Jiang and Tian (2002).

4.2 Robustness Tests:

Instrumental variables:

We next use lagged implied volatility as an instrumental variable in both the univariate and encompassing regressions. The results for S&P500 call options are presented in Table 4. While, the univariate results are similar to our earlier findings, the results from the encompassing regressions are interesting. We find that implied volatility does not subsume the information contained in the ARFIMA and ARFIMA-Lev forecast measures, but the historical volatility and GARCH volatility have no additional information content.

Constant horizons:

The analysis so far has pooled data for options with different horizons. In Figure 6, we plot the regression coefficients from equation 6a against the maturity of options. The plot shows that the coefficients are sensitive in short horizons (one month). Consequently in Table 5, we present the results for forecasting horizons of a day in Panel A and for 30 days in Panel B. The results for both forecasting horizons are similar to our earlier findings. The R^2 for the shorter horizon is larger compared to the longer horizon.

The results suggest that implied volatility is a biased predictor of realized volatility. We also find that there is incremental information in out-of-sample forecasts of realized volatility indicating that IV does not subsume all information about realized volatility. Next, we investigate if the incremental information in realized volatility forecasts can be used profitably to trade in options.

5. Option trading strategies

Table 6 presents the results for delta-neutral straddles based on realized volatility forecasts based on the procedure described in Appendix 1. Panel A shows that the average moneyness (*X/S*) is 1.013 while the average maturity is 22.21 days. The model price is lower compared to the option prices implying that options are over priced.

Panel B in Table 5 gives us the number of buys and sells of the delta-neutral straddles using a bid-ask filter ($0.50) for stock price changes. We find that the total trades are lower than that in Panel A because of attrition due to the filter rule. Straddles are sold more often because they are over-priced according to all the models. We find that in general straddles are sold in 75% of the trades.

Panel C presents percentage returns on trading in the delta-neutral straddles using a bid-ask filter and 0.5% transaction costs. We find that the trading strategy is profitable with a significant daily return of 2.78% after transaction costs.

6. Conclusions

We examine the information content in the S&P 500 index options market by using the "realized" volatility approach. We model realized volatility as an ARFIMA process to capture its long memory. We adopt a research design that minimizes potential measurement errors. We find that realized volatility has incremental value over implied volatility in forecasting future volatility. These findings are robust to sensitivity tests.

We evaluate the economic benefits of volatility timing by examining whether realized volatility forecasts can be used to formulate profitable out-of-sample trading strategies in the S&P500 index options market. We find that volatility timing using realized volatility has significant abnormal returns of 2.78% per day. Our findings are robust to trading costs and filters.

Additional research questions that we intend to examine include examining whether banks or financial institutions limit their risks using realized volatility forecasts and whether option prices based on realized volatility have lower pricing errors in mean squared error (MSE) sense compared to other volatility models.

Appendix 1
Trading strategy based on straddles

1. Estimate the realized volatility on day t and obtain the forecast of future volatility for each day until the maturity of the option. Obtain the arithmetic average of such future volatility forecasts for each model on day t. Use this measure as a volatility proxy to price an option on day t using the Black-Scholes pricing formula.
2. From the in-sample daily volatility forecast for day t from step 1, obtain the delta-neutral (DN) straddle for that day. In particular, given that delta of the call and put are respectively $N(d_1)$ and $N(d_1)-1$, the strike price x that gives a delta -neutral straddle on day t can be solved as :

$$N(d_1) + N(d_1) - 1 = 0; \quad x = \frac{S}{e^{\left(-r_f - \frac{\sigma^2}{2}\right)T}}$$

where S, r_f, σ *and* T refer to the spot price, risk free rate, volatility and time to maturity respectively. On day t, determine that traded straddle combination whose exercise price is closest to the x described above. Use only ATM calls and puts in this exercise. Price the ATM DN straddle using the Black-Scholes option-pricing model.
3. Next, buy or sell the ATM DN straddle on day t depending on whether the straddle model price is under or over-priced relative to the closing market straddle price on that day. When the straddle is sold, the agent invests the proceeds in a risk-free asset.
4. The rate of return is calculated as follows:

$$\text{Return on buying a straddle} = \frac{C_t + P_t - C_{t-1} - P_{t-1}}{C_{t-1} + P_{t-1}}$$

$$\text{Return on selling a straddle} = \frac{-(C_t + P_t - C_{t-1} - P_{t-1})}{C_{t-1} + P_{t-1}} + r_f$$

where C_t and P_t refer to the call and puts prices of S & P 500 index options.
5. Implement steps 1-4 for each trading day in the sample.
6. For all the trades, apply the bid-ask spread filter (that accounts for the bid-ask bounce) as in Noh et al. (1994). The agent trades only when the absolute price difference between the model and market price is expected to exceed $0.50.
7. Further, apply 0.5% trading costs, while calculating the net returns for the strategies. The 0.5% trading cost corresponds to a trader with $48,000 investment who pays a commission amounting to $120 + 0.0025 of the dollar amount as per a standard commission schedule (see Hull (2000) p. 160).

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Table 1

Summary Statistics

	σ	σ^2	$\ln(\sigma)$	IV call	IV put
Mean	0.1672	0.0355	-1.8979	0.2145	0.1985
S.D.	0.0872	0.0484	0.4568	0.0548	0.0569
Skewness	2.1357	5.2258	0.2695	1.1476	1.1718
Kurtosis	7.4751	41.8100	0.3519	2.7173	2.0248

Table 2

Panel A: Realized Volatility is specified as standard deviation

Unbiasedness Tests of S&P 500 data (Call Options)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
$\log(\sigma_{it})$									
α	**-0.3965**	**-0.4545**	**-0.3266**	**-0.5305**	**-0.3035**	**-0.3553**	**-0.2761**	**-0.3568**	**-0.2589**
	(20.6116)	(29.4124)	(17.5940)	(40.6266)	(16.4826)	(20.0003)	(14.4317)	(19.8731)	(13.6162)
IV	**0.5218**					**0.3420**	**0.2821**	**0.4486**	**0.2561**
	(18.5504)					(10.7638)	(9.7015)	(15.2669)	(9.0066)
HV		**0.3677**				**0.2053**			
		(19.1390)				(8.7015)			
ARFIMA			**0.5245**				**0.3527**		
			(22.9907)				(13.0591)		
GARCH				**0.2883**				**0.1206**	
				(17.1325)				(6.5110)	
					0.5540				**0.3963**
ARFIMA-LEV					(24.5183)				(14.8928)
Adj. R^2	0.2432	0.2227	0.2743	0.1203	0.2987	0.2834	0.3156	0.2590	0.3327
CS^2	150.87	159.25	120.86	182.21	119.39	162.93	186.63	156.07	200.30

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t,T}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV).CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Panel B: Realized Volatility is specified as variance
Unbiased tests of S& P 500 data (call options)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
σ_{it}^2									
α	**0.0172**	**0.0245**	**0.0165**	**0.0308**	**0.0155**	**0.0166**	**0.0128**	**0.0171**	**0.0122**
	(5.4991)	(10.5200)	(5.0195)	(11.7726)	(5.0250)	(5.5199)	(3.6319)	(5.5913)	(3.5085)
IV	**0.3712**					**0.2734**	**0.2102**	**0.3591**	**0.1923**
	(6.1472)					(4.3418)	(3.2043)	(4.6071)	(3.4024)
HV		**0.3683**				**0.1735**			
		(7.4235)				(2.5805)			
ARFIMA			**0.6927**				**0.4414**		
			(6.5995)				(3.1574)		
GARCH				**0.1427**				0.0187	
				(5.2467)				(0.5010)	
ARFIMA-LEV					**0.7291**				**0.4962**
					(7.4136)				(4.1772)
Adj. R^2	0.2462	0.1911	0.2610	0.0680	0.2822	0.2706	0.3051	0.2460	0.3189
CS^2	145.50	167.95	33.80	108.92	34.62	183.94	213.12	231.01	257.91

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t,T}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV).CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Panel C: Realized Volatility is specified as natural log of standard deviation

Unbiasedness Tests of S&P 500 data (Call Options)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
σ_{it}									
α	**0.0836**	**0.1192**	**0.0843**	**0.1414**	**0.0788**	**0.0813**	**0.0804**	**0.0356**	**0.0608**
	(3.5194)	(8.2023)	(3.8890)	(11.5208)	(3.8019)	(3.5718)	(3.4155)	(5.1120)	(2.4511)
IV	**0.4590**					**0.3208**	**0.4236**	**0.4231**	**0.2330**
	(4.2958)					(2.8770)	(4.0249)	(14.6043)	(3.0814)
HV		**0.3861**				**0.1915**			
		(4.4732)				(2.2690)			
ARFIMA			**0.6129**				**0.0571**		
			(4.7147)				(2.9103)		
GARCH				**0.2318**				**0.2877**	
				(4.0579)				(10.4940)	
ARFIMA-LEV					**0.6458**				**0.4408**
					(5.1883)				(4.6152)
Adj. R^2	0.2577	0.2169	0.2743	0.0989	0.2974	0.2874	0.2617	0.2979	0.3335
CS^2	100.13	69.06	38.62	186.08	39.50	124.10	120.32	139.20	242.91

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t,T}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV).CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Table 3

Unbiasedness Tests of S&P 500 data (Put Options)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
σ_{it}									
α	**0.0836**	**0.1192**	**0.0843**	**0.1414**	**0.0788**	**0.0875**	**0.0720**	**0.0862**	**0.0682**
	(3.5194)	(8.2023)	(3.8890)	(11.5208)	(3.8016)	(4.9114)	(3.5091)	(4.8439)	(3.3718)
IV	**0.4590**					**0.3604**	**0.2850**	**0.4364**	**0.2560**
	(4.2958)					(2.8533)	(2.5069)	(4.5569)	(2.4940)
HV		**0.3861**				**0.1400**			
		(4.4732)				(1.2550)			
ARFIMA			**0.6129**				**0.3333**		
			(4.7147)				(2.0837)		
GARCH				**0.2318**				**0.0512**	
				(4.0579)				(1.6945)	
ARFIMA-LEV					**0.6458**				**0.3920**
					(5.1883)				(2.7588)
Adj. R^2	0.2577	0.2169	0.2743	0.0989	0.2974	0.3000	0.3241	0.2897	0.3376
CS^2	100.13	69.06	38.62	186.08	39.50	55.88	63.75	55.33	72.11

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t,T}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV).CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Table 4

Unbiasedness Tests of S&P 500 data (Call Options: Lag IV as instrument)

	M1	M2	M3	M4	M5	M6	M7	M8	M9
σ_{it}									
α	**0.0658**	**0.1192**	**0.0843**	**0.1414**	**0.0788**	**0.0703**	**0.0601**	**0.0656**	**0.0581**
	(2.2258)	(8.2023)	(3.8890)	(11.5208)	(3.8016)	(2.3608)	(2.1039)	(9.4950)	(2.0665)
IV	**0.5383**					**0.4130**	**0.3062**	**0.5270**	**0.2679**
	(4.0480)					(2.4743)	(2.4275)	(2.8781)	(2.5441)
HV		**0.3861**				0.1356			
		(4.4732)				(1.4755)			
ARFIMA			**0.6129**				**0.3466**		
			(4.7147)				(3.2308)		
GARCH				**0.2318**				0.0145	
				(4.0579)				(0.6154)	
ARFIMA-LEV					**0.6458**				**0.4101**
					(5.1883)				(6.8362)
Adj. R^2	0.2500	0.2169	0.2743	0.0989	0.2974	0.2825	0.3166	0.2519	0.3327
CS^2	96.69	69.06	38.62	186.08	39.50	106.24	132.15	337.60	274.54

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t,T}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV). CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Table 5

Panel A

Information Content Regression (Call Options Forecasting Horizon T=1)

σ_{it}	M1	M2	M3	M4	M5	M6	M7	M8	M9
α	**-0.0531**	**0.0397**	**-0.0227**	**0.0726**	**-0.0261**	**-0.0565**	**-0.0807**	**-0.0611**	**-0.0824**
	(10.7676)	(5.5771)	(1.9803)	(11.4308)	(2.6952)	(4.9380)	(7.7069)	(5.2845)	(8.9301)
IV	**1.0200***					**0.8130**	**0.7341**	**0.9293***	**0.7286**
	(36.5110)					(10.6549)	(13.7959)	(14.9694)	(15.7474)
HV		**0.7800**				**0.2869**			
		(17.3766)				(4.9300)			
ARFIMA			**1.1894**				**0.5509**		
			(16.5954)				(5.3999)		
GARCH				**0.5297**				**0.1466**	
				(18.7633)				(3.0518)	
ARFIMA-LEV					**1.2097**				**0.5685**
					(19.7240)				(5.9605)
Adj. R^2	0.3418	0.2376	0.2771	0.1379	0.2799	0.3595	0.3740	0.3492	0.3753
CS^2	545.53	35.00	14.76	277.86	18.40	377.92	790.29	113.11	949.26

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t=1}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV). CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Panel B

Information Content Regression (Call Options Forecasting Horizon T=30)

σ_{it}	M1	M2	M3	M4	M5	M6	M7	M8	M9
α	**0.0555**	**0.1004**	**0.0557**	**0.1295**	**0.0478**	0.0524	0.0298	**0.0512**	**0.0252**
	(1.8009)	(5.1759)	(2.0799)	(8.6309)	(1.9066)	(1.7771)	(0.9257)	(7.3762)	(3.9510)
IV	**0.5933**					**0.4054**	**0.3271**	**0.5443**	**0.2922**
	(4.3295)					(2.7500)	(3.2591)	(14.0531)	(7.9680)
HV		**0.5063**				**0.2604**			
		(4.7878)				(2.2684)			
ARFIMA			**0.0798**				**0.5130**		
			(5.0346)				(4.2556)		
GARCH				**0.3036**				**0.0792**	
				(4.4989)				(3.0983)	
ARFIMA-LEV					**0.8446**				**0.5874**
					(5.6745)				(13.4912)
Adj. R^2	0.2435	0.2109	0.2626	0.0953	0.2876	0.2745	0.3028	0.2489	0.3196
CS^2	48.08	28.08	19.69	109.10	20.25	59.94	117.91	102.23	189.44

The models are estimated using the GMM approached proposed by Fleming (1998). The encompassing regression is defined by $\sigma_{t=30}^{realized} = a + b1\sigma_{t,T}^{IV} + b2\sigma_{t,T}^{FV} + \varepsilon_{t,T}$. $\sigma_{t,T}^{FV}$ is forecasted volatility that can be historical volatility (HV), autoregressive fractionally integrated moving average (ARFIMA) model, generalized autoregressive heteroskedasticity (GARCH) model, and ARFIMA model with leverage effect (ARFIMA-LEV). CS^2 is an asymptotic Wald test of the joint null that $\alpha = 0$ and $\beta = 1$ for a particular forecast. β is referring to the coefficient associated with the implied volatility. * The Wald test is performed for the corresponding forecast. HV is 20-day moving average of the realized volatility. The sample is from January 2, 1996 to December 31, 2002.

Table 6

Delta-neutral straddles from competing models for the ATM S & P 500 index options (Jan 1996-Dec 2002) using Black-Scholes Option Pricing Model

This table reports details of daily trading strategies using S&P500 index options. These strategies are determined using realized volatility forecasts. Option price forecasts are obtained using the Black-Scholes option-pricing model.

Panel A: Average prices of the delta-neutral straddles

	call	put	straddle
market price	**17.19**	**23.16**	**40.36**
Realized volatility	11.57	21.41	32.98

Number of observations: 1027. Average moneyness and maturity of the delta-neutral straddles are 1.013 and 22.21 days respectively

Panel B: Number of buys and sells of delta-neutral straddles with $0.50 filter for stock prices

	total trades	buys	sells
Realized volatility	997	253	744

Panel C: % Returns on trading in the delta-neutral straddles with $0.50 filter for stock prices

	Before transaction costs % daily return		After transaction costs of 0.5% % daily return	
	Mean	*t-stat*	Mean	*t-stat*
Realized volatility	3.252	5.307	2.776	4.531

Figure 1

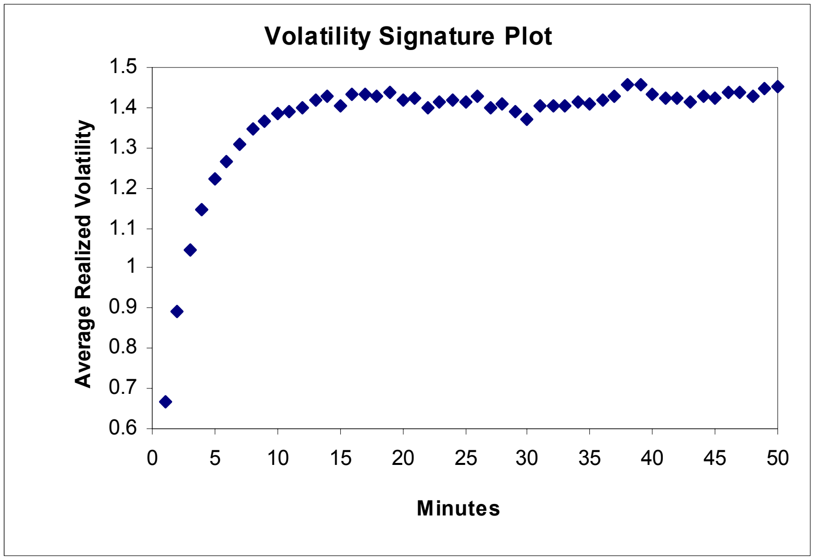


Figure 2

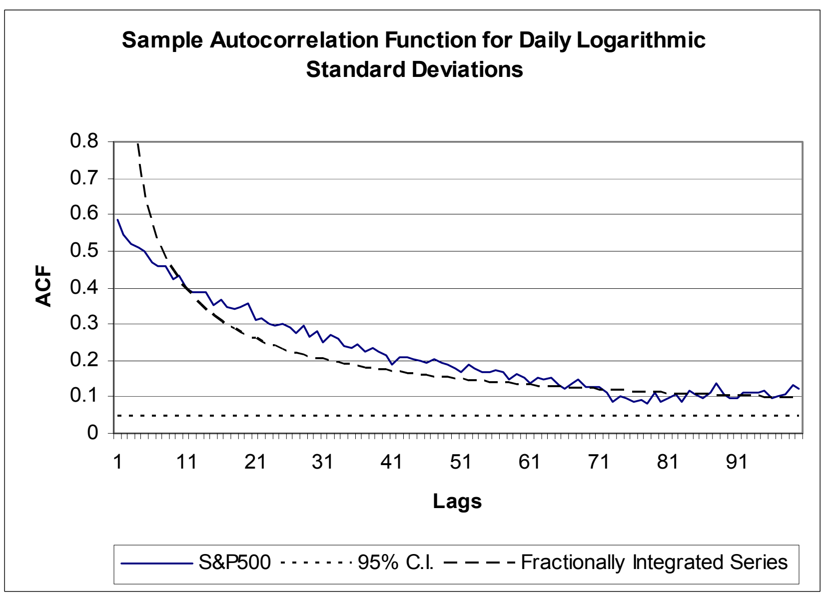


Figure 3

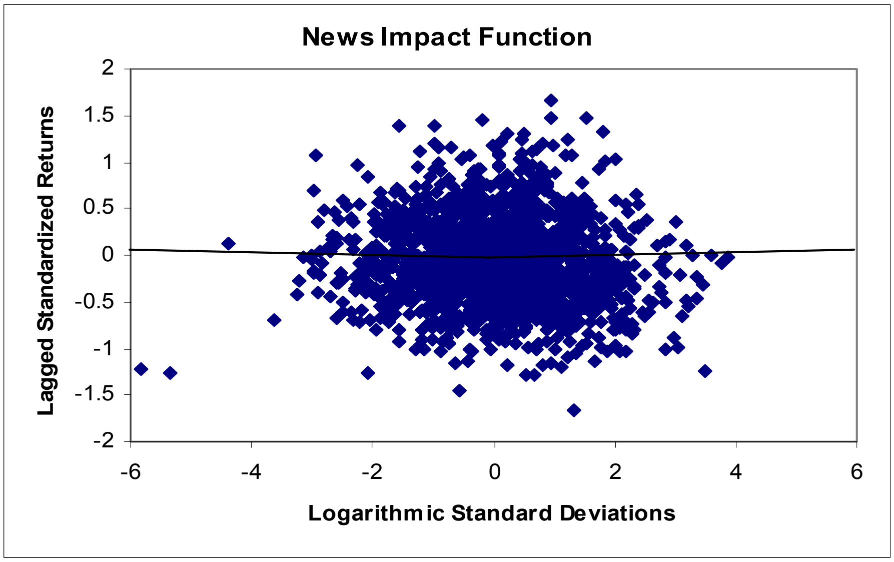

News Impact Function
Lagged Standardized Returns
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-6
-4
-2
0
2
4
6
Logarithmic Standard Deviations

Figure 4

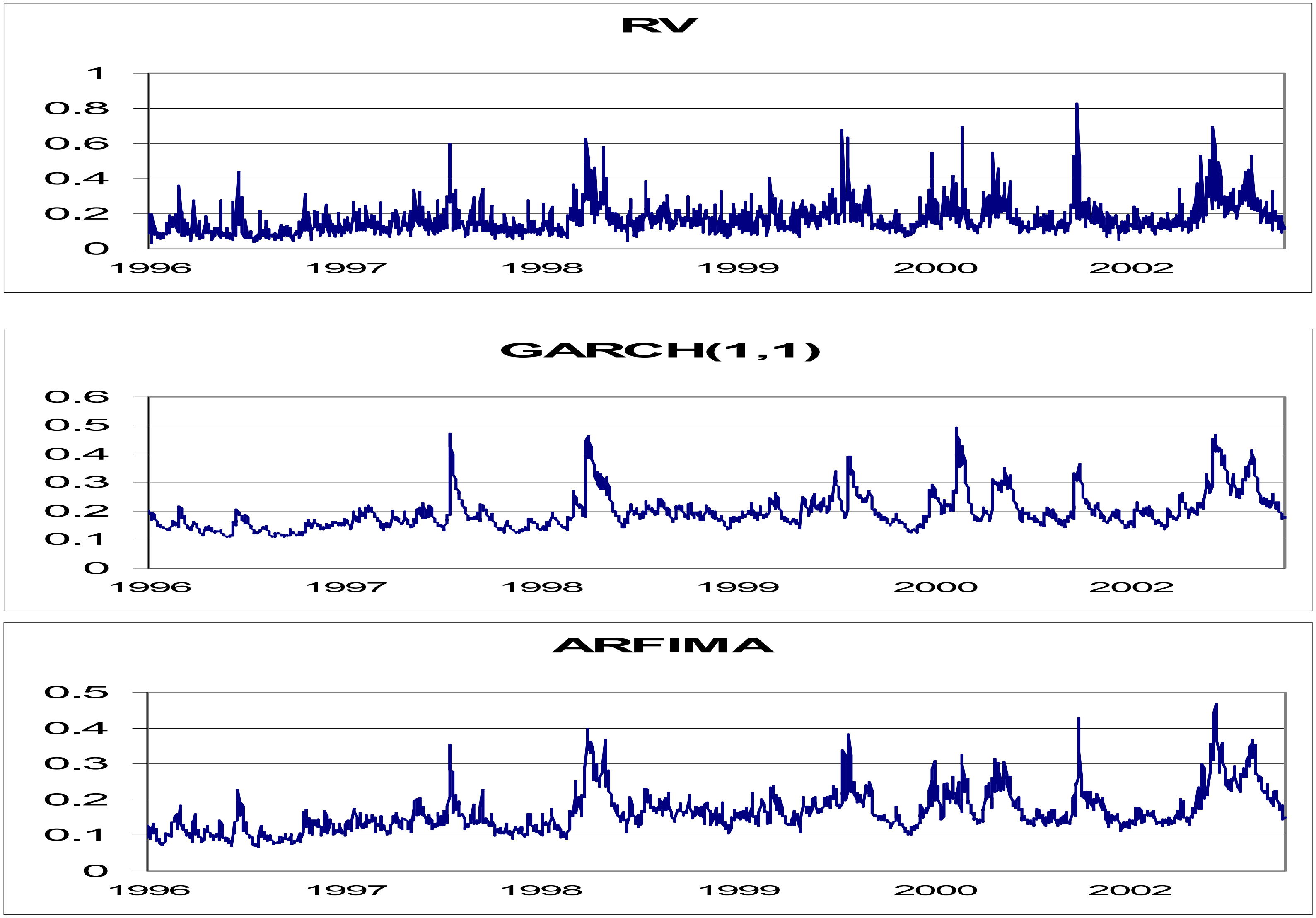
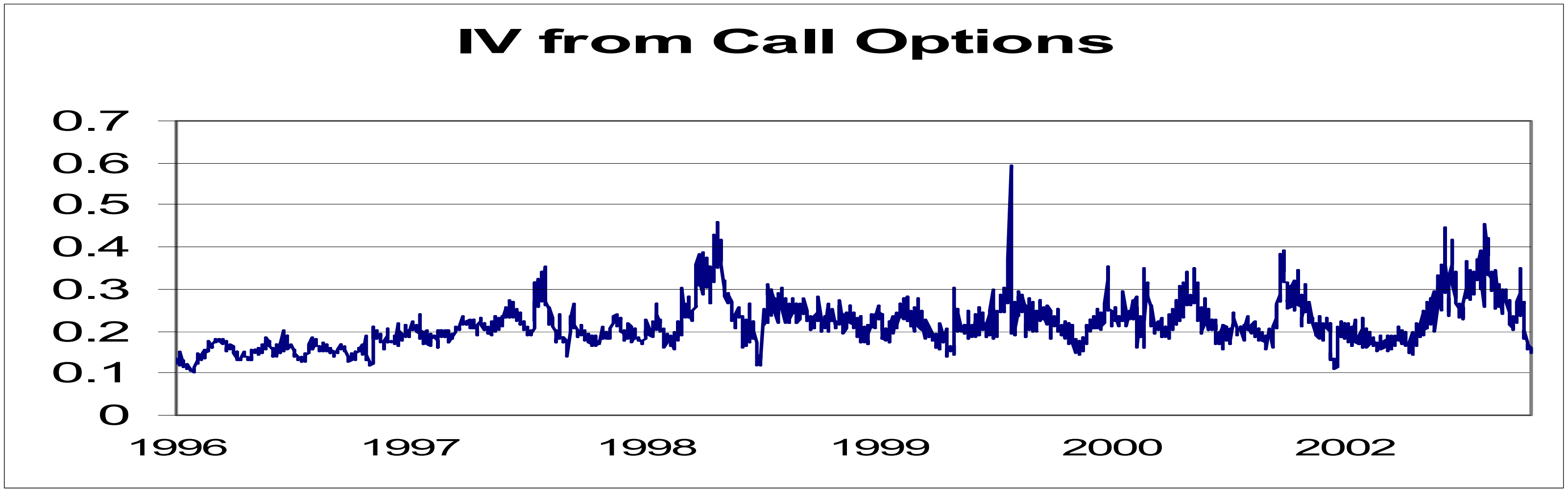

RV
1
0.8
0.6
0.4
0.2
0
1996
1997
1998
1999
2000
2002
GARCH(1,1)
0.6
0.5
0.4
0.3
0.2
0.1
0
1996
1997
1998
1999
2000
2002
ARFIMA
0.5
0.4
0.3
0.2
0.1
0
1996
1997
1998
1999
2000
2002

Figure 5


IV from Call Options
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1996
1997
1998
1999
2000
2002

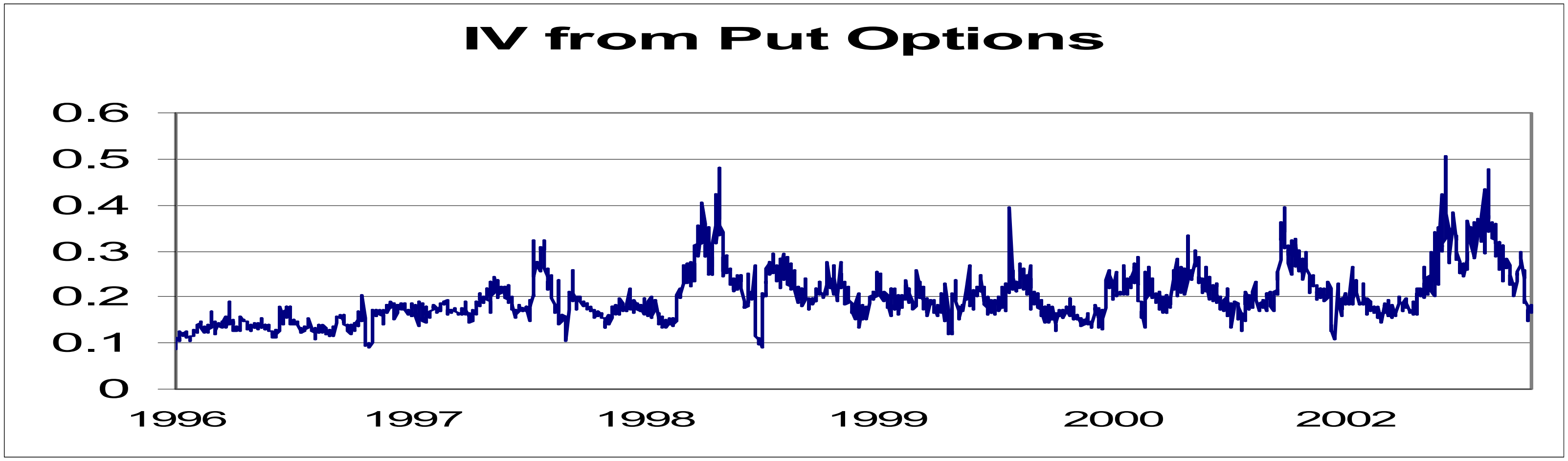
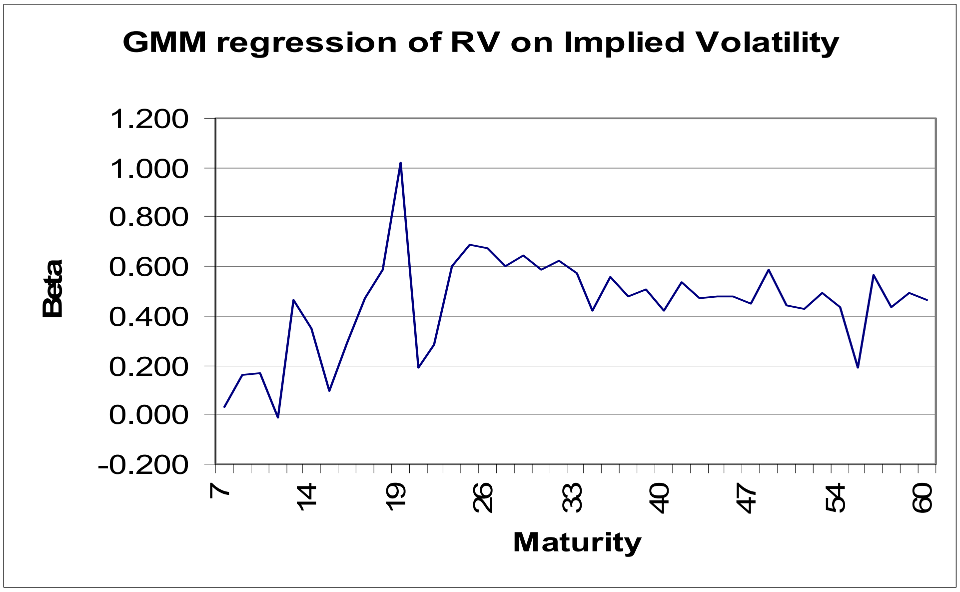
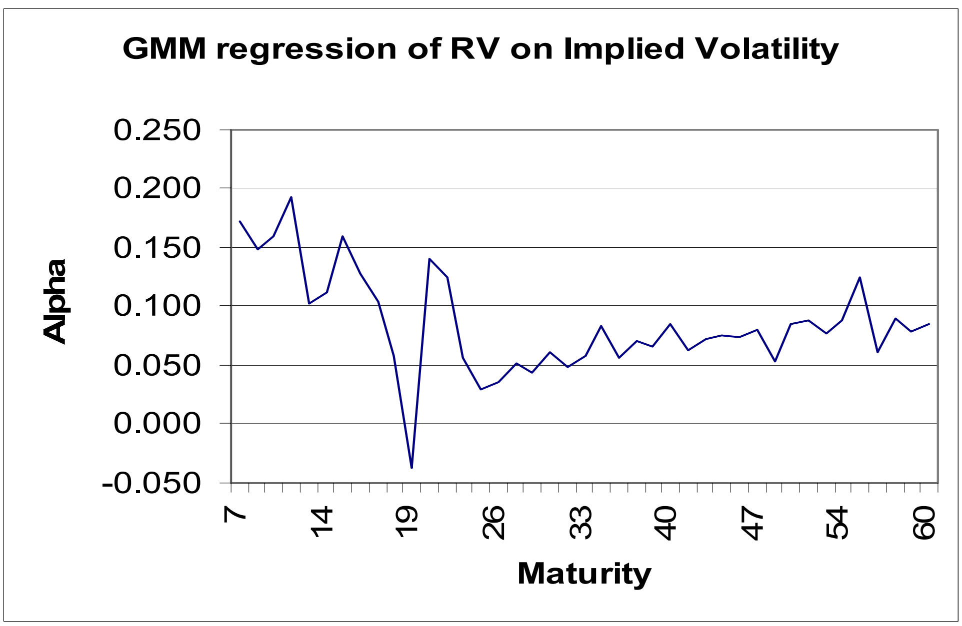

IV from Put Options
0.6
0.5
0.4
0.3
0.2
0.1
0
1996
1997
1998
1999
2000
2002

Figure 6


GMM regression of RV on Implied Volatility
1.200
1.000
0.800
0.600
0.400
0.200
0.000
-0.200
Beta
7
14
19
26
33
40
47
54
60
Maturity


GMM regression of RV on Implied Volatility
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
Alpha
7
14
19
26
33
40
47
54
60
Maturity