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Option trading for optimizing volatility forecasting

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Abstract

This paper investigates the forecasting ability of several volatility specifications that aim to quantify market risk. Using an options' trading strategy on volatility the comparison is implemented in a dynamic approach, applying the standardized prediction error criterion. The empirical findings of the paper suggest that the SPEC criterion outperforms all volatility models that assume normality on the data and exhibits similar forecasting ability with most of the models that assume skewed distributions of asset returns.

JEL classification numbers: G11, G13, G17
Keywords: SPEC; option trading; straddle; market risk; volatility forecasting; Black-Scholes.

1 Introduction

Forecasting time series data and volatility has is one of the cornerstones for finance and for that reason has attracted the interest of researchers. While most of the research focuses on the determination of models based on the minimization of the mean squared error or the maximization of the likelihood, this paper focuses

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on the maximization of the profitability of a hypothetical investor. This is motivated strongly by the work of Engle (1993) who applied a straddle technique with options that expire in one day and for which the payoff is directly linked with the volatility of the underlying asset. In that framework the maximization of a hypothetical investor's payoff would indicate an optimal volatility forecasting model.

The aim of this paper is the investigation of the optimum algorithm for choosing models, in terms of predictability power, for quantifying market risk. For that reason I examine the payoff of several volatility specifications that aim to forecast the payoff of a straddle options trading strategy. Among the volatility specification, which could be assumed as passive trading strategies on volatility, I also apply a dynamic approach that dictates a dynamic active trading approach according to which the volatility specification which is applied at each week is allowed to be different.

The main findings of the paper are in favour of an active trading strategy according to which investors benefit from choosing alternative volatility models in each period. This dynamic approach results in a profitable payoff for these investors who obtain similar rewards with those investors who base their expectations on skewed distributions and complicated volatility specifications.

The second chapter of the paper explains the simulation process of the necessary data, while the third one the methodology. The fourth chapter discusses the results and finally the fifth concludes the paper.

2 Data

For the purposes of the analysis of the paper two options are available; either to use real traded data or simulated data as was the case for **Engle** (1993) and

Degiannakis and **Xekalaki** (2005). Engle (1993) focused on the NYSE stock index simulating the corresponding option prices and applying many competitive models such as the MA variance in the squared residuals in order to forecast daily forecasts of volatility. While the former case (real data) offers a more realistic approach for developing forecasting criteria, the latter is more preferable as it overcomes several issues such as the autocorrelation of option prices, the bid-ask spread and the non-synchronous trading. The option prices of the Athens Derivatives Exchange exhibit autocorrelations because traders have the opportunity to trade options at their closing price for a short period of time after the closing time of the Derivatives Exchange each day. Another limitation for using real data is that the execution of the options at the Athens Derivatives Exchange takes place every third Friday of each month, resulting in a single observation over a period of 20 days for options with maturity term of one day. This consequently is very likely to rise many econometric questions when applying GARCH models; see among others **Drost** and **Nijman** (1992).

The data consists of daily spot prices for the ATHEX/FTSE-20 during the period form 03/01/2000 to 30/06/2005. The simulated option prices are derived from the **Black-Scholes** (1973) model assuming normality on our data:

$$C_t^{(\tau)} = S_t \cdot \Phi\left(d_1(t)\right) - K \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(d_2(t)\right) \tag{1}$$

$$P_t^{(\tau)} = -S_t \cdot \Phi\left(d_1(t)\right) + K \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(d_2(t)\right) \tag{2}$$

where

$$d_1(t) = \frac{\ln\left(\frac{S_t}{K}\right) + \left(r_t + \frac{1}{2}\left(\sigma_t^{(\tau)}\right)^2\right) \cdot (\tau)}{\sigma_t^{(\tau)} \cdot \sqrt{\tau}} \quad \text{and} \quad d_2(t) = d_1(t) - \sigma_t^{(\tau)} \cdot \sqrt{\tau}$$

S_t: Spot Prices at t, K: exercise price, σ: variance of the underlying asset, r: the risk free interest rate (Euribor), and τ: time to maturity. From the descriptive analysis of Figure 1 of the appendix, it seems that the Jarqua-Bera statistic casts doubt on the normality assumption mainly because of the leptokurtic and skewed distribution of asset returns.

3 Methodology

The future call and put option price at t+1, conditional on the available informational set up to t, with τ days to expiration (τ=T-t) is denoted with $C_{t+1|t}^{(\tau)}$ and $P_{t+1|t}^{(\tau)}$ and can be quantified according to the B-S formula by the following equations:

$$C_{t+1|t}^{(\tau)} = S_t \cdot \Phi\left(d_1(t)\right) - K \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(d_2(t)\right) \quad (3)$$

$$P_{t+1|t}^{(\tau)} = -S_t \cdot \Phi\left(d_1(t)\right) + K \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(d_2(t)\right) \quad (4)$$

where $d_1(t) = \dfrac{\ln\left(\dfrac{S_t}{K}\right) + \left(r_t + \dfrac{1}{2}\left(\sigma_{t+1|t}^{(\tau)}\right)^2\right) \cdot (\tau)}{\sigma_{t+1|t}^{(\tau)} \cdot \sqrt{\tau}}$

$$d_2(t) = \frac{\ln\left(\dfrac{S_t}{K}\right) + \left(r_t - \dfrac{1}{2}\left(\sigma_{t+1|t}^{(\tau)}\right)^2\right) \cdot (\tau)}{\sigma_{t+1|t}^{(\tau)} \cdot \sqrt{\tau}} = d_1(t) - \sigma_{t+1|t}^{(\tau)} \cdot \sqrt{\tau}$$

$\sigma_{t+1|t}^{(\tau)}$ is the standard deviation during t+1 to T given the informational set up to t.

Each passive strategy or agent adopts a forecast method for variance and trades options for a unique day investing 1€ on ATHEX/FTSE-20. Assuming that the option is at-the-money and that the exercise price is equal to S_t*exp(r_t) then the price for for an option that expires in a day (τ=1) would become:

$$d_{\mathbf{1}} = \frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t} \quad \text{and} \quad d_{\mathbf{2}} = -\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t} \tag{5}$$

$$\begin{aligned} C_{t+\mathbf{1}|t}^{(\tau=\mathbf{1})} &= S_t \cdot \Phi\left(\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) - S_t \cdot e^{r_t} \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(-\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) \\ &= S_t \cdot \Phi\left(\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) - S_t \cdot \Phi\left(-\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) = \mathbf{2} \cdot S_t \cdot \Phi\left(\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) - \mathbf{1} \end{aligned} \tag{6}$$

$$\begin{aligned} P_{t+\mathbf{1}|t}^{(\tau=\mathbf{1})} &= -S_t \cdot \Phi\left(\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) + S_t \cdot e^{r_t} \cdot e^{-r_t \cdot (\tau)} \cdot \Phi\left(-\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) \\ &= \mathbf{2} \cdot S_t \cdot \Phi\left(\frac{\mathbf{1}}{\mathbf{2}} \cdot \sigma_{t+\mathbf{1}|t}\right) - \mathbf{1} \end{aligned} \tag{7}$$

Then at expiration, the long straddle position that is the volatility trader would obtain a payoff equal to $\pi_T = \left|S_T - K\right|$ (8)

Consequently, the payoff of the straddle long position at any t would be equal to:

$$\pi_t \quad \underline{\underline{at-the-money}} \quad \left|S_t - e^{r_t}\right| \tag{9}$$

The transaction between two agents (i and i*) is executed at the median bid/ask prices according to the following payoff:

$$\pi_{t+\mathbf{1}}^{\left(i+i^*\right)} = \begin{cases} \pi_{t+\mathbf{1}} - \left(C_{t+\mathbf{1}|t,(i)} + C_{t+\mathbf{1}|t,\left(i^*\right)}\right), & \text{for} \quad C_{t+\mathbf{1}|t,(i)} > C_{t+\mathbf{1}|t,\left(i^*\right)} \\ \left(C_{t+\mathbf{1}|t,(i)} + C_{t+\mathbf{1}|t,\left(i^*\right)}\right) - \pi_{t+\mathbf{1}}, & \text{for} \quad C_{t+\mathbf{1}|t,(i)} < C_{t+\mathbf{1}|t,\left(i^*\right)} \end{cases} \tag{10}$$

Hence, whenever the i agent overestimates the future volatility compared to agent i*, then this agent (i) would overprice the option resulting at a long position trading position expecting a profit equal to:

$$profit_{t+1|t} = \pi_{t+1} - \left(C_{t+1|t,(i)} + C_{t+1|t,(i^*)} \right) = \left| S_{t+1} - e^{r_{t+1}} \right| - \left(C_{t+1|t,(i)} + C_{t+1|t,(i^*)} \right) \quad (11)$$

This equation at expiration would become:

$$profit_{T+1|T} = \left| S_{T+1} - e^{r_{T+1}} \right| - \left(C_{T+1|T,(i)} + C_{T+1|T,(i^*)} \right) \quad (12)$$

For the volatility forecasting process I use the GARCH family models with several extensions in order to account for the asymmetries on both the volatility specification and the distribution of the time series as shown in Table 1 of the appendix:

$$\varepsilon_t^{(m)} = z_t^{(m)} \cdot \sqrt{h_t^{(m)}} \text{ and } h_t^{(m)} = g\left(h_{t-1}^{(m)}, \ldots, h_{t-p}^{(m)}, \left[y_{t-1}^{(m)} - y_{t-i}^{(m)} \right], \ldots, \left[y_{t-q}^{(m)} - y_{t-i}^{(m)} \right] \right) \quad (13)$$

where the innovations ε_t represent the filtered time series:

$$y_t = y_t + \varepsilon_t = c_0 + c_1 \cdot y_{t-1} + \ldots + c_\kappa \cdot y_{t-k} + \varepsilon_t \quad (14)$$

The one-step ahead prediction error is given below:

$$\varepsilon_{t|t-1} = y_t - y_{t|t-1} \text{ or } \varepsilon_{t|t-1} = y_t - \left(\hat{c}_{0,t-1} + \hat{c}_{1,t-1} \cdot y_{t-1} \right) \quad (15)$$

Adopting a GARCH(1,1) model, the one-step ahead conditional variance forecast equals:

$$h_{t+1|t} = E\left[h_{t+1} \mid \Psi_t\right] = a_{0,t} + a_{1,t} \cdot E\left(\varepsilon_t^2 \mid \Psi_t\right) + \beta_{1,t-1} \cdot E\left(h_t \mid \Psi_t\right) \qquad (16)$$

which at expiration turns to:

$$h_{T+1|T} = E\left[h_{T+1} \mid \Psi_T\right] = a_0 + a_1 \cdot E\left(\varepsilon_T^2\right) + \beta_1 \cdot E\left(h_T\right) \qquad (17)$$

For increasing the accuracy of the volatility forecast I adopt also the APARCH(1,1) model using either symmetric distributions such as the Normal, the t-student and the GED or the skewed distribution of **Giot** and **Laurent** (2000) according to the following equations:

$$h_t^{\frac{\delta}{2}} = \alpha_0 + \sum_{i=1}^{q} a_i \cdot \left(\left|y_{t-1}\right| - \gamma_i \cdot y_{t-i}\right)^{\delta} + \sum_{j=1}^{p} b_j \cdot h_{t-j}^{\frac{\delta}{2}} \qquad (18)$$

$$f\left(y/n,\xi\right) = \begin{cases} \dfrac{\Gamma\left(\frac{n+1}{2}\right)}{\Gamma\left(\frac{n}{2}\right)\cdot\sqrt{\pi\cdot(n-2)}} \cdot \dfrac{2\cdot s}{\xi+\frac{1}{\xi}} \cdot \dfrac{1}{\sqrt{h_t}} \cdot \left(1 + \dfrac{s\cdot\frac{y_t - y_t}{\sqrt{h_t}} + m}{n-2} \cdot \xi\right)^{-\frac{n+1}{2}} & , \dfrac{y_t - y_t}{\sqrt{h_t}} < -\dfrac{m}{s} \\ \dfrac{\Gamma\left(\frac{n+1}{2}\right)}{\Gamma\left(\frac{n}{2}\right)\cdot\sqrt{\pi\cdot(n-2)}} \cdot \dfrac{2\cdot s}{\xi+\frac{1}{\xi}} \cdot \dfrac{1}{\sqrt{h_t}} \cdot \left(1 + \dfrac{s\cdot\frac{y_t - y_t}{\sqrt{h_t}} + m}{n-2} \cdot \xi^{-1}\right)^{-\frac{n+1}{2}} & , \dfrac{y_t - y_t}{\sqrt{h_t}} \geq -\dfrac{m}{s} \end{cases}$$

(19)

where $m = \dfrac{\Gamma\left(\frac{n-1}{2}\right)\cdot\sqrt{n-2}}{\Gamma\left(\frac{n}{2}\right)\cdot\sqrt{\pi}} \cdot \left(\xi - \dfrac{1}{\xi}\right)$ and $s^2 = \xi^2 + \dfrac{1}{\xi^2} - m^2 - 1$

Following Engle (1993) we adopt the standardized prediction error criterion (SPEC) for choosing models. SPEC is defined as the sum of the squared deviations of forecasted and observed returns as shown below:

$$SPEC_q^{(m)} = \sum_{i=0}^{q} z_{burn+i+1|(1+i):(burn+i)}^{(m)\,2} = \sum_{i=0}^{q} \left(\frac{\varepsilon_{burn+i+1}^{(m)}}{\sqrt{h_{burn+i+1}^{(m)}}} \right)^2 \Big| (1+i):(burn+i) \qquad (20)$$

where burn: is the sample which is used for making in-sample forecasts, q: is the number of one-step-ahead in-sample forecasts that are used when applying the SPEC. As q decreases, then the investor's flexibility for using different models is increased. At t (t=burn+k*q) according to SPEC the mth model will be chosen that minimized the sum of the squared standardized one-step-ahead prediction errors.

4 Empirical Findings

The implementation of the straddle trading strategy with maturity of one day is presented in Figure 2 of the Appendix. There are 23 agencies and the payoffs are estimated for 74 weeks. According to this figure it is shown that the first ten agencies exhibit the higher payoffs.

The SPEC criterion is applied for the examined series and it is represented in Figure 3 of the appendix. According to SPEC it is obvious that the rest agencies (10-23) are those that reward investors with the minimum prediction error.

5 Conclusion

This paper in strongly motivated by the work of Engle (1993) and investigates a model choice process that should be adopted when the predictive power matters instead of the model fit per se. I applied the afore-mentioned criterion using data from a relatively small Stock Exchange, the Athens Stock Exchange. The importance of this choice is that during the examined time period the Greek economy experienced a major development because of the Athens 2004 Olympic Games that were accommodated at Greece, having attracted many investors during the first half of the first decade of this century.

According to Figure 4, active trading on volatility which is the implication of adopting the SPEC criterion seems to be an important rule for maximizing the predictive power and thus the profitability of investors. This rule outperformed passive volatility trading strategies that are based on symmetric models, while it rewarded investors with high profitability similar to that of more advanced econometric approaches that account for asymmetries in the volatility and the returns' distributions.

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Appendix

List of Tables

Table 1. The definition of the applied volatility models.

MODELS	
Model 1:	GARCH(1,1)_AR(0)_Normal
Model 2:	GARCH(1,1)_AR(1)_Normal
Model 3:	GARCH(1,1)_AR(2)_Normal
Model 4:	GARCH(1,2)_AR(0)_Normal
Model 5:	GARCH(2,1)_AR(0)_Normal
Model 6:	GARCH(2,2)_AR(0)_Normal
Model 7:	GARCH(1,2)_AR(1)_Normal
Model 8:	GARCH(2,1)_AR(1)_Normal
Model 9:	GARCH(2,2)_AR(1)_Normal
Model 10:	GARCH(1,2)_AR(2)_Normal
Model 11:	GARCH(2,1)_AR(2)_Normal
Model 12:	GARCH(2,2)_AR(2)_Normal
Model 13:	GARCH(1,1)_AR(0)_T-Student
Model 14:	GARCH(1,1)_AR(2)_T-Student
Model 15:	AP-GARCH(1,1)_AR(0)_T-Student
Model 16:	AP-GARCH(1,1)_AR(1)_T-Student
Model 17:	AP-GARCH(1,1)_AR(2)_T-Student
Model 18:	GARCH(2,2)_AR(0)_T-Student
Model 19:	GARCH(2,2)_AR(1)_T-Student
Model 20:	GARCH(1,1)_AR(0)_GED
Model 21:	GARCH(1,1)_AR(0)_Skewed-T-Student
Model 22:	GARCH(1,1)_AR(1)_Skewed-T-Student
Model 23:	AP-GARCH(1,1)_AR(0)_Skewed-T-Student

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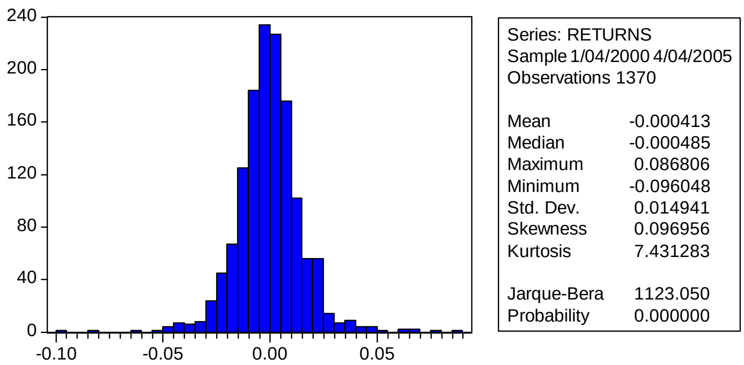

Figure 1. Histogram of the ATHEX/FTSE-20 returns

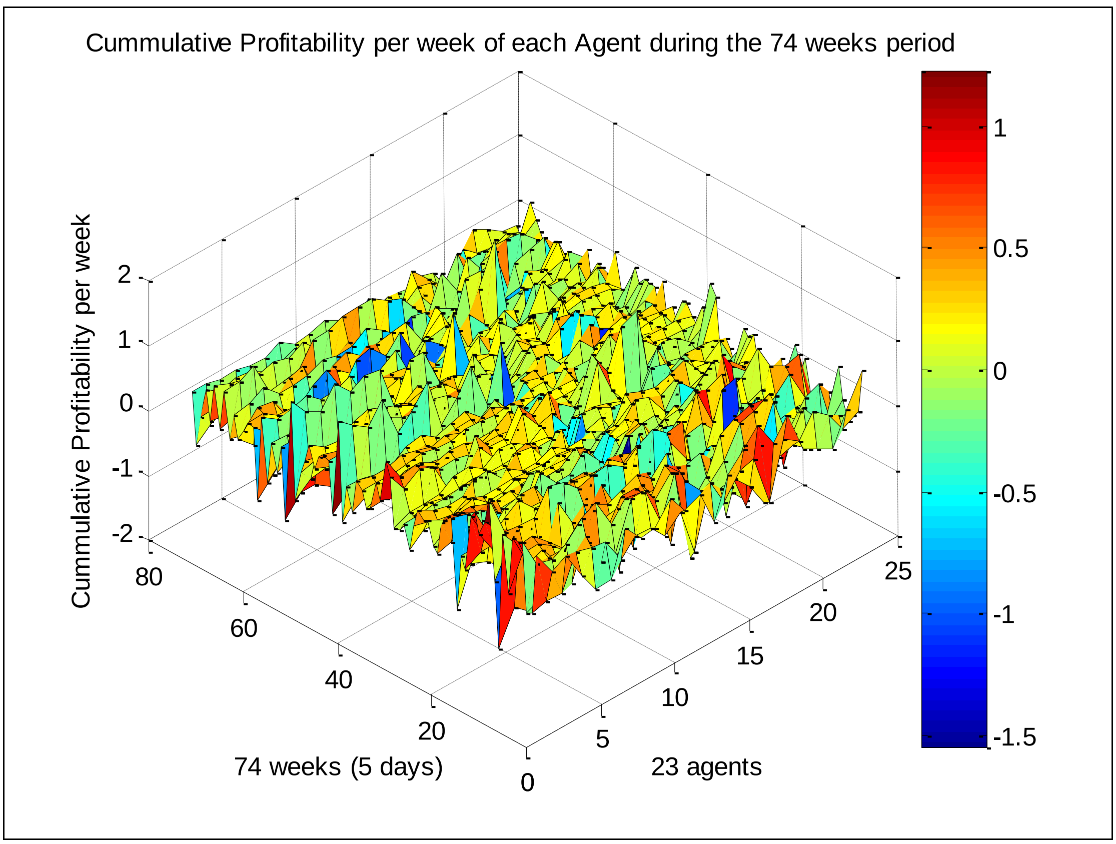

Figure 2. Cumulative weekly payoff for the different volatility forecasting approaches.

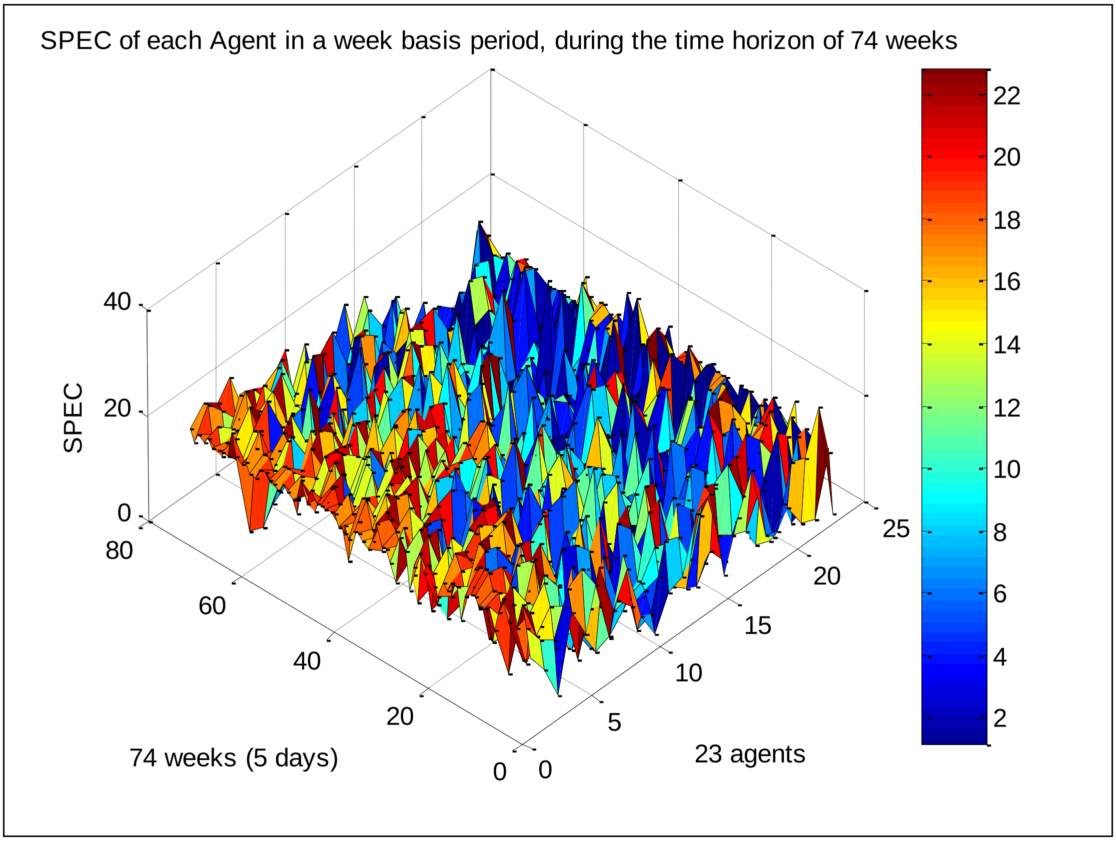

Figure 3. SPEC criterion over the whole period for each volatility model.

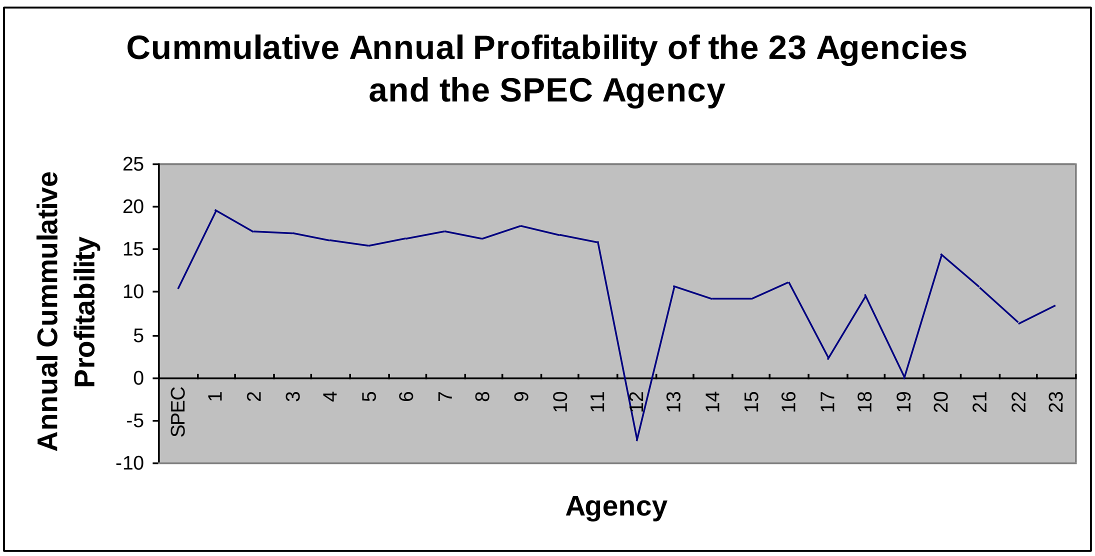

Figure 4. Cummulative annual profitability of the different volatility specifications.