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Modeling S&P500 returns with GARCH models

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Modeling S&P500 returns with GARCH models

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Abstract

This paper provides several estimates of the parameters of a GARCH model for the S&P500 index, based on: (i) returns, (ii) returns and CBOE VIX, and (iii) returns, CBOE VIX, and other option-based indexes reported by the Federal Reserve of Minneapolis. We conclude that by including option-based indexes alternative calibrations are obtained, which can be used to compute improved tail-risk statistics under the risk neutral measure, providing a better assessment of the occurrence of extreme events.

Resumen

Este artículo proporciona una serie de estimaciones para los parámetros de un modelo GARCH del índice S&P500, utilizando información de: (i) retornos, (ii) retornos y VIX de CBOE, y (iii) retornos, VIX de CBOE, y otros índices basados en opciones reportados por la Reserva Federal de Minneapolis. Concluimos que al incluir información de índices basados en opciones es posible obtener distintas calibraciones del modelo, las que pueden ser utilizadas para computar medidas de riesgo de cola bajo riesgo neutral mejoradas, al reflejar de mejor forma la probabilidad de eventos extremos.

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I. Introduction

GARCH models were introduced by Engle (1982) and then widely used in financial econometrics for empirical modeling of asset prices (Singleton, 2002), as they offer a powerful tool for characterizing the distribution of asset prices, which oftentimes requires Monte Carlo simulations to obtain relevant statistics such as tail-risk measures. Duan (1995) established that a GARCH model can also be used to value options by introducing the so-called locally risk-neutral valuation relationship (LRNVR), in which a simple algebraic manipulation is needed to change the probability measure. For instance, if the returns can be modeled with a standard GARCH in mean, which characterizes the physical measure, then option prices must be evaluated using an asymmetric GARCH model, which characterizes the risk-neutral measure. The extension to other GARCH models is straightforward if the disturbances are normally distributed; moreover, approximations formulae are already published (eg., Duan et al., 1999). Alternatives have been provided, such as Heston and Nandi (2000) based on Heston (1993), in which the conditional variance of the model is included in the return equation, allowing the computation of the conditional moments of the cumulated returns, although this requires solving a recursive system of equations. Different GARCH models allow us to compute density functions under both the physical and risk-neutral measures, however the shape of these density functions depend on the GARCH's parameters as well as the initial level of conditional variance. Since conditional variance is also estimated with the model, the GARCH's parameters are crucial for proper estimation of density functions.

Hao and Zhang (2013) and Kannianen et al. (2014) pointed out that the VIX, which is a well-known volatility index generated by the Chicago Board Option Exchange (CBOE) using option prices, can be obtained in closed-form from several GARCH models. Therefore, they proposed to include it as an additional variable to estimate GARCH's parameters, nonetheless, reaching opposite conclusions. On one side, Hao and Zhang (2013) argued that the joint estimation generates "unreasonable parameters", and that the implied VIX from the GARCH model is not in line with the observed one in "various statistical aspects". On the other, Kannianen et al. (2014) stated that joint estimates "improve option pricing performance", compared with other methods such as direct calibration. Zhang and Zhang (2020) tried to close that discrepancy by modifying the LRNVR, yet

the data does not support their approach. Still, CBOE VIX is one of multiple option-based indexes, providing a proxy of only one additional dimension of financial series. Thus, the approach can be enriched by including other measures, such as those provided by the Federal Reserve of Minneapolis (FRM), which calculates option-based indexes.

In this paper, we conducted several empirical strategies for estimating GARCH parameters. First, we consider daily data of the S&P500 returns and CBOE VIX from 2007Q1 to 2021Q3, confirming the conclusions of previous papers. Second, we include biweekly data of 6-month FRM skewness, attaching Monte Carlo simulations to the maximization process; therefore, our estimates are consistent with returns, VIX and FRM Skewness. Our main goal is to compare the risk-neutral densities derived from different datasets (returns only, returns and VIX, and returns, VIX and FRM Skewness); in particular, to compute the (risk-neutral) probabilities of extreme events. We conclude that by including a combination of the information of returns, VIX and Skewness, a better estimate of the probability of extreme events is obtained, thus allowing for an improved assessment of the occurrence of these events compared to the returns only estimate.

II. Model Setup

In this section we discuss: (i) the key elements of the GARCH model and the locally risk-neutral valuation relationship (LRNVR), (ii) the relationship of the GARCH model's parameters with VIX, and (iii) the Monte Carlo simulations approach to compute other option-based indexes.

1. GARCH model and the LRNVR assumption

In the GARCH model the log-return of the asset, which is the log-difference of the asset price (S_t) has the following dynamic:

$$\Delta \log S_t = f_t - \frac{1}{2} h_t + \lambda \sqrt{h_t} + \sqrt{h_t} u_t, \quad (1)$$

where f_t is the risk-free short-term interest rate, h_t is the conditional variance, and u_t is an independent Gaussian error term under the physical measure. Conditional on h_t , the log-return for the next period is normally distributed; however, for short or medium run the probability distribution function of the cumulated log-returns departs from Gaussian distribution. Note that log-returns equation includes one-half of the conditional variance, which is the Jensen term, due to the use of logarithmic returns. Also, the term $\lambda \sqrt{h_t}$ is the risk-premium component, which is the size of excess returns investors require as risk compensation.

The conditional variance is defined recursively as:

$$h_t = \omega + \alpha h_{t-1} u_{t-1}^2 + \beta h_{t-1}, \quad (2)$$

where α controls for the degree of heteroscedasticity, and ω for the level of unconditional variance. We further use $\theta = (\lambda, \omega, \alpha, \beta)'$, the vector of parameters.

Duan (1995) introduced the locally risk-neutral valuation relationship (LRNVR) by considering that log-returns in GARCH models are conditionally normal distributed; in other words, returns are conditional on the variance which is known at current time. Thus, there is $v_t = u_t + \lambda$, assumed to follow a standard Gaussian disturbance, using (1) we have: $\Delta \log S_t = f_t - 0.5h_t + \sqrt{h_t} v_t$. The expected value of the new equation is $f_t - 0.5h_t$, which implies that asset price is a discounted

martingale. This simple observation has relevant impact in the distribution process of the asset price because the conditional variance must be adjusted accordingly with the new disturbance. Using (2) we have: $h_t = \omega + \alpha h_{t-1}(\nu_{t-1} - \lambda)^2 + \beta h_{t-1}$. In summary: (i) under the physical measure the GARCH model has a volatility term in the mean equation, and (ii) under the risk-neutral measure the GARCH model imposes an expected value according to the risk-free rate and the conditional variance equation has some degree of asymmetry.

The unconditional variance under the risk-neutral measure ($\bar{h}$) can be obtained by applying the properties of standard Gaussian distribution, for which we have: $\bar{h} = \omega/(1 - \rho)$, where the persistence parameter is $\rho = \alpha[1 + \lambda^2] + \beta$, and it is assumed to be less than one.

2. VIX and other option-based indexes

The VIX is an index provided by the Chicago Board Options Exchange (CBOE), based on the squared root of a weighted average of 30-day option prices. The goal of the index is to approximate the expected value of the variance swap; thus, its interpretation should be in squared terms. As we discussed in previous section, Hao and Zhang (2013) and Kanninen et al. (2014) pointed out that GARCH models offer a discrete-time approximation of the variance swap, thus it is possible to get a closed-form expression for its expected value.

Considering the previous GARCH model, the relationship between the daily variance based on the VIX (X_t) and the conditional variance (h_{t+1}) is:

$$X_t \equiv \frac{1}{\tau} \left(\frac{VIX_t}{100} \right)^2 = \frac{1}{n} \sum_{k=1}^n E_t^*(h_{t+k}) = \left[1 - \frac{1 - \rho^n}{n(1 - \rho)} \right] \bar{h} + \left[\frac{1 - \rho^n}{n(1 - \rho)} \right] h_{t+1}, \quad (3)$$

where n stands for the maturity of the VIX and τ for the annualizing parameter. Following Kanninen et al. (2014) we use $n = 22$ for trading days, and $\tau = 365$ according to VIX calendar count convention. It is important to stress that X_t is related with “future” conditional variance since the latter is known at time t . We further reference (3) using: $X_t = A + B h_{t+1}$, with A and B according to (3).

The Federal Reserve of Minneapolis (FRM) computes several indexes based on option-prices with 6- and 12-months expirations, including skewness, kurtosis, and probabilities of extreme events. The procedure is based on Shimko (1993) and Malz (1997) in the sense that the available option prices are summarized into implied-volatilities and strike-price space. A cubic spline is used to characterize that relationship which is then used to generate call prices. Finally, indexes are computed in accordance with statistical formulae (eg., skewness and kurtosis) or by taking second derivative of call prices (eg., risk-neutral density).

3. Estimation of higher-order moments

The GARCH model does not have a closed-form expression for cumulated log-returns, and therefore some approximations must be considered. Duan et al. (1999) provided analytical solutions for the first and fourth moments, approximating the terms of conditional variance with fractional power. In line with Duan (1995), we rely on Monte Carlo simulations to compute both higher-order moments of the cumulated log-returns and other non-linear functions such as tail probabilities. For our implementation, we cast the problem as a given expected value, approximated by I replications of the asset-price process:

$$E_t[f(S_{t+n})] = \frac{1}{I} \sum_{i=1}^I f(S_{(i),t+n}), \quad (4)$$

where $S_{(i),t+n}$ is the terminal value ($t + n$) of the i -simulated path, and by averaging over all paths, we compute the expectation.

For skewness (Z_t) we compute power-payoff options of n -day log-return of the asset following CBOE procedure (CBOE, 2010). Thus, $P_{tk} = E_t[(\log S_{t+n} - \log S_t)^k]$, for $k = 1, 2, 3$. Based on that we compute: $Z_t = (P_{t2} - P_{t1}^2)^{-1.5}(P_{t3} - 3P_{t2}P_{t1} + 2P_{t1}^3)$. This is in line with CBOE procedure where estimates of P_{tk} are obtained as a weighted average of option-prices with the weights being strike values, analogous to the VIX computation (CBOE, 2019). It should be noted that formula used for VIX is not based on P_{t2} given that VIX is a continuous variance-swap, not the variance of a given terminal value. For the tail-risk, we compute the probability value of being below a given threshold. Following the ones published by the FRM we choose a threshold value of 80%, equivalent to a 20% loss.

III. Empirical Analysis

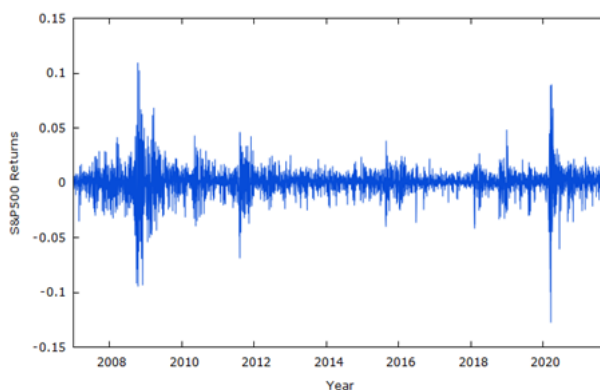
In this section we describe the variables used in the estimation. Then, discuss the procedure and the results obtained under different setups. Finally, we provide probability estimates, based on Monte Carlo simulations.

1. Data

The time-series data used to estimate the GARCH models are the daily closing prices of the S&P500, CBOE VIX and FRM Skewness, ranging from January 2, 2007, to September 30, 2021, which we further refer as 2007Q1-2021Q3. For the daily risk-free interest rate, we use the three-month (secondary market) Treasury bill rate retrieved from the Federal Reserve Bank of St. Louis website. These series have 3,849 daily observations available for study.¹

As portrayed in Figure 1, for the 2007Q1-2021Q3 period, we obtain the continuously compounded returns of the S&P500 series after log-differencing. Daily mean is at 0.03% with a standard deviation of 0.013, it exhibits a negative skewness of -0.567 and kurtosis of 16.730.

Figure 1. Returns after log-differencing
(percentage)



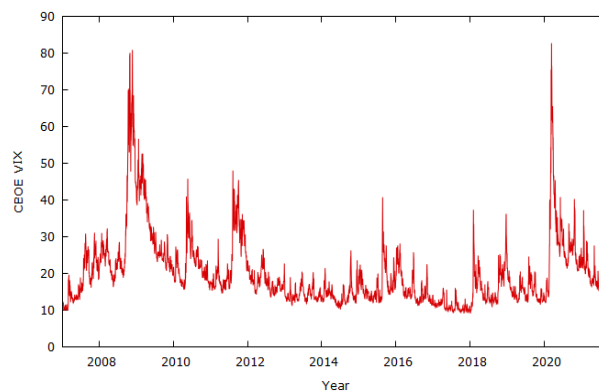
Source: Bloomberg

Figure 2 presents the CBOE VIX series, which is calculated from a portfolio of S&P500 options with maturity of 30 days and associated with perceived risk, easily noticeable at and after the 2008

¹ For non-trading days related to stock market holidays, we compute the value of the last trading day available.

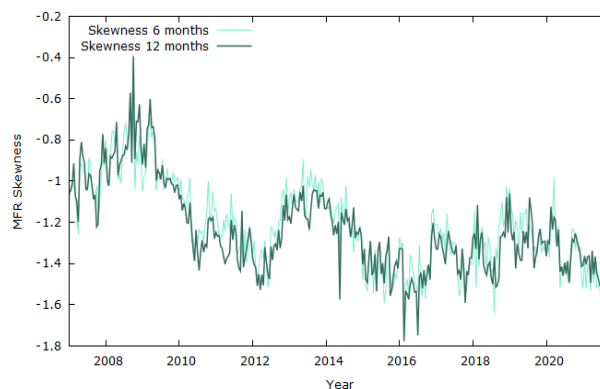
financial crisis, and at the beginning of 2020 in the surge of the COVID-19 pandemic. Finally, the Federal Reserve Bank of Minneapolis computes statistical indexes based on option prices such as mean, standard deviation, skewness and kurtosis. Figure 3 displays the skewness for 6 and 12 months, these estimates were retrieved from their website, available for the 2007Q1-2021Q3 period, with 354 biweekly observations for study.² Regarding the 6-month skewness, the biweekly mean for the sample period is at -1.215 with a standard deviation of 0.212, meanwhile for the 12-month skewness the figures are -1.238 and 0.2157, respectively.

Figure 2. The CBOE VIX.
(index)



Source: Bloomberg

Figure 3. Skewness of the S&P500 log-returns
(index)



Source: Federal Reserve of Minneapolis

² Note that our method can be extended to other indexes based on option-prices such as the kurtosis, which is also published by FRM.

2. Joint Likelihood

To estimate the GARCH model parameters we use the maximum likelihood (ML) approach, for returns, VIX and FRM Skewness. For the returns data, the loglikelihood function $\log L_{RET}$ is:

$$\log L_{RET}(\theta) = -\frac{1}{2} \sum_{t=1}^T \left[\log h_t + \frac{(\Delta \log S_t - f_t + 0.5h_t - \lambda\sqrt{h_t})^2}{h_t} \right], \quad (5)$$

and the corresponding function for the VIX data is:

$$\log L_{VIX}(\theta) = -\frac{T}{2} \log \left[\frac{1}{T} \sum_{t=1}^T (X_{t-1} - A - Bh_t)^2 \right]. \quad (6)$$

Thus, the joint likelihood on returns and VIX could be defined as a linear combination of both log-likelihood functions:

$$\log L_{TOT}(\theta) = (1 - \kappa) \log L_{RET}(\theta) + \kappa \log L_{VIX}(\theta) \quad (7)$$

where κ is the parameter that controls the weight assigned to the VIX data. Hao and Zang (2013) and Kannianen et al. (2014) consider 3 cases ($\kappa = 0$, $\kappa = 0.5$ and $\kappa = 1$).

To include option-based indexes from Federal Reserve of Minneapolis, we augmented (7) by adding the corresponding loglikelihood weighted by γ :

$$\log L_{TOT}(\theta) = (1 - \kappa - \gamma) \log L_{RET}(\theta) + \kappa \log L_{VIX}(\theta) + \gamma \log L_{OPT}(\theta). \quad (8)$$

Note that FRM indexes are in biweekly frequency, thus the sample size (J) is lower, therefore the last term in the augmented log-likelihood is:

$$\log L_{OPT}(\theta) = -\frac{T}{2} \log \left[\frac{1}{J} \sum_{j=1}^J (Z_j - \tilde{Z}_j)^2 \right], \quad (9)$$

where Z_j is the FRM Skewness, and $\tilde{Z}_j$ is its simulated counterpart.

3. Main Results

Our results consider the 6-month FRM Skewness since there is slight difference between maturities (see Figure 3), thus restricting the analysis to shorter maturities. Table 1 shows the results for the GARCH models; column (i) provides estimates using only returns, columns (ii – v) portray the estimates using 50% returns and different combinations of CBOE VIX and FRM Skewness, and columns (vi-ix) using 40% returns.

Table 1. ML estimates for GARCH models using returns, VIX and FRM Skewness
(daily data, 2007Q1-2021Q3)

C	i	ii	iii	iv	v	vi	vii	viii	ix
κ	0.0	0.5	0.4	0.3	0.2	0.6	0.4	0.2	0.3
γ	0.0	0.0	0.1	0.2	0.3	0.0	0.2	0.4	0.3
λ	0.1009 (0.0154)	0.2666 (0.0358)	0.3154 (0.0360)	0.3821 (0.0363)	0.5851 (0.0313)	0.3532 (0.0459)	0.4819 (0.0471)	0.6123 (0.0389)	0.6615 (0.0389)
ω	2.999E-06 (2.52E-07)	2.782E-06 (4.25E-07)	2.811E-06 (4.18E-07)	2.927E-06 (4.21E-07)	9.812E-06 (8.40E-07)	2.771E-06 (5.13E-07)	2.853E-06 (4.91E-07)	1.037E-05 (1.08E-06)	9.158E-06 (9.33E-07)
α	0.1522 (0.0097)	0.0425 (0.0044)	0.0443 (0.0045)	0.0496 (0.0051)	0.2508 (0.0232)	0.0404 (0.0051)	0.0446 (0.0054)	0.2516 (0.0284)	0.2318 (0.0248)
β	0.8283 (0.0098)	0.9278 (0.0073)	0.9241 (0.0074)	0.9146 (0.0081)	0.6117 (0.0196)	0.9287 (0.0086)	0.9184 (0.0090)	0.5996 (0.0239)	0.6117 (0.0232)
ρ	0.9821	0.9734	0.9729	0.9715	0.9482	0.9742	0.9733	0.9455	0.9449
$h^{0.5}$	0.2054	0.1623	0.1616	0.1607	0.2186	0.1645	0.1640	0.2189	0.2046

First, by increasing only κ , we put more relative weight into the VIX data compared to returns, yielding an increase in the risk-premium parameter (λ), that moves from 10% to 35% which implies that the adjusted GARCH model (under the risk-neutral measure) has a high degree of asymmetry; however, this is compensated with a decreasing heteroscedasticity parameter (α) that moves from 15% to 4%. The increase in the risk-premium parameter is in line with the results of previous papers, and in turn involves an increase in the persistence parameter under the risk-neutral measure.³ Second, we include the FRM Skewness by increasing γ , we also yield an increase in the risk-premium parameter being as large as 66% when VIX is weighted 30% and Skewness is weighted 30% (column ix). Thus, denoting some degree of substitution between κ and γ , as both parameters provide varying relative weights of the information contained in option-based indexes. Third, by

³ Additional results that combine returns and VIX, show that risk-premium parameter increases to 48% when returns are weighted 30% and 69% when are weighted 20%. Heteroscedasticity parameter are 3.8% and 3.5%, respectively.

over-weighting FRM Skewness (30% or 40%) α increases around 25%, which is higher than the one obtained under column (i). In these cases, the β parameter drops to 60% with a small persistence parameter (around 95%).

IV. Discussion

Now we illustrate the relevance of these alternative estimates by computing the probability of an extreme event (20% drop) under the risk-neutral measure in the next 6 months, which is also computed using Monte Carlo simulations. Figure 4 displays these probabilities using the estimates in Table 1 columns (i), (ii) and (v) against initial variance, over unconditional variance to normalize the x-axis. As expected, the probabilities are increasing with the normalized initial variance, but with different degree of sensibility. For the returns only case (blue line), the probabilities move in the range of 6.6-14.5%, when the VIX is weighted-in by increasing κ to 50% (red line), this range drops to 4.1-9.7%, lastly, as the VIX is partially replaced by FRM Skewness with γ at 30% (green line), the probabilities are between 10-12.5%.

Figure 4. Probabilities of an extreme event
(percentage point)

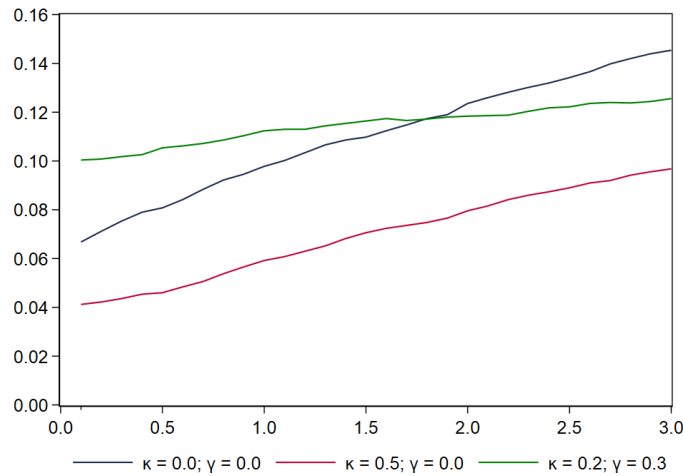
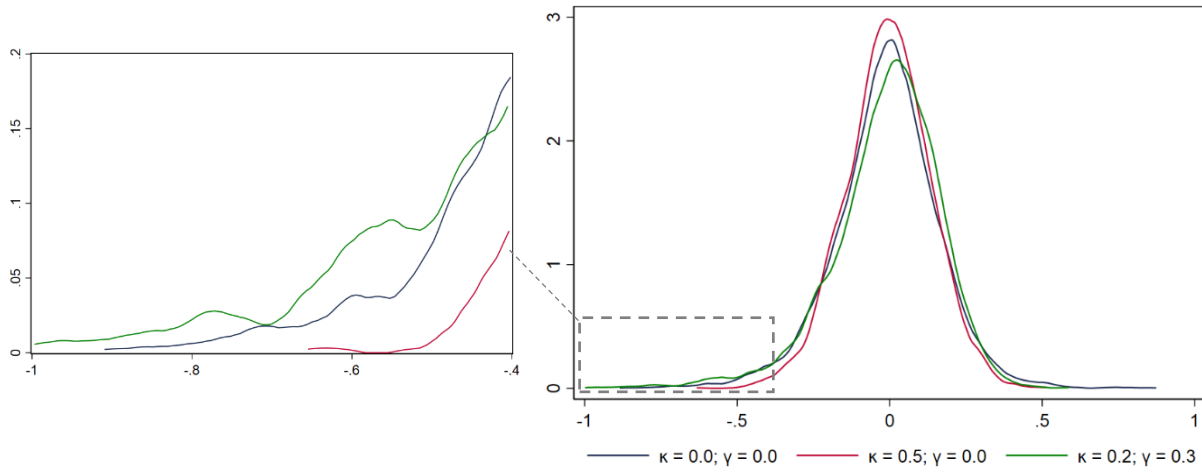


Figure 5 portrays the probability density at the initial variance equal to the unconditional variance, using Figure 4 as reference, this is the density at 1 in the x-axis, where the probability of an extreme event for the returns only case stands at 9.8%, with both returns and VIX at 5.9%, and using returns,

VIX and FRM Skewness at 11.2%. By zooming in the left side of the distribution, the probability density using both returns and the option-based indexes is above the return only estimate, thus providing a better estimate of tail-risk events. On the other hand, the return and VIX estimator stands under the returns only estimate, yielding a poorer estimate.

Figure 5. Probability density at unconditional variance and left-tail zoom
(density)



V. Conclusions

GARCH models combined with Monte Carlo simulations are useful tools for modelling asset prices, which can be in turn be used to compute tail-risk measures. We use information of log-returns, VIX and other option-based index (Skewness) to estimate GARCH models. Our empirical results are in line with previous papers in the area (Hao and Zhang, 2013; Kanniainen et al., 2014; Zhang and Zhang, 2020) in terms of including VIX information, and contribute by broadening this approach with different combinations of VIX and returns, in addition to market-based skewness. We found that the probability estimates change based on the information used to obtain the GARCH parameters, moreover a better assessment of the occurrence of extreme events is captured by including option-based indexes, therefore this type of information should be considered.

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