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Maximum likelihood estimation for stochastic volatility in mean models with heavy-tailed distributions

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Abstract

In this article, we introduce a likelihood-based estimation method for the stochastic volatility in mean (SVM) model with scale mixtures of normal (SMN) distributions (Abanto-Valle et al., 2012). Our estimation method is based on the fact that the powerful hidden Markov model (HMM) machinery can be applied in order to evaluate an arbitrarily accurate approximation of the likelihood of an SVM model with SMN distributions. The method is based on the proposal of Langrock et al. (2012) and makes explicit the useful link between HMMs and SVM models with SMN distributions. Likelihood-based estimation of the parameters of stochastic volatility models in general, and SVM models with SMN distributions in particular, is usually regarded as challenging as the likelihood is a high-dimensional multiple integral. However, the HMM approximation, which is very easy to implement, makes numerical maximum of the likelihood feasible and leads to simple formulae for forecast distributions, for computing appropriately defined residuals, and for decoding, i.e., estimating the volatility of the process.

Keywords

feedback effect; non-Gaussian and nonlinear state-space models; scale mixture of normal distributions; Value-at-Risk

1 Introduction

Over the last two decades, stochastic volatility models have proven to be useful for modeling time-varying variances, mainly in financial applications where policy makers or stockholders are constantly facing decision problems that usually depend on measures of volatility and risk. An attractive feature of the stochastic volatility model is its close relationship to financial economic theories (Melino and Turnbull, 1990) and its ability to capture the main empirical properties, i.e. the stylized facts, often observed in daily series of financial returns (Carnero et al., 2004).

Many empirical studies have shown strong evidence of heavy-tailed conditional mean errors in financial time series; see for example Mandelbrot (1963) and Fama (1965). In the stochastic volatility literature, Liesenfeld and Jung (2000), Chib et al. (2002), Jacquier et al. (2004) and Abanto-Valle et al. (2010), amongst others, have provided consistent evidence that leptokurtic distributions, such as the Student's t, the generalized error or the SMN distributions, which relax the normality assumption that is often made for the distribution of the returns, should be used in order to capture this feature.

Frequently, the volatility of daily stock returns has been modeled using stochastic volatility models, but the results have relied on an extensive pre-modeling of these series to avoid the problem of simultaneous estimation of the mean and variance. Koopman and Uspensky (2002) introduced the stochastic volatility in mean (SVM) model to deal with this problem, incorporating the unobserved volatility as an explanatory variable in the mean equation of the returns under a normality assumption for the innovations. Abanto-Valle et al. (2012) proposed to enhance the robustness of the specification of the innovation return in SVM models by introducing SMN distributions, referring to this generalization as the SVM-SMN class of models. This rich class contains as proper elements the SVM with normal (SVM-N), Student-t (SVM-T) and slash (SVM-S) distributions. Abanto-Valle et al. (2012) proposed a Markov Chain Monte Carlo (MCMC) procedure for Bayesian estimation of SVM-SMN models. However, the resulting MCMC algorithm has some undesirable features. In particular, the procedure is quite involved, requiring a large amount of computerintensive simulations. In addition, the computational cost increases rapidly with the sample size.

In this paper, we apply an alternative frequentist estimation method, numerically maximizing a (virtually exact) approximation of the likelihood function which is efficiently evaluated using recursive techniques routinely applied for hidden Markov models (HMMs). The key idea, the use of iterated numerical integration, was introduced by Kitagawa (1987). In the context of stochastic volatility models, it was applied by Fridman and Harris (1998), Bartolucci and De Luca (2001; 2003), and Clements et al. (2006), although none of these papers explicitly make the important link between stochastic volatility models and HMMs. The approximation to the SVM likelihood obtained through numerical integration can be made arbitrarily accurate while maintaining computational tractability, due to the powerful HMM forward algorithm becoming applicable. Further advantages of the (approximate) HMM representation of SVM-SMN models are that simple explicit formulae exist for the residuals and the forecast distributions, and that estimates of the latent log-volatility process can be obtained by using the Viterbi algorithm.

Rydén et al. (1998), Rossi and Gallo (2006), Bulla and Bulla (2006) and Fuertes and Papanicolaou (2014) discuss other HMM-based approaches to modelling financial time series. In Rydén et al. (1998), Rossi and Gallo (2006) and Bulla and Bulla (2006), and unlike within our approach, the (log-)volatility process is modelled as a Markov chain on a (small) finite number of states, in Rossi and Gallo (2006) with a very specific structure assumed for the between-state transitions. While our approach does also involve a discrete-state Markov chain in the fitting procedure, this is only used as a computational tool for approximating the *continuous* log-volatility space of the model of interest. Fuertes and Papanicolaou (2014) consider continuous-time models that are subject to regime switching.

The remainder of this paper is organized as follows. Section 2 gives a brief introduction to SMN distributions. Section 3 outlines the general class of SVM-SMN models as well as the maximum likelihood-based estimation procedure using HMM methods. In Section 4, we conduct a simulation study in order to verify frequentist properties of the likelihood estimators. Section 5 is devoted to the application and model comparison among particular members of the SVM-SMN models using international market indexes. Some concluding remarks and suggestions for future developments are given in Section 6.

2 Scale mixture of normal distributions

A random variable Y belongs to the SMN family if it can be expressed as

$$Y=\mu+\kappa(\lambda)^{1/2}X, \quad (1)$$

where p is a location parameter, $X \sim \mathscr{N}(0,\sigma^2)$, λ is a positive mixing random variable with cumulative distribution function (*cdf*) $H(\cdot|\, \boldsymbol{\nu})$ and probability density function $(pdf)\, h(\cdot|\boldsymbol{\nu}), \boldsymbol{\nu}$ is a scalar or parameter vector indexing the distribution of λ, and $\kappa(\cdot)$ is a positive weight function. As in Lange and Sinsheimer (1993) and Choy et al. (2008), we restrict our attention to the case where $\kappa(\lambda) = 1/\lambda$. Given λ, we have $Y|\lambda \sim \mathscr{N}(\mu, \lambda^{-1}\sigma^2)$, and the *pdf* of Y is given by

$$f_{SMN}(y|\mu,\sigma^2,\nu)=\int_{-\infty}^{\infty}\phi(y|\mu,\lambda^{-1}\sigma^2)dH(\lambda|\nu), \quad (2)$$

where $\phi(\cdot|\mu,\sigma^2)$ denotes the density of the univariate $\mathscr{N}(\mu,\sigma^2)$ distribution. From equation (2), we have that the *cdf* of the SMN distributions is given by

$$\begin{aligned}F_{SMN}(y|\mu,\sigma^2,\nu)&=\int_{-\infty}^{y}\int_{-\infty}^{\infty}\phi(u|\mu,\lambda^{-1}\sigma^2)dH(\lambda|\nu)du\\ &=\int_{-\infty}^{\infty}\Phi\left(\frac{\lambda^{1/2}[y-\mu]}{\sigma}\right)dH(\lambda|\nu),\end{aligned} \quad (3)$$

where $\Phi(\cdot)$ is the *cdf* of the standard normal distribution. The notation $Y \sim \mathscr{SMN}(\mu,\sigma^2,\nu;H)$ will be used when Y has *pdf* (2) and *cdf* (3). As mentioned above, the SMN family constitutes a class of thick-tailed distributions, including the normal, Student-t, and Slash distributions, which are obtained, respectively, by choosing the mixing variables as: $\lambda=1, \lambda \sim \mathscr{G}\left(\frac{\nu}{2},\frac{\nu}{2}\right)$, and $\lambda \sim \mathscr{B}e(\nu,1)$, where $\mathscr{G}(.,.)$ and $\mathscr{B}e(.,.)$ denote the gamma and beta distributions, respectively.

3 The heavy-tailed stochastic volatility in mean model

3.1 Model formulation

The SVM model with heavy-tails is defined by

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 e^{h_t} + e^{\frac{h_t}{2}} \varepsilon_t, \quad \text{(4a)}$$

$$h_{t+1} = \mu + \phi(h_t - \mu) + \sigma_\eta \eta_t, \quad \text{(4b)}$$

where y_t and h_t are, respectively, the compounded return and the log-volatility at time t. We assume that $|\phi| < 1$, i.e., the log-volatility process is stationary and the initial distribution is $h_1 \sim \mathcal{N}(\mu, \frac{\sigma_\eta^2}{1-\phi^2})$. The innovations ε_t and η_t are assumed to be mutually independent, $\varepsilon_t \sim \mathcal{SMN}(0, 1, v; H)$ and $\eta_t \sim \mathcal{N}(0, 1)$, respectively. The aim of the SVM-SMN class of models is to simultaneously estimate the *ex-ante* relation between returns and volatility and the volatility feedback effect in the presence of outliers. This class of models includes SVM models with normal distribution (SVM-N) (Koopman and Uspensky, 2002), the Student-t (SVM-T) and slash (SVM-S) distributions as special cases.

3.2 Likelihood evaluation by iterated numerical integration

To formulate the likelihood, we require the conditional *pdfs* of the random variables y_t, given h_t and y_{t-1} ($t = 1,\ldots, T$), and of the random variables h_t, given h_{t-1} ($t = 2,\ldots, T$). We denote these by $p(y_{t-1} \mid y_{t-1}, h_t)$ and $p(h_t \mid h_{t-1})$, respectively. For a member of the class of SMN distributions, the likelihood of the model defined by equations (4a) and (4b) can then be derived as

$$\begin{aligned}\mathcal{L} &= \int \ldots \int p(y_1, \ldots, y_T, h_1, \ldots, h_T | y_0)\, dh_T \ldots dh_1 \\ &= \int \ldots \int p(y_1, \ldots, y_T | y_0, h_1, \ldots, h_T)\, p(h_1, \ldots, h_T)\, dh_T \ldots dh_1 \\ &= \int \ldots \int p(h_1) p(y_1 | y_0, h_1) \prod_{t=2}^{T} p(y_t | y_{t-1}, h_t) p(h_t | h_{t-1}) dh_T \ldots dh_1,\end{aligned}$$

exploiting the dependence structure of the stochastic volatility models in the last step. Hence, the likelihood is a high-order multiple integral that cannot be evaluated analytically. Through numerical integration, using a simple rectangular rule based on m equidistant intervals, $B_i = (b_{i-1}, b_i)$, $i = 1,\ldots, m$, with midpoints b_i^* and length b, the likelihood can be approximated as follows:

$$\begin{aligned}\mathcal{L} \approx b^T \sum_{i_1=1}^{m} \ldots \sum_{i_T=1}^{m} p(h_1 = b_{i_1}^*) p(y_1 | y_0, h_1 = b_{i_1}^*) \\ \times \prod_{t=2}^{T} p(h_t = b_{i_t}^* | h_{t-1} = b_{i_{t-1}}^*) p(y_t | y_{t-1}, h_t = b_{i_t}^*) = \mathcal{L}_{\text{approx}}.\end{aligned} \quad (5)$$

This approximation can be made arbitrarily accurate by increasing m, provided that the interval (b_0, b_m) covers the essential range of the log-volatility process. We note that this simple midpoint quadrature is by no means the only way in which the integral can be approximated (cf. Langrock et al., 2012).

3.3 Fast evaluation and numerical maximization of the approximate likelihood using HMM techniques

In the form given in (5), the approximate likelihood can be evaluated numerically, but the evaluation will usually be computationally intractable since it involves m^T summands. However, instead of the brute force summation in (5), an efficient recursive scheme can be used to evaluate the approximate likelihood. To see this, we note that the numerical integration essentially corresponds to a discretization of the state space, i.e., the support of the log-volatility process h_t. Therefore, the approximate likelihood given in (5) can be evaluated using the tools well-established for HMMs, which are the models that have exactly the same dependence structure as the stochastic volatility models, but with a finite and hence discrete state space (cf. Langrock, 2011; Langrock et al., 2012). In the given scenario, the discrete states correspond to the intervals B_i, $i = 1,\ldots,m$, in which the state space has been partitioned. A key property of HMM, which we exploit here, is that the likelihood can be evaluated efficiently using the so-called forward algorithm, a recursive scheme which iteratively traverses forward along the time series, updating the likelihood and the state probabilities in each step (Zucchini et al., 2016). For an HMM, applying the forward algorithm results in a convenient closed-form matrix product expression for the likelihood, and this is exactly what is obtained also for the SVM-SMN class of models:

$$\mathscr{L}_{\text{approx}}=\delta\mathbf{P}(y_1)\mathbf{\Gamma}\mathbf{P}(y_2)\mathbf{\Gamma}\mathbf{P}(y_3)\cdots\mathbf{\Gamma}\mathbf{P}(y_{T-1})\mathbf{\Gamma}\mathbf{P}(y_T)\mathbf{1}^{\top}. \quad (6)$$

Here, the $m \times m$-matrix $\Gamma=(\gamma_{ij})$ is the analogue to the transition probability matrix in case of an HMM, defined by $\gamma_{ij}=p(h_t=b_j^*|h_{r-1}=b_i^*)\cdot b$, which is an approximation of the probability of the log-volatility process changing from some value in the interval B_i to some value in the interval B_j; this conditional probability is determined by Eq. (4b). The vector δ is the analogue to the Markov chain initial distribution in case of an HMM, here defined such that δ_i is the density of the $\mathscr{N}(\mu, \frac{\sigma_\eta^2}{1-\phi^2})$-distribution — the stationary distribution of the log-volatility process — multiplied by b. Furthermore, $\mathbf{P}(y_t)$ is an m × m diagonal matrix with the ith diagonal entry $p(y_t|y_{t-1}, h_t=b_i^*)$, hence the analogue to the matrix comprising the state-dependent probabilities in case of an HMM; this conditional probability is determined by Eq. (4a). Finally, $\mathbf{1}^{\top}$ is a column vector of ones. Using the matrix product expression given in (6), the computational effort required to evaluate the approximate likelihood is linear in the number of observations, T, and quadratic in the number of intervals used in the discretization, m.

In practice, this means that the likelihood can typically be calculated in a fraction of a second, even for T in the thousands and say $m = 100$, a value which renders the approximation virtually exact (see the simulation experiments below). Furthermore, the approximation can be made arbitrarily accurate by increasing m (and potentially widening the interval $[b_0,b_m]$). For any SVM-SMN model of interest, it is hence convenient and computationally inexpensive to estimate the model parameters using a numerical maximization of the approximate (log-)likelihood. Such a numerical maximization needs to address standard technical issues such as parameter constraints and numerical overflow (Langrock et al., 2012).

It should perhaps be noted here that, although we are using the HMM forward algorithm to evaluate the (approximate) likelihood, the specifications of $\boldsymbol{\delta}$, $\boldsymbol{\Gamma}$ and $\mathbf{P}(x_t)$ given above do not define exactly an HMM, since in general the row sums of $\boldsymbol{\Gamma}$ will only approximately equal one, and the components of the vector $\boldsymbol{\delta}$ will only approximately sum to one. If desired, this can be remedied by scaling each row of $\boldsymbol{\Gamma}$ and the vector $\boldsymbol{\delta}$ to total 1.

3.4 Forecasts and model checking

The HMM forward algorithm can also be used to obtain forecast distributions for SVM models. For example, it is straightforward to find the cumulative distribution function of the one-step-ahead forecast distribution on day $t-1$, i.e., the conditional distribution of the return on day t, given all previous observations. This is given by

$$F\left(y_t|y_{t-1},y_{t-2},\dots,y_0\right) \approx \sum_{i=1}^{m} \zeta_i F\left(y_t|y_{t-1},h_t=b_i^*\right), \quad (7)$$

where ζ_i is the ith entry of the vector $\alpha_{t-1}/(\alpha_{t-1}\mathbf{1}^\top)$, obtained from the forward probabilities,

$$\alpha_{t-1}=\delta\mathbf{P}(y_1)\mathbf{\Gamma}\mathbf{P}(y_2)\mathbf{\Gamma}\mathbf{P}(y_3)\cdots\mathbf{\Gamma}\mathbf{P}(y_{t-1}),$$

with $\boldsymbol{\delta}$, $\mathbf{P}(y_k)$ and $\boldsymbol{\Gamma}$ defined as above. The corresponding expression for longer forecast horizons is similar (see Chapter 5 of Zucchini et al., 2016, for details). The approximation in (7) usually becomes virtually exact for values of m about 100. A closed-form expression for obtaining state predictions, i.e., volatility predictions, is also available. Furthermore, the forecast distribution given in Eq. (7) can be used in order to perform model checking via residuals (Kim et al., 1998). The one-step-ahead forecast pseudo-residual (or quantile residual) is given by

$$r_t=\Phi^{-1}\left(F\left(y_t|y_{t-1},y_{t-2},\dots,y_0\right)\right), \quad (8)$$

for $t = 1, \dots, T$. For a correctly specified model, the r_t follow a standard normal distribution (Rosenblatt, 1952; Smith, 1985; Kim et al., 1998; Gerlach et al., 1999; Liesenfeld and Richard, 2003). Thus, forecast pseudo-residuals can be used to identify extreme values, and the suitability of the model can be checked by using, for example, qq-plots or formal tests for normality.

3.5 Decoding

Again building on standard HMM machinery, estimates of the underlying log-volatility values can easily be obtained using the Viterbi algorithm, which is an efficient dynamic programming algorithm for computing the most likely Markov chain state sequence to have given rise to observations stemming from an HMM (see Langrock et al., 2012; Zucchini et al., 2016, for details)

4 Simulation Study

In order to assess the performance of the methodology described in the previous section, we conducted some simulation experiments. All the calculations were performed using stand-alone code developed by the authors using the Rcpp interface inside R. First, we simulated a data set comprising $T = 6000$ observations from the SVM-T model, specifying $\boldsymbol{\beta} = (0.2, 0.07, -0.18)^\top$, $\mu = 0.1$, $\phi = 0.98$, $\sigma_\eta = 0.1$, $\nu = 8$ and $y_0 = 0.2$, which correspond to typical values found in daily series of returns. Figure 1 shows the resulting artificial data set.

In order to investigate the influence of the choice of m on the accuracy of the likelihood approximation, and of the sample size T on the computing time, we additionally fitted the SVM-T model using $m = 50,100,150,200$ (i.e., different levels of accuracy), $b_m = -b_0 = 4$, to subsamples of length T = 1500, 3000 of the original simulated series. Table 1 reports the results. We observe that the parameter estimates obtained by the approximate maximum likelihood method become stable for values of m around 100, for all the sample sizes considered here. Although the results are not reported here, we also investigated the influence of the choice of b_0 and b_m, finding that the estimator performance was not affected much unless these were chosen either much too small (thus not covering the essential support of the log-volatility process, which in the given setting would be the case for example for $b_m = -b_0 = 2$) or much too large (thus leading to a partition of the support into unnecessarily wide intervals in the numerical integration, and hence a poor approximation of the likelihood, for example with m = 50 and $b_m = -b_0 = 15$). In practice, it can easily be checked *post-hoc* if the chosen range, specified by b_0 and b_m, is adequate, by investigating the stationary distribution of the fitted log-volatility process. As regards the computing time to get the maximum likelihood estimators of the parameters, we observe that, for example, for the SVM-T with $m = 200$ and 6000 observations our approach using the HMM machinery takes about 14 minutes, instead of almost 4 hours to realize 50000 iterations in order to achieve convergence of an MCMC procedure. With the HMM approach, the computational effort increases linearly in T.

Next, we conducted a second simulation experiment with the objective to study properties of the maximum likelihood estimators of the SVM model's parameters. We generated 300 datasets from the SVM-T model, specifying $\boldsymbol{\beta} = (0.20, 0.07, -0.18)^\top$, $\phi = 0.98$, $\sigma_\eta = 0.1$, $\mu = 0.10$ and $\nu = 10$. For each generated data set, we fitted the SVM-T model using $m = 50, 100, 150, 200$ and $b_m = -b_0 = 4$, for $T = 2500$ and $T = 5000$, respectively. Tables 2 and 3 report the sample mean, the mean relative bias (MRB), the mean relative absolute deviation (MRAD) and the mean squared error (MSE) of the parameter estimates.

For both sample sizes, i.e., $T = 2500$ and $T = 5000$, the highest MRB was found for the estimator of μ, while none of the other estimators exhibited a notable bias. The bias found for $\hat{\mu}$ does not have a strong effect of the resulting model and its performance in forecasting, since it simply means a minor shift of the volatility process. With the exception of $\hat{\mu}$, the MSEs are smaller for the larger sample size, as would be expected. The results obtained when using $m = 50$ are again similar to those using higher values of m and hence finer approximations of the likelihood.

Overall, it can be concluded that the use of the HMM machinery to numerically maximize the approximate likelihood function of SVM models leads to good estimator performance, yet involves only a modest computational effort. At this point it may be worthwhile to reiterate that, given that the likelihood approximation considered is virtually exact for $m = 100$, we are effectively conducting maximum likelihood estimation.

Additional simulation experiments, for the SVM-N and SVM-S models, are provided in the supplementary material.

5 Empirical Application

5.1 The Data

In this section, we analyze the indexes from the São Paulo Stock, Mercantile & Futures Exchange, Tokyo Stock Exchange and the New York Stock Exchange. The considered indexes are the IBOVESPA (IBVSP), Nikkei 225 (NIKKEI) and the S&P 500 (SP500), respectively. The period of analysis is from January 5, 1998, until June 30, 2011. All the datasets were downloaded from http://finance.yahoo.com. Stock returns are computed as $y_t = 100 \times (\log P_t - \log P_{t-1})$, where P_t is the (adjusted) closing price on day t. Table 4 reports a summary of descriptive statistics for the series returns. The IBVSP returns show positive skewness and the NIKKEI and SP500 returns negative skewness (NIKKEI and SP500). All the series show kurtosis greater than three, confirming a well-known stylized fact for return series, namely the departure from normality. We analyze the data with the aim of providing robust inference by using the SMN class of distributions. In our analysis, we compare the SVM-N, SVM-T and SVM-S models for each one of the series described above.

In order to obtain the maximum likelihood estimates (MLEs) of the parameters in the SVM models, we apply the HMM machinery as introduced in Section 3. To ensure a good approximation of the estimates, we use $b_m = -b_0 = 4$ and $m = 200$. As before, all the calculations were performed using the stand-alone code developed by the authors using the Rcpp interface inside R package. Table 5 shows the results for the SVM-N, SVM-T and SVM-S models for each one of the return indexes series.

For all the three series of returns and all the three models considered, we find that the MLEs of ϕ were very close to 0.98, indicating a high persistence of the log-volatility process. The persistence in the log-volatility process underlying the SVM-N model was smaller than that found under the other two models. The MLEs of σ_η under the SVM-T and SVM-S were smaller than the one under the SVM-N, indicating that the volatility processes of the SVM-T and SVM-S were less variable than than those in the SVM-N case.

For the mean process, we find that the MLEs of β_0 were positive and statistically significant, since the 95% confidence intervals do not contain zero (for all models and series considered). For the IBVSP and the NIKKEI return series, there is an indication that β_1 might not be relevant. In the SP500 case, β_1 was significant. The β_2 parameter, which measures both the *ex ante* relationship between returns and volatility and the volatility feedback effect, was estimated to be negative and was deemed statistically significant, for all the models and the indexes considered. These results empirically confirm the previous results reported in the literature and indicate that when investors expect higher persistent levels of volatility in the future, they require compensation for this in the form of higher expected returns.

The magnitude of the tail fatness is measured by the shape parameter v in the SVM-T and SVM-S models. The MLEs of v were 13.11, 12.69, and 12.03, respectively, for the IBVSP, NIKKEI and SP500 under the SVM-T.

When we compare the models in terms of their relative in-sample fit, using the values of the Akaike Information Criterion (AIC) obtained for the different models and series considered (Table 6), the main results are as follows. For IBVSP, the SVM-S model clearly outperforms its competitors, while for NIKKEI and SP500, the SVM-T model has a slightly better AIC score than the SVM-S model. Thus, from this model selection exercise no clear pattern emerges as to which of the three model formulations is most suited to modelling indexes, though there is an indication that the SVM-N model is less suitable than its more flexible competitors.

We additionally performed an out-of-sample analysis of the forecast performance for the models covered in Table 6. For the observation period January 5, 1988 until September 29, 2014, each return series was divided into a calibration and a validation sample:

- Calibration sample: from January 5, 1998 until June 30, 2011.
- Validation sample: from July 1, 2011 until September 29, 2014.

As a first step, the SVM-N, SVM-S and SVM-T models were fitted to the calibration sample of each series. This was done by using the HMM method with $m = 200$, a value that is large enough to ensure that any anomalies that may occur could not be attributed to inaccuracies in the approximation of the likelihood. Then, for each one of the observations in the validation sample, the (one-step-ahead forecast) pseudo-residual was computed according to equation 8. As described in Section 3.4, non-normality of these residuals is an indication of mis-specification of the corresponding model.

Jarque-Bera tests were applied to the pseudo-residuals obtained for the different models and series considered; the corresponding p-values are listed in Table 7. The qq-plots for the three return series under the SVM-N, SVM-S and SVM-T models are shown in Figures 3, 4 and 5, respectively. For the IBVSP return index, the qq-plot indicates a lack of fit in the left tail (SVM-N) and in the right tail (SVM-T and SVM-S). The JB test accepts the hypothesis of normality of the residuals under the three models at the 5% and 10% level. For the NIKKEI return index, the qq-plot reveals a poor fit in left tail (SVM-N) and a similar lack of fit in the right tail. The JB test accepts the normality assumption of the pseudo-residuals at the 10%

level for the SVM-N and SVM-S models and rejects the SVM-T. At the 5% level, the JB test accepts normality of the three models. Finally, considering the SP500 returns, the qq-plot reveals a poor fit in the left tail for the three models, which is most pronounced under the SVM-N model. The JB test confirms these findings and leads to a rejection of the normality assumption of the pseudo-residuals. The indicated mis-specification could be caused by the presence of correlation between the perturbation terms defined by equations (4a) and (4b).

The plots and tests discussed above are useful for assessing the relative and absolute fit of a model, but, for the purpose of assessing the risk associated with a share or index, it is the extreme left tail of the forecast distribution that is of particular interest. It determines the value-at-risk (VaR), defined as the maximum possible loss of a portfolio (over a specified period) at a given confidence level. For example, the one-day 1% VaR is the 0.01-quantile of the one-day-ahead forecast distribution. Whenever the return falls below that quantile, an *exception* is said to have occurred. If the model used for forecasting is correct, then, using a 100α%VaR, the number of exceptions, X, in n days follows a Binomial(n, α) distribution. This distributional result makes it possible to implement backtesting, where the adequacy of the time series model is assessed through a comparison of the observed number of exceptions and the corresponding theoretical distribution. A standard approach to test the accuracy of VaR forecasts is to assess the violation rate, which is estimated as $\hat{\alpha}=X/n$. In order to examine the accuracy of VaR forecasts, we adopt the unconditional coverage test introduced in Kupiec (1995). This is a likelihood ratio test with $\chi_1^2-\mathrm{distributed}$ test statistic

$$LRuc=2\left\{log\left[\hat{\alpha}^x(1-\hat{\alpha})^{n-x}\right]-log\left[\alpha^x(1-\alpha)^{n-x}\right]\right\}. \quad (9)$$

The null hypothesis is that the achieved violation rate is equal to the predetermined nominal probability a. See Kupiec (1995) for more details. According to the unconditional coverage test, we accept the null hypothesis that the achieved violation rate is equal to 5 % for all the returns under all the models considered here. We reject that the achieved violation is 1% only for SP500 under the SV-S model.

6 Discussion

In this article, we presented an implementation of an easy-to-implement maximum likelihood-based estimation approach for the SVM model. This model allows us to investigate the dynamic relationship between returns and their time-varying volatility. The commonly made Gaussian assumption of the mean innovation was replaced by univariate thick-tailed processes, known as scale mixtures of normal distributions. While we focused on practical and computational aspects of fitting these models to real data, there may of course also be interest in deriving theoretical properties of the estimators, which could be accomplished using general maximum likelihood theory for state-space models (see, e.g., Douc et al., 2011).

For all the indexes and the models considered in our real data application, the estimate, which measures both the *ex ante* relationship between returns and volatility and the volatility feedback effect, was found to be negative. The results are in line with those of French et al. (1987), who found a similar relationship between unexpected volatility dynamics and returns, and confirm the hypothesis that investors require higher expected returns when unanticipated increases in future volatility are highly persistent. This is consistent with our findings of higher values of ϕ combined with larger negative values for the in-mean parameter.

Our SVM-SMN models showed considerable flexibility to accommodate outliers, however their robustness aspects could be seriously affected by the presence of skewness and heavy-tailedness simultaneously. To remedy this problem, the scale mixtures of skew-normal distributions can be used, or alternatively, the conditional distribution of the retunrs could be modeled nonparametrically (Langrock et al., 2015).

Finally, another important stylized fact often attributed to financial time series, the so-called *leverage effect*, is not explicitly incorporated in the class of models presented in this paper. Models with leverage effect involve a (negative) correlation between the innovations in the returns and subsequent innovations in the log-volatility process. While relatively easy to accomplish when both innovations are Gaussian — in which case the joint distribution of the innovations can simply be taken to be a bivariate normal — it is not quite as straightforward to formulate corresponding models where the distribution of the innovations in the returns is from the general class of SMN distributions. We believe that the way forward to constructing corresponding models is via the use of copulas, which can be used to couple arbitrary marginal densities, in particular SMN distributions and normal distributions, respectively. This strategy was first proposed by Smith (2007), but has since not been pursued further, and in particular not within classes of models as flexible as the one discussed in the present paper. The copula-based extension of SVM models, which is beyond the scope of the present paper, is currently under investigation.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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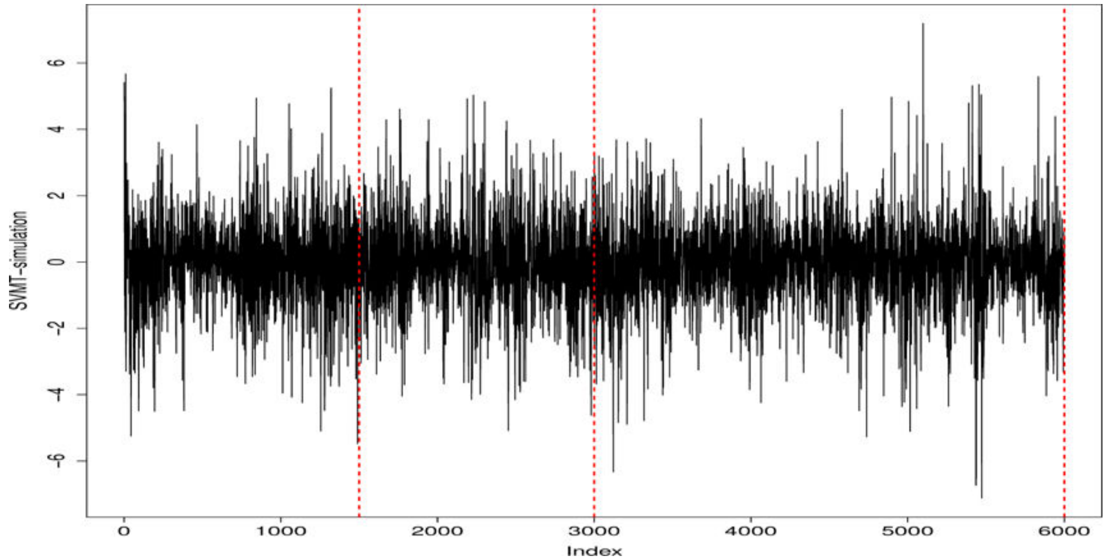

Figure 1.

Simulated data set from the SVM-T with $\boldsymbol{\beta} = (0.2, 0.07, -0.18)^{\top}$, $\mu = 0.1$, $\phi = 0.98$, $\sigma_{\eta} = 0.1$ and $\nu = 8$ and $y_0 = 0.2$.

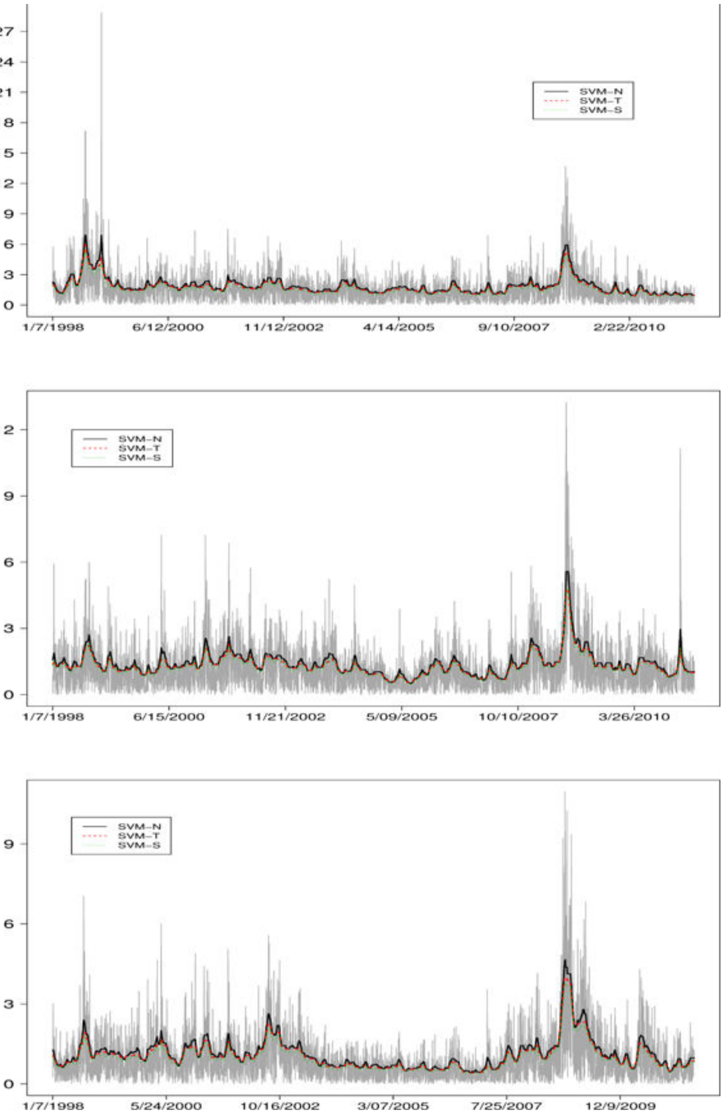

Figure 2.

Decoded $e^{\frac{h_t}{2}}$ using the viterbi algorithm: top (IBVSP), center (NIKKEI) and bottom (SP500). The solid line (SVM-N), dotted red line (SVM-T) and dotted green line (SVM-S). The grey line indicates the absolute returns.

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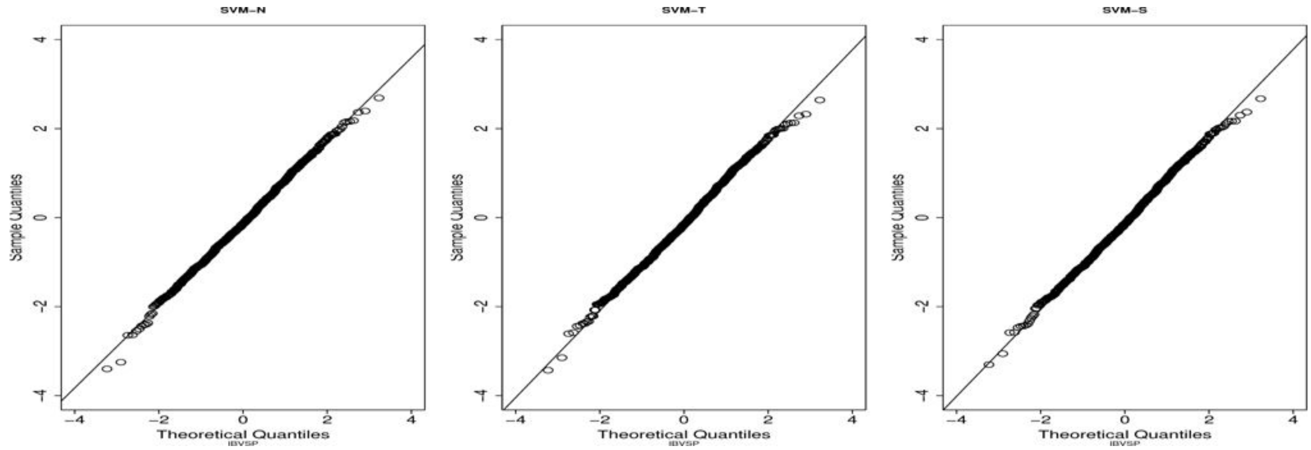

Figure 3.
qq-plot of the forecast pseudo-residuals for SVM-N (left), SVM-T (middle) and SVM-S (right) for the IBVSP returns.

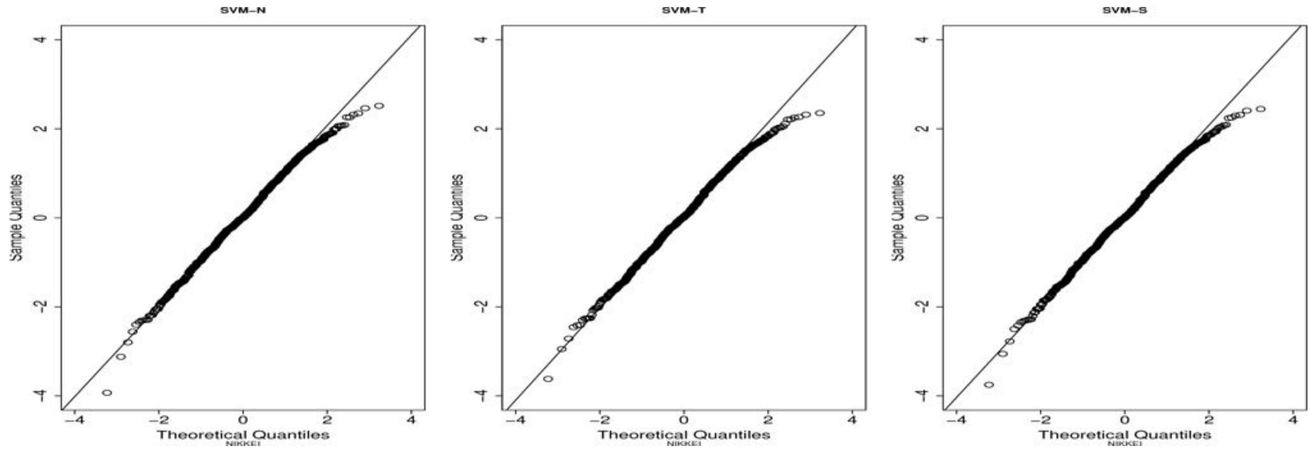

Figure 4.
qq-plot of the forecast pseudo-residuals for SVM-N (left), SVM-T (middle) and SVM-S (right) for the NIKKEI returns.

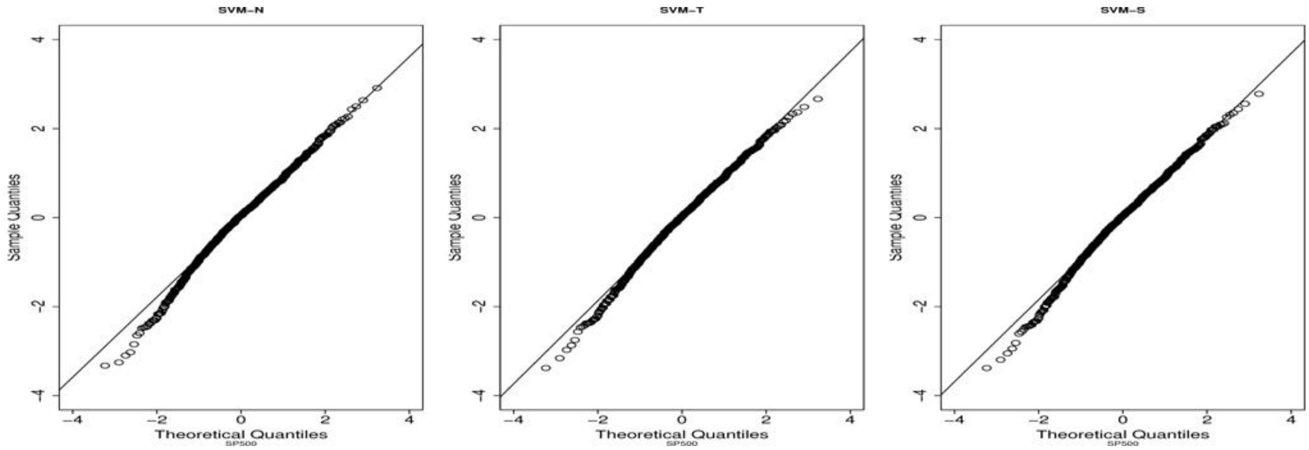

Figure 5.
qq-plot of the forecast pseudo-residuals for SVM-N (left), SVM-T (middle) and SVM-S (right) for the SP500 returns.

Table 1

SVM-T model, simulated data set: maximum likelihood estimates of the parameters and computing times in seconds for the HMM method ($b_m = -b_0 = 4$. True values of the parameters: $\beta = (0.2, 0.07, -0.18)^\top$, $\mu = 0.1$, $\phi = 0.98$, $\sigma_\eta = 0.1$ and $\nu = 8$).

size	m	$\mathcal{L}$	ϕ	σ_η	μ	β_0	β_1	β_2	ν	time
1500	50	2437.26	0.9869 (0.9747,0.9991)	0.0833 (0.0504,0.1162)	0.1418 (−0.2120,0.4957)	0.1918 (0.0474,0.3362)	0.0693 (0.0203,0.1184)	−0.1448 (−0.2774, −0.0124)	7.2929 (4.4666,10.1191)	39.45
	100	2437.24	0.9880 (0.9738,1.0021)	0.0788 (0.0321,0.1255)	0.1381 (−0.2086,0.4849)	0.1922 (0.0471,0.3372)	0.0687 (0.0197, 0.1177)	−0.1458 (−0.2792, −0.0125)	7.2712 (4.4592,10.0832)	91.99
	150	2437.24	0.9880 (0.9738,1.0021)	0.0788 (0.0321,0.1255)	0.1381 (−0.2086,0.4849)	0.1922 (0.0471,0.3372)	0.0687 (0.0197, 0.1177)	−0.1458 (−0.2792, −0.0125)	7.2712 (4.4592,10.0832)	156.68
	200	2437.24	0.9880 (0.9738,1.0021)	0.0788 (0.0321,0.1255)	0.1381 (−0.2086,0.4849)	0.1922 (0.0471,0.3372)	0.0687 (0.0197, 0.1177)	−0.1458 (−0.2792, −0.0125)	7.2712 (4.4592,10.0832)	246.29
3000	50	4901.58	0.9772 (0.9623,0.9921)	0.1191 (0.0798,0.1585)	0.1774 (−0.0301,0.3850)	0.1875 (0.0904,0.2847)	0.0705 (0.0349,0.1063)	−0.1561 (−0.2415, −0.0707)	8.9200 (5.8739,11.9661)	96.22
	100	4901.53	0.9741 (0.9587,0.9895)	0.1202 (0.0801,0.1601)	0.1206 (−0.0663,0.3075)	0.1924 (0.0931,0.2917)	0.0699 (0.0343,0.1056)	−0.1632 (−0.2523, −0.0740)	8.1263 (5.6410,10.6116)	203.26
	150	4901.53	0.9741 (0.9587,0.9895)	0.1202 (0.0801,0.1601)	0.1206 (−0.0663,0.3075)	0.1924 (0.0931,0.2917)	0.0699 (0.0343,0.1056)	−0.1632 (−0.2523, −0.0740)	8.1263 (5.6410,10.6116)	335.65
	200	4966.28	0.9741 (0.9587,0.9895)	0.1202 (0.0801,0.1601)	0.1206 (−0.0663,0.3075)	0.1924 (0.0931,0.2917)	0.0699 (0.0343,0.1056)	−0.1632 (−0.2523, −0.0740)	8.1263 (5.6410,10.6116)	501.72
6000	50	9609.13	0.9783 (0.9688,0.9880)	0.1071 (0.0823,0.1320)	0.0537 (−0.0858,0.1934)	0.2048 (0.1320,0.2777)	0.0652 (0.0403,0.0901)	−0.1982 (−0.2689, −0.1276)	7.7256 (6.1679,9.2833)	150.45
	100	9609.12	0.9783 (0.9684,0.9883)	0.1073 (0.0813,0.1333)	0.0541 (−0.0854,0.1936)	0.2043 (0.1316,0.2771)	0.0652 (0.0403,0.0901)	−0.1978 (−0.2685, −0.1273)	7.7325 (6.1711,9.2939)	318.13
	150	9609.12	0.9783 (0.9684,0.9883)	0.1073 (0.0813,0.1333)	0.0541 (−0.0854,0.1936)	0.2043 (0.1316,0.2771)	0.0652 (0.0403,0.0901)	−0.1978 (−0.2685, −0.1273)	7.7325 (6.1711,9.2939)	557.27
	200	9609.12	0.9783 (0.9684,0.9883)	0.1073 (0.0813,0.1333)	0.0541 (−0.0854,0.1936)	0.2043 (0.1316,0.2771)	0.0652 (0.0403,0.0901)	−0.1978 (−0.2685, −0.1273)	7.7325 (6.1711,9.2939)	839.15

Table 2

SVM-T model: Simulaton study results based on 300 replicates using the HMM method ($b_{max} = -b_{min} = 4$ and T = 2500).

Parameter	True value	Mean	MRB	MARB	MSE
		$m = 50$			
ϕ	0.98	0.9854	0.0045	0.0101	0.0002
σ_η	0.10	0.1002	0.0026	0.1879	0.0007
μ	0.10	0.2077	1.0774	1.3727	0.0307
β_1	0.20	0.1942	−0.0289	0.2424	0.0039
β_2	0.07	0.0716	0.0234	0.2320	0.0004
β_3	−0.18	−0.1711	−0.0493	0.2391	0.0032
ν	8.00	8.7098	0.0696	0.2669	1.8567
		$m = 100$			
ϕ	0.98	0.9859	0.0044	0.0099	0.0002
σ_η	0.10	0.0953	−0.0046	0.2210	0.0009
μ	0.10	0.1852	0.8524	1.3024	0.0285
β_1	0.20	0.1962	−0.0187	0.2515	0.0046
β_2	0.07	0.0713	0.0181	0.2271	0.0004
β_3	−0.18	−0.1736	−0.0351	0.2592	0.0034
ν	8.00	8.6057	0.0675	0.2612	1.8471
		$m = 150$			
ϕ	0.98	0.9857	0.0044	0.0100	0.0002
σ_η	0.10	0.0952	−0.0047	0.2221	0.0009
μ	0.10	0.1868	0.8644	1.3143	0.0289
β_1	0.20	0.1967	−0.0164	0.2451	0.0043
β_2	0.07	0.0713	0.0164	0.2455	0.0004
β_3	−0.18	−0.1736	−0.0321	0.2544	0.0037
ν	8.00	8.6056	0.0671	0.2617	1.8422
		$m = 200$			

Parameter	True value	Mean	MRB	MARB	MSE
ϕ	0.98	0.9857	0.0044	0.0100	0.0002
σ_η	0.10	0.0952	−0.0480	0.2227	0.0009
μ	0.10	0.1868	0.8644	1.3143	0.0289
β_1	0.20	0.1967	−0.0146	0.2479	0.0044
β_2	0.07	0.0711	0.0163	0.2253	0.0004
β_3	−0.18	−0.1742	−0.0304	0.2572	0.0039
ν	8.00	8.6056	0.0671	0.2619	1.8422

Table 3

SVM-T model: Simulaton study results based on 300 replicates using the HMM method ($b_{max} = b_{min} = 4$ and $T = 5000$).

Parameter	True value	Mean	MRB	MARB	MSE
		$m = 50$			
Φ	0.98	0.9861	0.0061	0.0087	0.0001
σ_η	0.10	0.0947	−0.0534	0.1167	0.0002
M	0.10	0.2067	1.0774	1.4030	0.0331
β_1	0.20	0.1987	−0.0066	0.1866	0.0021
β_2	0.07	0.0714	0.0204	0.1654	0.0002
β_3	−0.18	−0.1764	−0.0197	0.1925	0.0022
N	8.00	8.4403	0.0550	0.1124	1.3137
		$m = 100$			
Φ	0.98	0.9865	0.0067	0.0091	0.0001
σ_η	0.10	0.0908	−0.0921	0.1542	0.0003
M	0.10	0.2062	1.0624	1.3551	0.0320
β_1	0.20	0.2012	0.0062	0.1869	0.0023
β_2	0.07	0.0712	0.0184	0.1638	0.0002
β_3	−0.18	−0.1783	−0.0090	0.1909	0.0021
N	8.00	8.4334	0.0541	0.1129	1.5173
		$m = 150$			
Φ	0.98	0.9865	0.0066	0.0091	0.0001
σ_η	0.10	0.0909	−0.0901	0.1523	0.0003
M	0.10	0.2033	1.0335	1.3411	0.0317
β_1	0.20	0.2013	0.0067	0.1858	0.0023
β_2	0.07	0.0713	0.0191	0.1633	0.0002
β_3	−0.18	−0.1784	−0.0087	0.1900	0.0021
N	8.00	8.4138	0.0535	0.1117	1.6200
		$m = 200$			

Parameter	True value	Mean	MRB	MARB	MSE
Φ	0.98	0.9865	0.0066	0.0091	0.0001
σ_η	0.10	0.0909	−0.0901	0.1524	0.0003
M	0.10	0.2033	1.0335	1.3411	0.0317
β_1	0.20	0.2013	0.0067	0.1858	0.0023
β_2	0.07	0.0713	0.0191	0.1633	0.0002
β_3	−0.18	−0.1784	−0.0087	0.1900	0.0021
N	8.00	8.4138	0.0535	0.1117	1.5090

Table 4

Summary statistics of the return indexes

Return	size	mean	SD	Minimum	Maximum	Skewness	Kurtosis
IBVSP	3338	0.0531	2.1964	−17.2082	28.8325	0.5748	16.7109
NIKKEI	3310	−0.0127	1.6010	−12.1110	13.2346	−0.3206	9.0383
SP500	3393	0.0089	1.3385	−9.4695	10.9572	−0.1494	10.2474

Table 5

Results obtained when fitting the SVM-N, SVM-T and SVM-S models to the three series of index returns considered (using $m = 200$ and $b_{max} = -b_{min} = -4$).

–	length	*llk*	ϕ	σ_η	μ	β_0	β_1	β_2	ν	time
SVM-N										
IBVSP	3338	−6792.32	0.9756 (0.9655,0.9857)	0.1590 (0.1283,0.1898)	1.1358 (0.911,1.3605)	0.1971 (0.1075,0.2867)	0.0030 (−0.032,0.038)	−0.0309 (−0.0568, −0.0051)	– –	158.21
Nikkei	3310	−5812.40	0.9773 (0.9672,0.9874)	0.1586 (0.1297,0.1874)	0.5763 (0.3354,0.8172)	0.1343 (0.0672,0.2013)	−0.0228 (−0.058,0.0123)	−0.0592 (−0.0947,−0.0237)	– –	162.07
SP500	3393	−5062.53	0.9806 (0.9728,0.9884)	0.1660 (0.1353,0.1967)	−0.0636 (−0.3595,0.2324)	0.1146 (0.0736,0.1556)	−0.0834 (−0.1179, −0.0488)	−0.0726 (−0.1086,−0.0367)	– –	147.20
SVM-T										
IBVSP	3338	−6793.81	0.9880 (0.9796,0.9964)	0.1218 (0.0923,0.1513)	0.8718 (0.4926,1.2509)	0.2096 (0.118,0.3012)	0.10 (−0.0333,0.0353)	−0.0338 (−0.0645,−0.0032)	13.1162 (8.0314,18.201)	366.29
NIKKEI	3310	−5815.45	0.9826 (0.9738,0.9913)	0.1288 (0.0997,0.1580)	0.3725 (0.1057,0.6393)	0.1094 (0.0395,0.1793)	−0.0323 (−0.0666,0.0020)	−0.0622 (−0.1058,−0.0186)	12.6989 (7.3276,18.0701)	366.51
SP500	3393	−5056.31	0.9878 (0.982,0.9936)	0.1267 (0.0997,0.1537)	−0.1257 (−0.4774,0.226)	0.1196 (0.0781,0.1612)	−0.0516 (−0.0848,−0.0183)	−0.0799 (−0.1237,−0.0361)	12.0287 (7.0504,17.007)	377.98
SVM-S										
IBVSP	3338	−6788.26	0.9843 (0.9754,0.9933)	0.1368 (0.1057,0.1678)	0.9315 (0.6112,1.2518)	0.2061 (0.1153,0.2969)	0.0101 (−0.0246,0.0449)	−0.0455 (−0.0802,−0.0108)	4.4962 (2.3816,6.6107)	1070.63
NIKKEI	3310	−5811.25	0.9808 (0.9710,0.9906)	0.1430 (0.1111,0.1749)	0.3284 (0.0376,0.6193)	0.1344 (0.066,0.2028)	−0.0273 (−0.0624,0.0077)	−0.0765 (−0.1247,−0.0282)	4.3333 (2.0783,6.5884)	922.22
SP500	3393	−5056.46	0.9881 (0.9819,0.9942)	0.1331 (0.1057,0.1606)	−0.3523 (−0.7472,0.0426)	0.1019 (0.0609,0.1429)	−0.0605 (−0.0943,−0.0267)	−0.0741 (−0.1249,−0.0234)	3.4195 (2.2619,4.5772)	1080.35

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Table 6

Model comparison via AIC; for each series considered, the minimum AIC is highlighted in bold.

		AIC	
Return	**SVM-N**	**SVM-T**	**SVM-S**
IBVSP	13596.64	13601.62	**13590.52**
NIKKEI	11636.80	**11636.40**	11636.50
SP500	10137.06	**10126.62**	10126.92

Table 7

p-values of Jarque-Bera tests applied to one-step-ahead ahead forecast pseudo-residuals

	SVM-N	SVM-S	SVM-T
IBVSP	0.97	0.51	0.49
NIKKEI	0.11	0.12	0.07
SP500	0.0002	0.0006	0.004

Table 8

Violation rate (VR) as a percentage in *n* one-day-ahead forecast, *P*-values of the unconditional coverage test at the 1% and 5% levels.

			0.01		0.05	
Return	**Model**	**n**	**VR (%)**	**P-value**	**VR (%)**	**P-value**
	SVM-N	807	0.011	0.747	0.050	0.956
IBVSP	SVM-S	807	0.010	0.975	0.052	0.791
	SVM-T	807	0.011	0.747	0.052	0.791
	SVM-N	808	0.007	0.441	0.046	0.578
NASDAQ	SVM-S	808	0.007	0.441	0.045	0.470
	SVM-T	808	0.007	0.441	0.045	0.470
	SVM-N	816	0.016	0.117	0.056	0.413
SP500	SVM-S	816	0.020	0.015	0.058	0.330
	SVM-T	816	0.016	0.117	0.056	0.413