# On Equity Risk Prediction and Tail Spillovers

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**Abstract**

This paper studies the impact of modelling time-varying variances of stock returns in terms of risk measurement and extreme risk spillover. Using a general class of regime-dependent models, we find that volatility can be disaggregated into distinct components: a persistent stable process with low sensitivity to shocks and a high volatility process capturing rather short-lived rare events. Out-of-sample forecasts show that, once regime shifts are accounted for, accuracy is improved compared to the standard GARCH or the historical volatility model. Volatility plays an important role in controlling and monitoring financial risks. Therefore, by means of a risk management application, we illustrate the economic value and the practical implications of risk control ability of the models in terms of value-at-risk. Finally, tests for predictability in co-movements in the tails of stock index returns suggest that large losses are strongly correlated, supporting asymmetric transmission processes for financial contagion in the left tail of return distributions whereas contagion in reverse direction (gains) is weak.

**Keywords:** stock markets, regime volatility, forecasting, risk spillover

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# 1 Introduction

Volatility is of great concern to economic agents involved in the decision making process under uncertainty. The traditional framework for modelling volatility is the generalized autoregressive conditional heteroscedasticity (GARCH) process, pioneered by Engle (1982) and Bollerslev (1986). This model class captures the salient features of financial time series, such as volatility clustering, persistence, non-linear dependence and thick tails. Yet, the value of volatility lies in the capability of the model to predict market fluctuations, contributing, inter alia, to risk exposure evaluation, stress testing, asset allocation, derivatives pricing, and risk management. This corroborates the importance of developing volatility models able to replicate the salient features of financial time series.

Regardless of its interesting properties, the common GARCH model has several shortcomings. Among others, Bollerslev (1987) and Baillie and Bollerslev (1989) find that the observed non-normalities in return distributions are more pronounced than those implied by GARCH. In effect, the model fails to reproduce skewed unconditional distributions or time variability in higher moments, unless explicitly modelled (see Harvey and Siddique, 1999). As a result, a number of variants have been put forward accounting for asymmetries (e.g., leverage effect, see Glosten et al., 1993), long memory (Baillie et al., 1996), and non-normal densities (Bollerslev, 1987; Politis, 2004), while other developments make use of non-parametric structures for which a priori knowledge of the innovation distribution is not required (Bühlmann and McNeil, 2002). Another drawback of GARCH is the rather strong degree of persistence imputed to volatility, suggesting that distant past shocks can have a nontrivial impact in the current variance. However, excessive persistence may be due to structural breaks in the data generating process (Lamoureux and Lastrapes, 1990). In fact, economic variables may appear to have integrated variance disturbances, but inclusion of regime-specific dummies might lead to stationary GARCH movements within regimes (Diebold, 1986). Therefore, neglecting structural breaks might lead to impaired forecasts, particularly in periods of high turbulence (Hamilton and Susmel, 1994). A popular approach to modelling regime changes is the family of Markov regime switching (MRS) models introduced by Hamilton (1989, 1990). In this setting, regime classification is based on optimal probabilistic inference[1] and model parameters are functions of a hidden Markov chain. Following the above ideas, the first to combine MRS and GARCH in a unified framework are Hamilton and Susmel (1994) and Cai (1994), whereas other generalizations have been proposed by Gray (1996) and Haas et al. (2004b).

To overcome the previous limitations, this paper builds on a general class of regime volatility models described by a normal mixture conditional density. Besides disaggregating volatility persistence into its sources (due to shocks or shifts in the variance parameters), these models are able to reproduce a skewed leptokurtic distribution and capture time variation in conditional higher moments. To this end, we revisit the MRS GARCH (Haas et al., 2004b) and the normal mixture GARCH (Haas et al., 2004a; Alexander and Lazar, 2006) models to examine stock return volatility dynamics. In doing so, we advance a comprehensive discussion on firms' risk measurement and assess the efficacy of the proposed framework in predicting extreme market risk and describing its spillover function.

In addition, we evaluate the economic significance of model choice in a forecasting exercise using a robust set of loss functions (Patton, 2011). Nevertheless, volatility alone cannot effectively replicate the risk of extreme rare events especially in periods of financial turmoil (e.g., see Longin, 2000). Moreover, as volatility is unobserved, statistical loss functions based on imperfect proxies may be of little value from a practitioner's perspective. Thus, we also assess risk control ability using the notion of Value-at-Risk (VaR), which serves as an essential financial regulation tool, setting risk capital requirements to reduce the likelihood of financial distress. Out-of-sample VaR forecasts are validated for the left and right tails based on coverage rates (Christoffersen, 1998) and in terms of losses to the level of utility they generate (Sarma et al., 2003; Gonzalez-Rivera et al., 2004); incremental predictive aptitude against benchmarks is tested by implementing the reality check of Hansen (2005). Further,

[1]Another nomenclature of regime switching models include Tsay (1989) and Teräsvirta (1994); however, these inexorably require auxiliary information or prior beliefs about how regime switching is manifested.

we extend the research on stock markets' interconnectedness by examining tail co-movements featuring financial contagion. Understanding the mechanism of causality in tail risk (Hong et al., 2009) when markets are integrated and exposed to the same global shocks has crucial implications for predicting and monitoring risk spillover. For example, how large shocks transmit across different sectors offers valuable insights for market participants who deal with investment, portfolio and financial risk management decisions, and regulatory policies (see, for example, Longin and Solnik, 2001), supporting the planning of relevant strategies to ease adverse impacts on the economy.

As a case study, our numerical experiments focus on a segment of the consumer services sector, namely, travel and leisure. Despite the broad economic and financial impact of the volatility of the industry, research on the risk profile of global tourism stocks is scant. This is surprising given that the wealth of the sector impacts all aspects of economic activity, creating employment, generating export revenues or advancing infrastructure developments[2]. Many empirical studies confirm the strong links of tourism to economic growth with regard to policy and decision making in the public and private sectors (see Chen and Chiou-Wei, 2009). Stock investors are vital constituents of the industry and stock markets serve as fundamental indicators of business activity, reflecting investors' expectations about future corporate earnings (e.g., see Choi et al., 1999). Hence, it is important to examine how risk responds to investing, financing and operating decisions and provide benchmarks against which to measure the risk of stock portfolios. Our results show that volatility regimes constitute key factors to improve both in-sample fit and forecast accuracy, i.e., the model choice has a material effect on risk forecasting. We also report significant cross-sector asymmetric spillover effects. Tail dependence increases during periods of large losses, but not when mar-

[2]In the OECD (Organization for Economic Co-operation and Development) area, tourism contributes more than 4% of GDP, 5.9% of employment, and 21.3% of service exports, while around 80% of the tourism exports convert into domestic value added (World Tourism Organization, 2016). The industry key challenges are the growth in tourism flows, changing consumer trends, concerns over security, economy digitalization and adaptation to climate change. These require innovative and integrated policy responses to improve competitiveness and support sustainable tourism growth, and efficient tools and solutions pertinent to accurate risk assessments for consistent decision making and rational planning.

kets experience large gains (Longin and Solnik, 2001); this way, we provide evidence on the degree of diversification benefits in times of extreme return fluctuations.

The proposed risk analysis framework extends beyond the tourism sector as failing to account for regime dependence can lead to inferior projections. There are many possible applications of the considered models, including asset allocation, investment analysis, or derivatives pricing. In terms of risk management, the results have implications for risk managers, market makers, traders, institutional investors, and fund managers. Therefore, our paper is of potential interest to stakeholders (public shareholders or private equity investors) for understanding and evaluating the risk of their portfolios, as well as responding to emerging issues and new risks; providers of credit (banks or bond investors) for determining and monitoring the covenants included in loans and bond issues; and finally, regulators and governmental organizations, as the lack of cohesive risk policies could undermine stability in the system, especially when the overall sentiment is bearish.

The remainder of this paper is organized as follows. Section 2 outlines the details of the postulated regime-dependent models for the volatility dynamics and presents the forecasting valuation framework. In Section 3, we present the data and discuss our model calibration results, our volatility and VaR forecasts. This is accompanied by an analysis of Granger causality in risk. Section 4 concludes.

# 2 Methodology

This section is divided into three main subsections. First, we present the univariate model employed to estimate conditional volatility dynamics. Second, we describe the criteria employed to evaluate forecasting performance. Finally, we present the methodology to measure the economic value of forecasts in terms of value-at-risk and extreme risk spillovers.

## 2.1 The model

Let the daily log-returns $\{r_t\}$ satisfy

$$r_t = \mu_{s_t} + \epsilon_{s_t,t}, \tag{1}$$

where

$$\epsilon_{s_t,t} := \varepsilon_t \sigma_{s_t,t}, \tag{2}$$

$\varepsilon_t \overset{\text{iid}}{\sim} \mathcal{N}(0,1)$ and $s_t$ is a Markov chain with finite state space $\mathcal{S} = \{1,2\}$, describing the state/regime the system is in, and $2 \times 2$ transition matrix with elements $p_{ij} := P(s_t = j|s_{t-1} = i)$, $i, j = 1, 2$. $(\mu_1, \mu_2)'$ is the vector of regime means. The vector $\sigma_t^{(2)} := (\sigma_{1t}^2, \sigma_{2t}^2)'$ of regime variances follows the GARCH(1,1) model

$$\sigma_t^{(2)} = \alpha_0 + \alpha_1 \epsilon_{s_{t-1},t-1}^2 + \beta \sigma_{t-1}^{(2)}, \tag{3}$$

where $\alpha_i := (\alpha_{i1}, \alpha_{i2})'$, $i = 0, 1$, and $\beta$ is a $2 \times 2$ diagonal matrix satisfying element-wise $\alpha_0 > 0, \alpha_1, \beta \geq 0$ to ensure positivity of the variance process. We will dub the model defined by equations (1)–(3) MRS (Haas et al., 2004b). Under conditional normality within each regime, the aggregate variance is given by

$$\sigma_t^2 = \pi_{1t}(\mu_1^2 + \sigma_{1t}^2) + \pi_{2t}(\mu_2^2 + \sigma_{2t}^2) - (\pi_{1t}\mu_1 + \pi_{2t}\mu_2)^2, \tag{4}$$

where $\pi_{1t}$ ($\pi_{2t} = 1 - \pi_{1t}$) is the probability that the process is in regime 1 (regime 2) at time $t$ (see Gray, 1996). The process defined by (1)–(3) is stationary if and only if $\rho(M) < 1$, where $\rho(M)$ denotes the largest eigenvalue in modulus of the matrix

$$M := \begin{pmatrix} M_{11} & M_{21} \\ M_{12} & M_{22} \end{pmatrix}, \tag{5}$$

$M_{ji} := p_{ji}(\beta + \alpha_1 u_i')$, $i, j = 1, 2$, and $u_i$ is the $i$th $2 \times 1$ unit vector, i.e.,

$$M = \begin{pmatrix} p_{11}(\alpha_{11} + \beta_1) & 0 & p_{21}(\alpha_{11} + \beta_1) & 0 \\ p_{11}\alpha_{12} & p_{11}\beta_2 & p_{21}\alpha_{12} & p_{21}\beta_2 \\ p_{12}\beta_1 & p_{12}\alpha_{11} & p_{22}\beta_1 & p_{22}\alpha_{11} \\ 0 & p_{12}(\alpha_{12} + \beta_2) & 0 & p_{22}(\alpha_{12} + \beta_2) \end{pmatrix}.$$

A necessary condition for the process to be stationary is $\beta_1, \beta_2 < 1$.

In addition, we consider certain special cases of the MRS model, i.e., the mixed normal (Mix-N) GARCH(1,1) model with a constant vector of mixing weights $(\lambda_1, \lambda_2)'$ (Haas et al., 2004a), and the normal model with $\lambda_2 = 0$. For the Mix-N model, $M_{11} = M_{21} = \lambda_1(\beta + \alpha_1 u_1')$ and $M_{12} = M_{22} = \lambda_2(\beta + \alpha_1 u_2')$, i.e.,

$$M = \begin{pmatrix} \lambda_1(\alpha_{11} + \beta_1) & 0 & \lambda_1(\alpha_{11} + \beta_1) & 0 \\ \lambda_1\alpha_{12} & \lambda_1\beta_2 & \lambda_1\alpha_{12} & \lambda_1\beta_2 \\ \lambda_2\beta_1 & \lambda_2\alpha_{11} & \lambda_2\beta_1 & \lambda_2\alpha_{11} \\ 0 & \lambda_2(\alpha_{12} + \beta_2) & 0 & \lambda_2(\alpha_{12} + \beta_2) \end{pmatrix}.$$

Mix-N and MRS are models of finite mixtures, flexible to accommodate many different types of conditional distributions. For this reason, once a variance regime structure is allowed, there is not much gain from assuming other component distributions, such as $t$, to explain the fat tails of the distribution of conditional returns (see Susmel, 2000). For illustration purposes, Fig. 1 portrays four density plots of two-component mixture of normal distributions with mixing weight $\lambda_1$: the two mixing components include the standard normal (blue line) and a normal $\mathcal{N}(-2, 2)$ or $\mathcal{N}(-5, 2)$ (red line) as indicated in each sub-plot. Clearly, the resulting normal mixture density can capture fat tails and asymmetries (see Haas et al., 2004a; 2004b), i.e., models that provide such flexibility pose as attractive alternatives for modelling financial time series with multimodal conditional distributions and heteroscedasticity (see Wong and Li, 2001).

[INSERT FIGURE 1 HERE]

## 2.2 Volatility forecast evaluation

Although more sophisticated models are expected to provide better fit than the basic (single-regime) model, a primary concern remains whether the additional parameterization warrants its use. We investigate the appropriateness of our modelling approach by studying the empirical performance of one-step-ahead volatility forecasts. We use as benchmarks the normal GARCH(1,1) model and the constant historical volatility (hist. vol.).

We compare the accuracy of the out-of-sample volatility model forecasts $\hat{\sigma}_t^2$ from (4) against the realized squared returns $r_t^2$ which we use as a proxy for the true, but unobserved, conditional variance. Andersen and Bollerslev (1998) argue that imperfect volatility proxies may affect the power of traditional tests as well as their asymptotic size. Hence, to avoid distortions in the rankings of competing forecasts, we employ the parametric family of robust loss functions of Patton (2011) indexed by a scalar parameter $b$:

$$LF(\hat{\sigma}_t^2, r_t^2; b) = \begin{cases} \frac{\hat{\sigma}_t^2}{r_t^2} - \ln \frac{\hat{\sigma}_t^2}{r_t^2} - 1, & b = -2 \\ r_t^2 - \hat{\sigma}_t^2 + \hat{\sigma}_t^2 \ln \frac{\hat{\sigma}_t^2}{r_t^2}, & b = -1 \\ \frac{\hat{\sigma}_t^{2b+4} - r_t^{2b+4}}{(b+1)(b+2)} - \frac{r_t^{2b+2}\left(\hat{\sigma}_t^2 - r_t^2\right)}{b+1}, & \text{otherwise} \end{cases} . \tag{6}$$

We note that the Mean Squared Error ($MSE$) and Quasi-Likelihood ($QLIKE$) loss functions are given by $T^{-1}\sum_{t=1}^{T} LF(\hat{\sigma}_t^2, r_t^2; b)$, where $T$ is the total number of forecasts, for $b = 0$ and $b = -2$, respectively. $QLIKE$ is less sensitive to extreme observations in the sample period, as opposed to $MSE$ which also depends on the level of return volatility (see Patton, 2011). The loss functions (6) can be symmetric ($b = 0$) or asymmetric with heavier penalty to under-prediction ($b < 0$) or over-prediction ($b > 0$) of the true variance.

## 2.3 Measuring the economic value of volatility forecasts: Application in VaR and causality in tail risk

In order to provide a more informative insight into the economic benefits and the practical implications of the volatility forecasts, we develop a risk management exercise based on VaR forecasts. $\mathrm{VaR}_t^c$ is defined as the maximum expected loss of an asset or a portfolio of assets over a target horizon for a given confidence level $100(1-c)\%$. Given the predictions ($\hat{\mu}_t$, $\hat{\sigma}_t$) of the competing models, we quantify the one-day-ahead risk (VaR) as

$$P(r_t < \mathrm{VaR}_t^c|\Omega_{t-1}) = c, \tag{7}$$

where $\Omega_{t-1} = \sigma\{r_s\colon\ s \leq t\}$ is the information set available up to $t-1$ based on $r$. From (7), we may retrieve $\mathrm{VaR}_t^c = \hat{\mu}_t + \hat{\sigma}_t F^{-1}(c)$, where $F$ denotes the cumulative distribution function of the model-filtered standardized residuals.

We assess the performance of the VaR estimates by conducting likelihood ratio tests for unconditional ($LR_{UC}$) and conditional coverage ($LR_{CC}$). $LR_{UC}$ tests the null hypothesis that the probability of realizing a loss which exceeds the forecasted VaR is statistically equal to the nominal level $c$. $LR_{CC}$ is a joint test of correct unconditional coverage and independent VaR violations against the alternative of a first-order Markov process for the violations (see Christoffersen, 1998 ). Under iid Bernoulli VaR violations,

$$LR_{UC} = -2\ln\left(\frac{c^n(1-c)^{T-n}}{\hat{c}^n(1-\hat{c})^{T-n}}\right) \xrightarrow{d} \chi_1^2 \tag{8}$$

and

$$LR_{CC} = -2\ln\left[\frac{\hat{c}^n(1-\hat{c})^{T-n}}{(1-\hat{q}_{01})^{n_{00}}\hat{q}_{01}{}^{n_{01}}(1-\hat{q}_{11})^{n_{10}}\hat{q}_{11}{}^{n_{11}}}\right] \xrightarrow{d} \chi_2^2, \tag{9}$$

where $\chi_m^2$ denotes the chi-squared distribution with $m$ degrees of freedom, $\hat{c} = T^{-1}\sum_{t=1}^{T}\mathbf{1}_{\{r_t<\mathrm{VaR}_t^c\}}$ is the empirical level of coverage, $n$ the realized number of violations, $n_{ij}$ the number of violations ($i=1$) or non-violations ($i=0$) followed by violations ($j=1$) or non-violations

($j = 0$), and $\hat{q}_{ij}$ the corresponding 'transition' probabilities.

To further assess the relative size of losses when model violations occur, we follow Sarma et al. (2003) and calculate the Quadratic Loss ($QL$) function

$$QL = (r_t - \mathrm{VaR}_t^c)^2 \mathbf{1}_{\{r_t < \mathrm{VaR}_t^c\}}, \tag{10}$$

which measures the magnitude of violations assigning heavier penalty to large ones. Also important is the Predictive Quantile Loss ($PQL$) function

$$PQL = (r_t - \mathrm{VaR}_t^c)(c - \mathbf{1}_{\{r_t < \mathrm{VaR}_t^c\}}), \tag{11}$$

which penalizes more heavily observations for which a violation occurs, but also takes into account the capital forgone from over-predicting the true VaR. In fact, this represents a measure of fit of the predicted tail for a given confidence level, rather than just a measure of the violations' size. In this sense, $PQL$ is asymmetric and controls for the diverse implications of under and over-prediction of risk.

Next, to investigate whether large risks interconnect, we test for causality. In doing so, we focus on the tail co-movement between two distributions rather than Granger causality in mean (Granger, 1969) or variance (Granger et al., 1986), and examine causality in risk by implementing the Hong et al. (2009) kernel-based test. We define the occurrence of a large risk at a specific confidence level, when actual loss exceeds VaR at the given level. This way, extreme downside risk spillover between markets can arise not only from co-movements in mean and in variance, but also from co-movements in higher order conditional moments (and in the absence of causality in mean and/or in variance).

Let $\{r_{1,t}\}_{t=1}^T$, $\{r_{2,t}\}_{t=1}^T$ be the returns of the two sectors with $\Omega_{j,t} = \sigma\{r_{j,s}\colon\ s \le t\}$, $j = 1, 2$, denoting the individual information set up to $t$ based on $r_j$, and associated $\mathrm{VaR}_{j,t}^c$; also, let $\Omega_t = \sigma\{r_s\colon\ s \le t\}$ be the overall information set based on $(r_1, r_2)$. If the null hypothesis $H_0$: $P(r_{2,t} < \mathrm{VaR}_{2,t}^c | \Omega_{2,t-1}) = P(r_{2,t} < \mathrm{VaR}_{2,t}^c | \Omega_{t-1})$ holds, we say that the time series $\{r_{1,t}\}$

does not Granger-cause $\{r_{2,t}\}$ in risk at level $c$ with respect to $\Omega_{t-1}$. Rejection of $H_0$ implies that the time series $\{r_{1,t}\}$ Granger-causes $\{r_{2,t}\}$ in risk at level $c$, hence VaR exceedances in $\{r_{1,t}\}$ can be used to predict VaR exceedances in $\{r_{2,t}\}$. Let $\hat{Z}_{j,t} = \mathbf{1}_{\{r_{j,t}<\text{VaR}^c_{j,t}\}}$ be a VaR exceedance at time $t$,

$$\hat{G}(l) = \begin{cases} T^{-1}\sum_{l=1+l}^{T}(\hat{Z}_{1,t-l}-\hat{c}_1)(\hat{Z}_{2,t}-\hat{c}_2), & 0 \leq l \leq T-1 \\ T^{-1}\sum_{l=1-l}^{T}(\hat{Z}_{1,t}-\hat{c}_1)(\hat{Z}_{2,t+l}-\hat{c}_2), & 1-T \leq l < 0 \end{cases}$$

the $l$th sample cross-covariance function between $\{\hat{Z}_{1,t}\}$ and $\{\hat{Z}_{2,t}\}$, and $\hat{c}_j = T^{-1}\sum_{t=1}^{T}\hat{Z}_{j,t}$ the empirical coverage rate with sample variance $\hat{S}_j^2 = \hat{c}_j(1-\hat{c}_j)$. Then, the test statistic of Hong et al. (2009) is given by

$$Q(L) = \frac{T}{\sqrt{\nu_2(L)}}\left(\sum_{l=1}^{T-1} k^2(l/L)\frac{\hat{G}^2(l)}{\hat{S}_1^2\hat{S}_2^2} - \nu_1(L)\right), \tag{12}$$

where $L$ is an appropriate bandwidth, $k(z)$ is a symmetric kernel satisfying $k(0) = 1$ and $\int_{-\infty}^{\infty} k^2(z)dz < \infty$, and

$$\begin{aligned} \nu_1(L) &= \sum_{l=1}^{T-1}(1-l/T)k^2(l/L), \\ \nu_2(L) &= 2\sum_{l=1}^{T-1}(1-l/T)(1-(l+1)/T)k^4(l/L) \end{aligned}$$

are, respectively, centering and standardization constants. Under certain regularity conditions (see Hong et al., 2009, Theorem 1), $Q(L) \xrightarrow{d} \mathcal{N}(0,1)$ as $T \to \infty$. We conduct two directional tests for one-way Granger causality in risk for pairwise sector indices, for the left and right tails of the distribution, adopting the Daniell kernel $k(z) = \sin(z\pi)/(z\pi)$ as suggested by Hong et al. (2009).

# 3 Empirical results

In what follows, we introduce our dataset and present the parameter calibration results of the MRS and Mix-N models with two regimes associated with periods of low and high volatility, capturing the second-moment dynamics in a parsimonious way. Out-of-sample predictive performance of the proposed volatility models is compared to that of a single-regime GARCH(1,1) and the historical volatility benchmark. Finally, to illustrate some of the possible uses of the model forecast, we present a VaR application and investigate the existence of Granger causality in risk.

## 3.1 Data description

Our dataset comprises daily observations of seven Datastream global stock indices. The closing index price levels include an aggregate index of travel and leisure (TL) stocks, and six individual sectors including airlines (AL), gambling (GM), hotels (HT), recreational services (RS), restaurants and bars (RB), and travel and tourism (TT) stocks. Our sample period spans from 12 April 1973 to 13 September 2016. The Datastream global indices are capitalization-weighted and cover a minimum of 75% of the total market value. TL stocks cover a total average market value over the last year in our sample of more than 1.5 trillion USD with min-max sector market values of 126 (HT) and 413 (RB) billion USD. All indices are updated daily while all index constituents are reviewed quarterly to determine the new top group of stocks by market value. In total, as of September 2016, 334 tourism stocks are included, representing stock exchanges from 59 different countries.

[INSERT TABLE 1 HERE]

Our sample period encompasses a total of $11,260$ observations of USD log-returns. Table 1 presents summary statistics and the results of unit-root tests for the price indices of interest. The seven indices have diverse mean, volatility, skewness and kurtosis values. For example, returns realized for the AL and HT sector are not impressive compared to the remaining stock indices. Annualized mean returns for the GM sector are the highest of the cohort with also highest annualized volatility. As expected, the TL index volatility is the lowest due to diversification effects (there are 334 stocks included in the index). The third and fourth moments indicate negative skewness and high excess kurtosis for all log-returns. This is confirmed by the strong rejections of the Jarque and Bera (1980) tests for normality. The historical log-return distributions are fat-tailed (thin-tailed) relative to the 1% (5%) tails of the normal distribution implying higher likelihood of extreme events. Over a given estimation period, regime-dependent models assign weights to different market regimes, essentially assuming that sub-samples are drawn from different distributions, i.e., structural breaks can be effectively captured by a regime-dependent model (Li and Lin, 2004). Moreover, the Ljung and Box (1978) statistic shows significant signs of autocorrelation, whereas the autocorrelations of the squared returns indicate existing heteroscedasticity in the return series (Engle, 1982). In addition, given the above statistics, the chosen sector offers an ideal platform to illustrate our empirical framework as the sectoral indices present diverse dynamics, which are representative of the stock market properties. For example, the first four moments of the unconditional distribution of the Datastream global non-sector stock market index are 6.3%, 13%, $-0.52$ and 10.20 with the time series exhibiting similar signs of autocorrelation, heteroscedasticity and tail thickness.

## 3.2 Estimation results

The 'regime-switching' literature typically uses maximum likelihood estimation. Having specified the log-return model (1), the log-likelihood function can be written as

$$\mathscr{L} = \sum_t \log \left[ \pi_{1t} \frac{1}{2\pi\sigma_{1t}} \exp\left\{ \frac{-(r_t - \mu_1)^2}{2\sigma_{1t}^2} \right\} + \pi_{2t} \frac{1}{2\pi\sigma_{2t}} \exp\left\{ \frac{-(r_t - \mu_2)^2}{2\sigma_{2t}^2} \right\} \right] \tag{13}$$

(subject to straightforward amendment for the special case models). Table 2 presents the Mix-N and MRS model parameters for all stock indices. For brevity, we report parameter estimates for the normal GARCH(1,1) only for the TL index, however estimates for the remaining indices can be made available from the authors upon request; it is worth noting that the normal GARCH parameters are described by a high degree of volatility persistence, i.e., $0.9785 < \alpha_{11} + \beta_1 < 0.9915$.

[INSERT TABLE 2 HERE]

When fitting the regime-dependent models (Mix-N and MRS) the components of the mixture distributions are clearly differentiated. For example, in terms of sign and significance, the constituent means of the regime processes ($\mu_1$ and $\mu_2$) are not equal, hence the observed skewness can be captured. Whereas the basic GARCH formulation has zero conditional excess kurtosis as well as unconditional and conditional skewness, Mix-N and MRS capture the time variation of the conditional skewness and kurtosis; for more technical details and derivation of the moments, we refer, for example, to Haas et al. (2004a; 2004b).

The first (second) regime process in Table 2 is associated with high (low) regime probabilities in the range 82.01-97.89% (2.11-17.99%); this is the frequency of the regime occurrence within the estimation period and corresponds to the mixing weight ($\lambda_1$ for Mix-N) or the unconditional regime probability ($\pi_1$ for MRS). Therefore, the model captures two distinct regimes in stock index volatility: a 'stable' volatility process (dominant state), which prevails most of the time, and a rather high 'extreme' volatility process, which occurs rarely. The long-term volatility $\sqrt{E(\sigma_{2t}^2)}$ of the 'extreme' regime is almost twice as large as $\sqrt{E(\sigma_{1t}^2)}$ of the 'stable' regime in all sectors. In the case of MRS, it is observed that the probability of switching from the low to the high variance state (max. $p_{12} = 1 - p_{11} = 15.16\%$ in the case of GM) is lower than the probability of switching from the high to the low variance state (min. $p_{21} = 1 - p_{22} = 26.96\%$ in the case of RB). This is consistent with the short duration of the high-variance state.

The estimated Mix-N and MRS models exhibit asymmetry across the regime-variance dynamics with significant ARCH and GARCH terms. The low-variance states are described by lower degree of persistence ($0.92 < \alpha_{11} + \beta_1 < 0.99$), as opposed to the high-variance states with $0.97 < \alpha_{12} + \beta_2 < 2.80$. This is in line with other studies in the literature such as Haas et al. (2004a; 2004b), Alexander and Lazar (2006) and Nomikos and Pouliasis (2011). All, but the HT and RB MRS, models have non-stationary high volatility regime processes; nevertheless the overall variance process is covariance-stationary in all cases as $\rho(M) < 1$ (see Section 2.1). The 'stable' volatility regime has low sensitivity with respect to shocks ($\alpha_{11} < 0.11$), which dissipate slowly as evidenced by the high lagged variance coefficient $\beta_1 > 0.86$ across sectors. On the contrary, in the 'extreme' volatility regime, market shocks affect the variance more and dissipate at a much faster rate. Fig. 2 depicts historical patterns of volatility in tourism stocks and highlights the varying effect of shocks: 'stable' volatility regimes are less variable than 'extreme' volatility processes (for completeness, we present also the aggregate volatility process (4) which lies between the two regime volatilities).

[INSERT FIGURE 2 HERE]

Table 2 exhibits the values of the maximized log-likelihood (13), the Schwarz (1978) Bayesian and Akaike (1973) information criteria. All model selection criteria are favoring MRS to Mix-N, marginally though. The effect of parameter restrictions is formally assessed via the standard likelihood ratio test statistic $-2(L_R - L_U)$, where $L_R$ ($L_U$) is the log-likelihood of the restricted (unrestricted) parameterization. (Due to existence of nuisance parameters, the likelihood ratio test statistic $p$-value has been corrected upwards, see Davies, 1987.) These tests do not favor the normal model at the 1% significance level against MRS and Mix-N. The same applies when comparing Mix-N against MRS at the 5% significance level. Overall, our results support MRS highlighting the importance of modelling variance switches stochastically between the states of the market.

## 3.3 Forecasting accuracy

In the ensuing analysis, MRS, Mix-N and the normal and hist. vol. benchmarks are used to produce daily volatility forecasts for each stock price index. We calibrate to $5,630$ daily log-returns over the sample period 12 April 1973 to 30 December 1994. Then, using rolling windows of $5,630$ days, we recalibrate the models every twenty trading days, allowing thus the parameters to change over time. It is worth noting that model recalibration does not affect the significance of the ARCH and GARCH terms in our models and the qualitative implications remain consistent with the analysis of the previous section.

[INSERT TABLE 3 HERE]

We obtain $5,630$ daily one-step-ahead volatility forecasts from 2 January 1995 to 13 September 2016. Table 3 presents our forecast results. More specifically, MRS is more accurate when considering symmetric loss functions ($b = 0$) and functions that assign heavier penalty to under-prediction ($b \in \{0, -1, -2\}$). Instead, Mix-N generates lower over-prediction errors ($b = 1$). Asymmetric errors have important implications. For example, volatility under-prediction leads to downward-biased stock option premia (undesirable to option writers). In addition, under-estimating risk results in assigning less resources to prospective risks, increasing thus the likelihood of financial distress (undesirable to regulators and banks). On the other hand, risk over-prediction leads to unnecessary accrual of funds for capital adequacy requirements (undesirable for portfolio managers or hedge funds).

Our $MSE$ reports are smaller for the RB sector and the TL aggregate stock index, whereas the volatilities of the RS, HT and GM sectors are the most unpredictable (see Table 2). RB and TL have a relatively high unconditional probability of being in the 'stable' volatility regime ($\pi_1 > 95\%$) implying that the 'extreme' volatility state exhibits sudden jumps rather than a persistent process; jumps are due to random shocks that are harder to predict. RS, with the highest $MSE$, has the most erratic 'extreme' volatility regime (see Fig. 2), whereas GM has the highest volatility (see also Table 1). Similar are the results for over-prediction ($b = 1$), yet GM has in this case lower errors (even compared to AL and TL), implying that volatility under-prediction is the main source of high errors for GM; when assigning more weight to under-prediction ($b = -1$) errors are higher for GM.

We statistically evaluate whether the regime-dependent extensions of the basic GARCH model yield significant improvement in the forecasts by approximating the empirical distribution of the loss function differential $\Delta LF_{i,j} = LF_i(\hat{\sigma}_t^2, r_t^2; b) - LF_j(\hat{\sigma}_t^2, r_t^2; b)$, where $i, j \in$ {MRS, Mix-N, hist.vol., normal}. For given $j$, consider the null hypothesis $H_0$: $\max_i E(\Delta LF_{i,j}) \leq 0$, i.e., model $i$ is not outperformed by model $j$. Using the stationary bootstrap procedure (see Politis and Romano, 1994 and Sullivan et al., 1999), we obtain the loss functions based on 10,000 bootstrap simulations and a smoothing parameter of 0.1 (results were not affected by different choices). Table 3 reports significance at the 5% level obtained using the Hansen (2005) test of superior predictive ability. Mix-N and MRS models' superiority is obvious across all sectors, especially when focusing on under-prediction ($b = -1$ and $b = -2$). When $b = 1$ ($b = 0$), it is only for the AL and HT (AL) sectors that the benchmarks lead to statistically equivalent forecasting ability, although in terms of nominal values they still appear inferior.

A collective view of the results so far suggests that Mix-N and MRS capture better the persistence in volatility and tend to perform better out-of-sample than the benchmarks[3]: across all criteria (Table 3), MRS outperforms the competing models in 18 out of 28 cases; Mix-N performs better in the remaining 36% of the cases. Evidently, allowing volatility to switch stochastically across different states, as in MRS, provides a flexible and reasonable characterization of stock return volatility generating more realistic forecasts.

## 3.4 Application to VaR

Portfolio managers develop different risk models, therefore it is necessary to assess the relative performance. In this section, we explore the economic implications of the forecasting results of Section 3.3 in a risk management exercise based on computation of VaR forecasts, which

[3] To discount the possibility that our results are sample period-specific, we also partition the dataset into: (i) fixed windows (time-partitioned), i.e., 1995–2005 versus 2006–2016, and (ii) expansions versus contractions (market condition-partitioned) based on the OECD recession indicator from the Federal Reserve Bank of St. Louis. Results are similar, i.e., regime-dependent models consistently produce significant lower errors, and can be made available upon request. In addition, forecast ability deteriorates during 1995–2005 and during recessions, but mainly due to over-prediction errors; under-prediction errors are alike across sub-samples.

constitutes the basis to calculate the minimum required capital to cover market risk.

[INSERT TABLE 4 HERE]

[INSERT FIGURE 3 HERE]

Table 4 reports the 1%, 5% VaR $PF$ for the left and and right tails, that is, the realized % number of violations (failures), i.e., instances when $r_t < \text{VaR}_t^c$. Recalling that $\hat{c}$ denotes the empirical coverage rate, we test the null hypothesis $H_0$: $\hat{c} = c$ based on (8). We also test the null hypothesis that violations do not arrive in clusters based on (9). We find that the regime models pass these tests in most of the cases. In particular, MRS (Mix-N) passes both tests in 21 (17) out of 28 cases, whereas the benchmarks in a total of 3 cases. Fig. 3 exhibits the TL stock index log-returns against the MRS-based VaR forecasts at the 5% and 95% levels. Table 4 presents also the $QL$ results (see equation 10) to assess the size of the realized % violations. MRS and Mix-N give the smallest $QL$ in, respectively, 18 and 6 out of 28 cases. The benchmarks generate lower $QL$ in only 4 cases with, however, empirical coverage rate far below the theoretical 1%, as confirmed by the unconditional coverage tests (0.44 and 0.30, respectively), deeming the interpretation of the loss function dubious. Finally, in terms of $PQL$ (see equation 11), reports in Table 4 suggest that the benchmarks do rather poor; regime-dependent models are superior in 27 (17 for MRS and 10 for Mix-N) out of 28 cases, with the hist. vol. and normal model being significantly outperformed in 28 and 16 cases.

Summing up, the above application further corroborates the robust out-of-sample forecasting performance of the regime-dependent models relative to the hist. vol. and normal benchmarks; hence, MRS matches more accurately the moments of the predictive distribution of the stock price changes.

#### 3.4.1 Granger causality in risk

Controlling and monitoring extreme downside market risk are important for risk management and investment diversification. We now proceed to test for extreme downside risk spillover, where risk is measured by the VaR, aiming to investigate the existence of bilateral Granger-causal relationships interconnecting large losses of our sector indices. To this end, we use the MRS-based violations (out-of-sample), which proved to be the most efficient and robust, and follow the approach outlined in Section 2.3.

[INSERT TABLE 5 HERE]

Table 5 reports the $Q(L)$ statistic (12). In consistency with the regularity conditions of Hong et al. (2009, Theorem 1) based on our models and sample size of choice, we consider bandwidth $L \leq 8$, e.g., $L \in \{4, 8\}$. The one-way tests for risk causality at the 1% VaR level from the aggregate index (TL) to the sector indices yield statistic values in the range $-0.465$ to 37.94, for $L = 4$, suggesting a two-way feedback mechanism with strong extreme risk spillover from TL to all but the GM and RS sectors. Similar observations apply for the 5% VaR level and $L = 8$. AL is the only sector that uniformly Granger-causes all indices. Accordingly, a large downward movement exceeding the VaR levels in airline stocks is a useful predictor of future contractions in the other sectors. In fact, for the majority of the sectors analyzed, risk causality is strong. GM seems to be the sector for which large downside risk is the most difficult to predict by looking at the occurrence of large downside risk in another sector. In addition, GM and RS exhibit the least systemic vulnerability as the statistic is significant in fewer cases. Overall, causality at the left tail of the distributions is significant in about 80% of the cases considered. For the right tail of the distributions, i.e., 95% and 99% VaR (equivalent to loss of short position, also interpreted as value within reach), risk causality is significant in less than 15% of the cases. This is in agreement with various empirical findings in the literature suggesting that the correlation between financial assets or markets becomes stronger in large downside market movements, i.e., as Longin and Solnik (2001) argue “correlation increases in bear markets, but not in bull markets”.

# 4 Conclusion

Risk analysis applications share the need for continuous evaluation, especially in the aftermath of the 1998 currency crisis, the 2000–2001 internet bubble, and the collapse of collateralized debt securities in 2007–2008. In this paper, we employ a set of regime-dependent GARCH-type models to examine stock return volatility dynamics and tail risk. The rationale behind the use of these models is that the volatility can be characterized by regime shifts; by allowing the second moments to depend on the state of the market, one can obtain more efficient estimates associated with enhanced forecast ability. As a case study for the empirical applications, we use capitalization-weighted tourism stock indices which serve as a broad barometer of the well-being of the industry.

Our main findings can be summarized as follows. First, MRS and Mix-N models fit the data well and capture volatility persistence better than the standard GARCH. Volatility can be described by a persistent 'stable' process with low sensitivity to shocks that die out slowly, and a short-lived 'extreme' process with high sensitivity to shocks that dissipate fast. Second, regarding the relative forecasting performance, regime-dependent models provide significant gains, compared to appropriate benchmarks, and further improve VaR backtests at the 1% and 5% left and right tail probability levels. Loss functions which measure the magnitude of losses when models fail to forecast the true VaR and the capital forgone as a result of over-predictions also verify the consistency of MRS and Mix-N. Overall, results are in line with the existing studies on commodity (Nomikos and Pouliasis, 2011), stock index (Haas et al., 2004a), interest rate (Gray, 1996) and foreign exchange rate markets (Alexander and Lazar, 2006; Haas et al., 2004b). Third, we document asymmetric cross-sector spillover effects favouring the explanation that correlation increases mostly in bear markets. In effect, large downside past movements Granger-cause large future price falls between related sectors. In contrast, the transmission process for financial contagion in the right tail of return distributions is weak. This finding is in agreement with the existing literature (e.g., see Hong et al., 2009 for exchange rates; Longin and Solnik, 2001 for equity indices) and has implications for international policies aimed at relieving adverse impacts on the economy as a whole.

This research highlights the importance of closely monitoring firms as large idiosyncratic shocks convey useful information about expected shocks in other related economic sectors. Therefore, it constitutes one of the few applications of stock return volatility modelling and the first to assess the predictive potential of regime-dependent models in the sector. However, the suggested risk analysis framework extends to all segments of the economy as robust volatility forecasts support effective evaluation of strategic decisions, facilitate good governance and lead to sound risk policies that reflect market risks. Such analysis offers insights on the vulnerability of economic sectors and the stability of the system, thus advances the knowledge of investors by providing the means for identifying global economic changing patterns and signals of where capital should flow, as volatility can be used in the decision making process of investment strategies and governmental policies.

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Table 1: Summary statistics: tourism firms global stock price indices

This table reports the summary statistics of the index log-returns based on the period 12 April 1973–13 September 2016, i.e., a total of 11,261 daily closing price levels. The closing index price levels include an aggregate index of travel and leisure (TL) stocks and six individual sectors: airlines (AL), gambling (GM), hotels (HT), recreational services (RS), restaurants and bars (RB), and travel and tourism (TT) stocks. The first line of the table shows the number of index constituents with the figures in $(\cdot)$ indicating the number of countries represented in each index. JB is the Jarque and Bera (1980) statistic for normality, LB(5) and LB(10) the Ljung and Box (1978) statistic for the 5th and 10th order sample autocorrelation of the returns series, whereas $LB^2(5)$ and $LB^2(10)$ are based on the squared returns series. Asterisk * indicates significance at the 5% level.

| | TL | AL | GM | HT | RS | RB | TT |
|---|---|---|---|---|---|---|---|
| No. of constituents | 334 (59) | 42 (30) | 49 (21) | 77 (32) | 49 (22) | 61 (16) | 56 (22) |
| Annualized mean (%) | 7.836 | 5.074 | 15.008 | 5.669 | 7.310 | 8.768 | 6.350 |
| Annualized vol. (%) | 16.20 | 17.76 | 33.20 | 17.25 | 20.40 | 17.24 | 18.13 |
| Skew | -0.525 | -0.542 | -0.005 | -0.763 | -0.438 | -0.317 | -0.243 |
| Exc kurt | 10.746 | 10.559 | 25.159 | 12.297 | 12.017 | 5.977 | 13.639 |
| JB | 54,699* | 52,861* | 296,966* | 72,035* | 68,109* | 16,949* | 87,381* |
| LB(5) | 373.2* | 316.7* | 62.15* | 365.4* | 154.5* | 104.7* | 80.59* |
| LB(10) | 380.3* | 328.1* | 75.40* | 380.1* | 161.5* | 113.8* | 105.8* |
| $LB^2(5)$ | 1736* | 966.2* | 1161* | 962.3* | 832.1* | 1653* | 1076* |
| $LB^2(10)$ | 2197* | 1141.7* | 1562* | 1306* | 1084* | 3218* | 1326* |
| *Cutoff points of standardized returns distributions* | | | | | | | |
| 1% tail | -2.753 | -2.627 | -2.694 | -2.784 | -2.747 | -2.737 | -2.592 |
| 5% tail | -1.563 | -1.518 | -1.383 | -1.544 | -1.509 | -1.554 | -1.446 |
| 95% tail | 1.473 | 1.538 | 1.415 | 1.487 | 1.526 | 1.535 | 1.535 |
| 99% tail | 2.573 | 2.595 | 2.929 | 2.584 | 2.648 | 2.525 | 2.897 |

Table 2: Calibrated model parameters for global tourism stocks by sector (12 April 1973–13 September 2016)

This table reports the parameter estimates of the Markov Regime Switching GARCH (MRS) model with unconditional regime probabilities $(\pi_1, \pi_2)$, the mixture of normals GARCH (Mix-N) model with mixing weights $(\lambda_1, \lambda_2)$ and the single-regime GARCH (normal) model (for brevity, only for TL; results for remaining sectors available by the authors upon request). Figures in $(\cdot)$ are the estimated standard errors and the asterisk $^*$ indicates significance at the 5% level. Also reported are $\rho(M)$, i.e., the largest eigenvalue in modulus of matrix (5), the log-likelihood function $\mathscr{L}$, and the Schwarz (1978) Bayesian and Akaike (1973) information criteria BIC and AIC. $\sqrt{E(\sigma^2_{1t})}$, $\sqrt{E(\sigma^2_{2t})}$ are the annualised unconditional volatilities in the low and high volatility regimes, respectively, whereas $\sqrt{E(\sigma^2_t)}$ the corresponding figure for the aggregate variance process.

| | Travel & Leisure (TL) | | | Airlines (AL) | | Gambling (GM) | | Hotels (HT) | | Recreational Services (RS) | | Restaurants & Bars (RB) | | Travel & Tourism (TT) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Normal | Mix-N | MRS | Mix-N | MRS | Mix-N | MRS | Mix-N | MRS | Mix-N | MRS | Mix-N | MRS | Mix-N | MRS |
| $\mu_1$ | 0.0662* | 0.0662* | 0.1048* | 0.0337* | 0.0415* | 0.0616* | 0.0645* | 0.0550* | 0.0660* | 0.0482* | 0.0485* | 0.0562* | 0.0811* | 0.0021 | 0.0022 |
| | (0.007) | (0.008) | (0.008) | (0.009) | (0.009) | (0.014) | (0.014) | (0.008) | (0.008) | (0.009) | (0.009) | (0.011) | (0.010) | (0.009) | (0.009) |
| $\alpha_{01}$ | 0.0209* | 0.0086* | 0.0051* | 0.0123* | 0.0088* | 0.0400* | 0.0354* | 0.0134* | 0.0111* | 0.0098* | 0.0098* | 0.0042* | 0.0031* | 0.0093* | 0.0083* |
| | (0.002) | (0.001) | (0.001) | (0.002) | (0.001) | (0.005) | (0.004) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\alpha_{11}$ | 0.1054* | 0.0557* | 0.0366* | 0.0550* | 0.0398* | 0.0636* | 0.0508* | 0.0618* | 0.0444* | 0.0447* | 0.0448* | 0.0313* | 0.0246* | 0.0435* | 0.0379* |
| | (0.003) | (0.004) | (0.004) | (0.004) | (0.003) | (0.005) | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) | (0.004) | (0.003) | (0.003) | (0.003) |
| $\beta_1$ | 0.8757* | 0.9243* | 0.9443* | 0.9210* | 0.9406* | 0.8694* | 0.8834* | 0.9134* | 0.9334* | 0.9416* | 0.9417* | 0.9534* | 0.9648* | 0.9238* | 0.9334* |
| | (0.004) | (0.005) | (0.005) | (0.005) | (0.005) | (0.008) | (0.008) | (0.005) | (0.005) | (0.004) | (0.004) | (0.005) | (0.004) | (0.005) | (0.005) |
| $p_{11}$ | - | - | 0.9489* | - | 0.964* | - | 0.8484* | - | 0.9819* | - | 0.9816* | - | 0.9501* | - | 0.9069* |
| | | | (0.008) | | (0.006) | | (0.012) | | (0.003) | | (0.004) | | (0.012) | | (0.010) |
| $\lambda_1$ or $\pi_1$ | 1 | 0.9592* | 0.8830 | 0.9535* | 0.9392 | 0.8328* | 0.8301 | 0.9680* | 0.9534 | 0.9789* | 0.9811 | 0.8201* | 0.8438 | 0.8815* | 0.8869 |
| | | (0.007) | | (0.006) | | (0.010) | | (0.005) | | (0.004) | | (0.030) | | (0.009) | |
| $\mu_2$ | - | -0.0105 | -0.3729* | -0.0538 | -0.2514* | 0.1603* | 0.1371* | 0.1039 | -0.7058* | 0.5970* | 0.6548* | 0.0503 | -0.1630* | 0.0752 | 0.0827 |
| | | (0.086) | (0.052) | (0.135) | (0.102) | (0.069) | (0.069) | (0.154) | (0.133) | (0.210) | (0.276) | (0.043) | (0.054) | (0.049) | (0.054) |
| $\alpha_{02}$ | - | 0.0742 | 0.0000 | 0.1623* | 0.1028* | 0.0001 | 0.0000 | 0.6284* | 0.4581 | 0.9144 | 1.1601 | 0.0798* | 0.1107* | 0.0863* | 0.0810* |
| | | (0.077) | (0.017) | (0.068) | (0.042) | (0.010) | (0.010) | (0.239) | (0.332) | (0.485) | (0.634) | (0.020) | (0.021) | (0.016) | (0.015) |
| $\alpha_{12}$ | - | 0.9766* | 0.2264* | 0.4501* | 0.2459* | 0.1483* | 0.1324* | 0.8261* | 0.0838* | 1.4996* | 2.1937* | 0.2427* | 0.1099* | 0.3429* | 0.2784* |
| | | (0.179) | (0.018) | (0.076) | (0.033) | (0.011) | (0.011) | (0.222) | (0.035) | (0.511) | (0.978) | (0.040) | (0.022) | (0.042) | (0.039) |
| $\beta_2$ | - | 0.8065* | 0.9076* | 0.8861* | 0.9192* | 0.9583* | 0.9610* | 0.7701* | 0.8866* | 0.6914* | 0.5997* | 0.8519* | 0.884* | 0.8881* | 0.9061* |
| | | (0.033) | (0.007) | (0.022) | (0.014) | (0.003) | (0.003) | (0.053) | (0.068) | (0.062) | (0.087) | (0.022) | (0.022) | (0.011) | (0.012) |
| $p_{22}$ | - | - | 0.6145* | - | 0.4433* | - | 0.2594* | - | 0.6302* | - | 0.0481 | - | 0.7304* | - | 0.2698* |
| | | | (0.045) | | (0.062) | | (0.042) | | (0.053) | | (0.044) | | (0.046) | | (0.049) |
| $\lambda_2$ or $\pi_2$ | 0 | 0.0408* | 0.1170 | 0.0465* | 0.0608 | 0.1672* | 0.1699 | 0.0320* | 0.0466 | 0.0211* | 0.0189 | 0.1799* | 0.1562 | 0.1185* | 0.1131 |
| | | (0.007) | | (0.006) | | (0.010) | | (0.005) | | (0.004) | | (0.030) | | (0.009) | |
| $\rho(M)$ | 0.9811 | 0.9923 | 0.9947 | 0.9872 | 0.9896 | 0.9970 | 0.9970 | 0.9818 | 0.9776 | 0.9905 | 0.9913 | 0.9908 | 0.9897 | 0.9883 | 0.9890 |
| $\sqrt{E(\sigma^2_{1t})}$ | - | 16.98 | 13.56 | 16.95 | 16.48 | 25.05 | 23.62 | 16.08 | 14.96 | 18.31 | 19.05 | 14.48 | 13.79 | 15.67 | 15.47 |
| $\sqrt{E(\sigma^2_{2t})}$ | - | 43.35 | 24.49 | 42.03 | 37.19 | 64.91 | 61.19 | 42.37 | 34.91 | 51.08 | 54.88 | 24.34 | 21.63 | 36.69 | 36.05 |
| $\sqrt{E(\sigma^2_t)}$ | 16.69 | 18.79 | 15.25 | 18.87 | 18.42 | 35.03 | 33.16 | 17.55 | 16.43 | 19.58 | 20.32 | 16.69 | 15.28 | 19.39 | 18.95 |
| $\mathscr{L}$ | -14691 | -14407 | -14402 | -15792 | -15780 | -20918 | -20916 | -15231 | -15226 | -17036 | -17034 | -15464 | -15460 | -15455 | -15450 |
| BIC | 14672 | 14365 | 14355 | 15750 | 15733 | 20876 | 20869 | 15189 | 15180 | 16994 | 16988 | 15422 | 15413 | 15413 | 15404 |
| AIC | 14687 | 14398 | 14392 | 15783 | 15770 | 20909 | 20906 | 15222 | 15216 | 17027 | 17024 | 15455 | 15450 | 15446 | 15440 |

Table 3: Comparison of forecasting performance of different volatility models

The table reports the average loss functions for different parameter $b$ values (note that $b = 0$ and $b = -2$ correspond to $MSE$ and $QLIKE$, respectively), for each sector and model, based on 5,630 daily volatility forecasts obtained by the rolling-window forecasting scheme (5,630 observations at each step). Asterisk * indicates that the loss function of a given model is statistically higher than that of the competing models at the 5% significance level based on the Hansen (2005) test using 10,000 (stationary) bootstrap simulations.

| | $b = 1$ | $b = 0$ | $b = -1$ | $b = -2$ |
|---|---|---|---|---|
| Travel & Leisure (TL) | | | | |
| Hist. vol. | 168.77* | 6.441* | 1.449* | 1.837* |
| Normal | 168.71* | 6.036* | 1.098* | 1.504* |
| Mix-N | 160.77* | 4.816* | 0.739* | 1.278* |
| MRS | **135.89** | **3.371** | **0.577** | **1.227** |
| Airlines (AL) | | | | |
| Hist. vol. | 581.38 | 10.400* | 1.594* | 1.639* |
| Normal | 581.06 | 9.837 | 1.259* | 1.409* |
| Mix-N | **563.39** | **8.156** | 0.916 | 1.241* |
| MRS | 570.08 | 8.376 | **0.854** | **1.180** |
| Gambling (GM) | | | | |
| Hist. vol. | 286.12* | 15.710* | 2.873* | 1.860* |
| Normal | 269.94* | 12.080* | 1.904* | 1.536* |
| Mix-N | 249.85 | 9.609 | 1.389* | 1.361* |
| MRS | **242.72** | **9.104** | **1.235** | **1.264** |
| Hotels (HT) | | | | |
| Hist. vol. | 896.24 | 14.980* | 1.932* | 1.848* |
| Normal | 897.36 | 14.320* | 1.489* | 1.541* |
| Mix-N | **862.36** | **11.530** | 0.995 | 1.299* |
| MRS | 889.05 | 12.800 | **0.994** | **1.251** |
| Recreational Services (RS) | | | | |
| Hist. vol. | 1,460.9* | 22.100* | 2.418* | 1.857* |
| Normal | 1,461.3* | 21.250* | 1.966* | 1.604* |
| Mix-N | **1,423.4** | 17.770 | 1.325* | 1.343* |
| MRS | 1,430.2 | **17.550** | **1.170** | **1.264** |
| Restaurants & Bars (RB) | | | | |
| Hist. vol. | 21.699* | 2.811* | 1.136* | 1.689* |
| Normal | 20.790* | 2.399* | 0.874* | 1.469* |
| Mix-N | **18.720** | **1.921** | **0.658** | **1.299** |
| MRS | 18.850 | 1.969 | 0.688 | 1.343 |
| Travel & Tourism (TT) | | | | |
| Hist. vol. | 287.85* | 6.181* | 1.252* | 1.678* |
| Normal | 288.74* | 5.979* | 1.026* | 1.489* |
| Mix-N | **281.17** | 5.013 | 0.737* | 1.298* |
| MRS | 282.85 | **4.888** | **0.602** | **1.198** |

## Table 4: VaR forecasting accuracy

The table presents, for each sector and model, the VaR results across the out-of-sample period: percentage number of failures, i.e., violations, ($PF$), average quadratic loss ($QL$) and average predictive quantile loss ($PQL$). Superscipts $a$ and $b$ indicate when the model does not pass the test of unconditional coverage (8) and conditional coverage (9), respectively. Asterisk * indicates that the average $PQL$ of a given model is statistically higher than that of the competing models at the 5% significance level (see also notes in Table 3).

| | 1% VaR | | | 5% VaR | | | 95% VaR | | | 99% VaR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $PF$ | $QL$ | $PQL$ | $PF$ | $QL$ | $PQL$ | $PF$ | $QL$ | $PQL$ | $PF$ | $QL$ | $PQL$ |
| Travel & Leisure (TL) | | | | | | | | | | | | |
| Hist. vol. | $1.723^{a,b}$ | 0.416 | $0.425^*$ | $6.270^{a,b}$ | 0.327 | $1.286^*$ | $5.435^{b}$ | 1.062 | $1.145^*$ | $1.332^{a,b}$ | 0.779 | $0.374^*$ |
| Normal | $1.208^{b}$ | 0.231 | 0.331 | $5.897^{a,b}$ | 0.218 | $1.112^*$ | $6.483^{a,b}$ | 0.606 | $0.960^*$ | $1.474^{a,b}$ | 0.485 | $0.273^*$ |
| Mix-N | 0.977 | 0.211 | 0.331 | $4.973^{b}$ | 0.188 | 1.099 | 5.382 | 0.531 | $0.956^*$ | 0.924 | 0.382 | 0.270 |
| MRS | 0.924 | **0.208** | **0.324** | 4.583 | **0.178** | **1.086** | 5.044 | **0.501** | **0.941** | 0.817 | **0.355** | **0.262** |
| Airlines (AL) | | | | | | | | | | | | |
| Hist. vol. | $1.439^{a,b}$ | 0.581 | $0.440^*$ | $6.750^{a,b}$ | 0.124 | $1.379^*$ | $5.506^{b}$ | 1.398 | $1.217^*$ | $0.941^{b}$ | 0.547 | $0.362^*$ |
| Normal | $1.297^{a,b}$ | 0.423 | 0.383 | $5.702^{a,b}$ | 0.034 | 1.246 | $4.636^{b}$ | 0.904 | 1.073 | $0.710^{a,b}$ | 0.242 | $0.290^*$ |
| Mix-N | $1.314^{a}$ | 0.423 | **0.373** | $5.808^{a,b}$ | **0.028** | 1.230 | 4.973 | 0.865 | **1.073** | 0.764 | **0.232** | **0.285** |
| MRS | $1.367^{a,b}$ | **0.402** | 0.375 | $5.452^{b}$ | 0.032 | **1.229** | 5.258 | **0.839** | 1.081 | 0.924 | 0.235 | 0.290 |
| Gambling (GM) | | | | | | | | | | | | |
| Hist. vol. | $0.675^{a,b}$ | 0.266 | $0.584^*$ | $3.623^{a,b}$ | 0.223 | $1.713^*$ | $2.842^{a,b}$ | 1.082 | $1.662^*$ | $0.604^{a,b}$ | 0.813 | $0.582^*$ |
| Normal | $1.119^{b}$ | 0.289 | $0.448^*$ | $4.937^{b}$ | **0.153** | 1.484 | $4.795^{b}$ | 0.839 | 1.444 | 0.817 | 0.674 | **0.415** |
| Mix-N | 0.906 | 0.231 | **0.434** | $4.316^{a,b}$ | 0.158 | 1.467 | $4.334^{a,b}$ | **0.736** | **1.442** | 0.888 | **0.631** | 0.420 |
| MRS | 1.101 | **0.230** | 0.436 | 4.742 | 0.187 | **1.464** | 4.742 | 0.767 | 1.450 | $0.728^{a}$ | 0.669 | 0.425 |
| Hotels (HT) | | | | | | | | | | | | |
| Hist. vol. | $1.634^{a,b}$ | 0.813 | $0.474^*$ | $7.176^{a,b}$ | 0.340 | $1.423^*$ | $6.377^{a,b}$ | 1.765 | $1.306^*$ | $1.616^{a,b}$ | 0.997 | $0.431^*$ |
| Normal | $1.332^{a,b}$ | 0.612 | 0.379 | $5.719^{a,b}$ | 0.131 | $1.235^*$ | $6.270^{a,b}$ | 1.073 | $1.114^*$ | $1.545^{a,b}$ | 0.462 | $0.320^*$ |
| Mix-N | 1.012 | 0.587 | 0.374 | $4.991^{b}$ | 0.117 | 1.222 | $5.382^{b}$ | 1.043 | 1.110 | 1.083 | 0.410 | 0.312 |
| MRS | 1.137 | **0.577** | **0.371** | 5.506 | **0.098** | **1.214** | $5.950^{a,b}$ | **0.976** | **1.095** | 1.243 | **0.366** | **0.307** |
| Recreational Services (RS) | | | | | | | | | | | | |
| Hist. vol. | $1.883^{a,b}$ | 0.851 | $0.525^*$ | $7.123^{a,b}$ | 0.585 | $1.580^*$ | $6.057^{a,b}$ | 1.892 | $1.516^*$ | $1.563^{a,b}$ | 1.417 | $0.483^*$ |
| Normal | $1.634^{a,b}$ | 0.649 | $0.430^*$ | $6.306^{a,b}$ | 0.440 | $1.376^*$ | $7.052^{a,b}$ | 1.226 | $1.337^*$ | $1.581^{a,b}$ | 1.014 | $0.384^*$ |
| Mix-N | 1.119 | 0.626 | 0.418 | $5.399^{b}$ | 0.394 | $1.362^*$ | 5.524 | 1.126 | $1.315^*$ | 1.066 | 0.860 | $0.381^*$ |
| MRS | 1.243 | **0.614** | **0.411** | 5.222 | **0.371** | **1.345** | $5.950^{a,b}$ | **1.104** | **1.287** | 1.226 | **0.813** | **0.364** |
| Restaurants & Bars (RB) | | | | | | | | | | | | |
| Hist. vol. | $1.261^{b}$ | 0.191 | $0.369^*$ | $5.471^{b}$ | 0.155 | $1.182^*$ | $4.742^{b}$ | 0.637 | $1.106^*$ | $1.137^{b}$ | 0.477 | $0.340^*$ |
| Normal | $1.758^{a,b}$ | 0.087 | $0.305^*$ | $5.435^{b}$ | 0.054 | 1.070 | 5.488 | 0.369 | 0.990 | 1.137 | 0.290 | $0.278^*$ |
| Mix-N | 0.959 | 0.075 | 0.296 | 4.920 | **0.036** | **1.057** | 5.115 | 0.324 | **0.985** | 0.959 | **0.248** | **0.268** |
| MRS | 1.030 | **0.071** | **0.294** | 4.813 | 0.050 | 1.058 | 4.991 | **0.316** | 0.991 | 0.924 | 0.261 | 0.274 |
| Travel & Tourism (TT) | | | | | | | | | | | | |
| Hist. vol. | $0.444^{a,b}$ | **0.301** | $0.379^*$ | $3.091^{a,b}$ | 0.036 | $1.125^*$ | $2.487^{a,b}$ | 0.637 | $1.103^*$ | $0.302^{a}$ | **0.207** | $0.368^*$ |
| Normal | $0.782^{b}$ | 0.377 | $0.339^*$ | $4.281^{a,b}$ | **0.031** | 1.067 | $4.210^{a,b}$ | 0.670 | $0.996^*$ | $0.462^{a}$ | 0.211 | 0.294 |
| Mix-N | $0.977^{b}$ | 0.354 | $0.328^*$ | 5.258 | 0.033 | 1.061 | 4.671 | 0.659 | **0.989** | $0.515^{a}$ | 0.219 | **0.285** |
| MRS | 0.959 | 0.332 | **0.316** | 5.560 | 0.034 | **1.060** | 4.902 | **0.612** | 0.999 | $0.675^{a}$ | 0.212 | 0.286 |

Table 5: Extreme risk spillover effects between tourism sectors: Granger causality in risk

The table reports the Hong et al. (2009) statistic $Q(L)$ (see equation 12) for testing the null hypothesis that the $i$th sector does not Granger-cause the $j$th sector in risk at the 1% and 5% levels (for both tails of the log-return distributions). $Q(L)$ is computed for different values of the lag order parameter $L$ based on the Daniell kernel. $i \Rightarrow j$ indicates one-way causality in risk from the $i$th to the $j$th sector.

| | 1% VaR | | 5% VaR | | 95% VaR | | 99% VaR | |
|---|---|---|---|---|---|---|---|---|
| | $L=4$ | $L=8$ | $L=4$ | $L=8$ | $L=4$ | $L=8$ | $L=4$ | $L=8$ |
| Travel & Leisure (TL) | | | | | | | | |
| AL⇒TL | 4.152* | 6.491* | 4.560* | 3.849* | 1.495 | 0.584 | -0.404 | -0.732 |
| GM⇒TL | -0.672 | -0.923 | 0.102 | 1.346 | -0.315 | -0.021 | -0.725 | -1.010 |
| HT⇒TL | 4.784* | 8.985* | 0.283 | 0.669 | 2.400* | 1.590 | -0.571 | -0.819 |
| RS⇒TL | 2.055* | 2.773* | 0.232 | 0.102 | -0.091 | -0.123 | -0.439 | -0.697 |
| RB⇒TL | 2.936* | 3.514* | 3.397* | 2.623* | 0.834 | 0.557 | -0.489 | -0.633 |
| TT⇒TL | 3.639* | 3.938* | -0.287 | -0.273 | -0.100 | 1.399 | 0.080 | -0.456 |
| Airlines (AL) | | | | | | | | |
| TL⇒AL | 16.34* | 11.76* | 21.51* | 15.78* | 0.484 | 1.197 | 2.895* | 1.856* |
| GM⇒AL | 12.05* | 8.252* | 2.858* | 3.512* | 0.376 | 0.320 | 5.085* | 6.326* |
| HT⇒AL | 15.49* | 11.76* | 16.19* | 12.21* | -0.171 | 0.059 | 0.339 | 0.116 |
| RS⇒AL | 14.87* | 10.54* | 20.96* | 16.29* | 1.966* | 1.919* | 1.250 | 0.770 |
| RB⇒AL | 23.03* | 17.39* | 18.54* | 14.41* | 0.423 | 1.176 | -0.580 | -0.833 |
| TT⇒AL | 8.712* | 7.883* | 3.751* | 2.456* | 0.096 | -0.477 | -0.380 | -0.552 |
| Gambling (GM) | | | | | | | | |
| TL⇒GM | 0.305 | 0.758 | 5.424* | 4.298* | -0.639 | -0.153 | -0.547 | -0.954 |
| AL⇒GM | 2.360* | 3.142* | 1.787* | 2.283* | 0.793 | 3.083* | -0.460 | 3.505* |
| HT⇒GM | 2.258* | 3.509* | 9.341* | 7.271* | 0.671 | 2.941* | -0.408 | -0.336 |
| RS⇒GM | 0.113 | 0.894 | 2.989* | 2.628* | 1.239 | -0.554 | -0.384 | 0.240 |
| RB⇒GM | 5.484* | 4.040* | 8.702* | 8.658* | 1.615 | -0.144 | -0.066 | -0.835 |
| TT⇒GM | 0.879 | 3.623* | 2.105* | 3.566* | -0.547 | 2.613* | -0.568 | -0.348 |
| Hotels (HT) | | | | | | | | |
| TL⇒HT | 4.347* | 6.963* | 2.015* | 2.532* | -0.408 | -0.383 | 1.475 | 0.783 |
| AL⇒HT | 7.350* | 10.73* | 5.930* | 5.531* | 2.002* | 1.412 | -0.339 | 1.569 |
| GM⇒HT | 0.659 | 0.224 | 2.286* | 3.058* | 0.619 | 0.887 | -0.556 | -0.792 |
| RS⇒HT | -0.238 | 0.258 | 9.513* | 7.466* | 0.744 | -0.075 | -0.442 | -0.494 |
| RB⇒HT | 10.79* | 13.22* | 6.432* | 5.615* | 0.780 | 0.278 | -0.371 | -0.656 |
| TT⇒HT | 1.872* | 3.105* | 1.943* | 2.276* | -0.252 | 0.353 | -0.244 | -0.523 |
| Recreational Services (RS) | | | | | | | | |
| TL⇒RS | -0.465 | -0.132 | -0.750 | -0.545 | -0.314 | 1.894* | -0.316 | -0.547 |
| AL⇒RS | 3.009* | 2.567* | 9.559* | 7.200* | 2.363* | 1.545 | 0.920 | 6.263* |
| GM⇒RS | 3.105* | 4.316* | -0.117 | 0.767 | -0.422 | 0.944 | -0.120 | 0.559 |
| HT⇒RS | 0.414 | 2.506* | 2.162* | 2.449* | 1.161 | 3.389* | -0.825 | 2.761* |
| RB⇒RS | 0.087 | -0.276 | 1.918* | 1.319 | 3.253* | -0.375 | -0.703 | -0.712 |
| TT⇒RS | 1.415 | 1.739* | 2.944* | 2.133* | 0.865 | 4.641* | -0.404 | 1.075 |
| Restaurants & Bars (RB) | | | | | | | | |
| TL⇒RB | 9.937* | 8.921* | 7.373* | 5.592* | 0.825 | 3.752* | -0.416 | 0.454 |
| AL⇒RB | 2.332* | 2.333* | 2.548* | 2.310* | -0.363 | -0.753 | -0.362 | -0.522 |
| GM⇒RB | 0.064 | 0.059 | 3.061* | 3.259* | -0.122 | 1.599 | -0.272 | -0.655 |
| HT⇒RB | 4.829* | 5.883* | 4.244* | 3.959* | 0.713 | 6.034* | -0.832 | -1.009 |
| RS⇒RB | 4.021* | 3.721* | -0.676 | -0.183 | -0.029 | 1.493 | -0.686 | -0.865 |
| TT⇒RB | 5.953* | 3.918* | 5.480* | 4.671* | -0.709 | 3.026* | -0.436 | -0.489 |
| Travel & Tourism (TT) | | | | | | | | |
| TL⇒TT | 37.94* | 27.26* | 6.657* | 5.211* | -0.830 | -0.646 | -0.662 | -0.980 |
| AL⇒TT | 8.879* | 6.228* | 3.873* | 3.345* | 0.783 | 0.395 | -0.402 | -0.589 |
| GM⇒TT | 11.68* | 8.076* | 1.308 | 1.412 | -0.739 | -1.147 | -0.748 | -1.095 |
| HT⇒TT | 36.23* | 26.79* | 10.62* | 7.408* | -0.513 | 0.184 | -0.510 | -0.776 |
| RS⇒TT | 20.25* | 17.14* | 3.960* | 3.193* | 0.561 | 1.083 | -0.545 | -0.784 |
| RB⇒TT | 12.76* | 8.812* | 7.329* | 7.539* | -0.970 | -0.954 | -0.139 | -0.520 |

Fig. 1

Illustrative examples of two-component mixture of normal densities for varying mixing weight $\lambda_1$ (yellow lines) against the standard normal density $\mathcal{N}(0,1)$ (blue lines) and normal densities $\mathcal{N}(\mu,\sigma)$ (red lines).

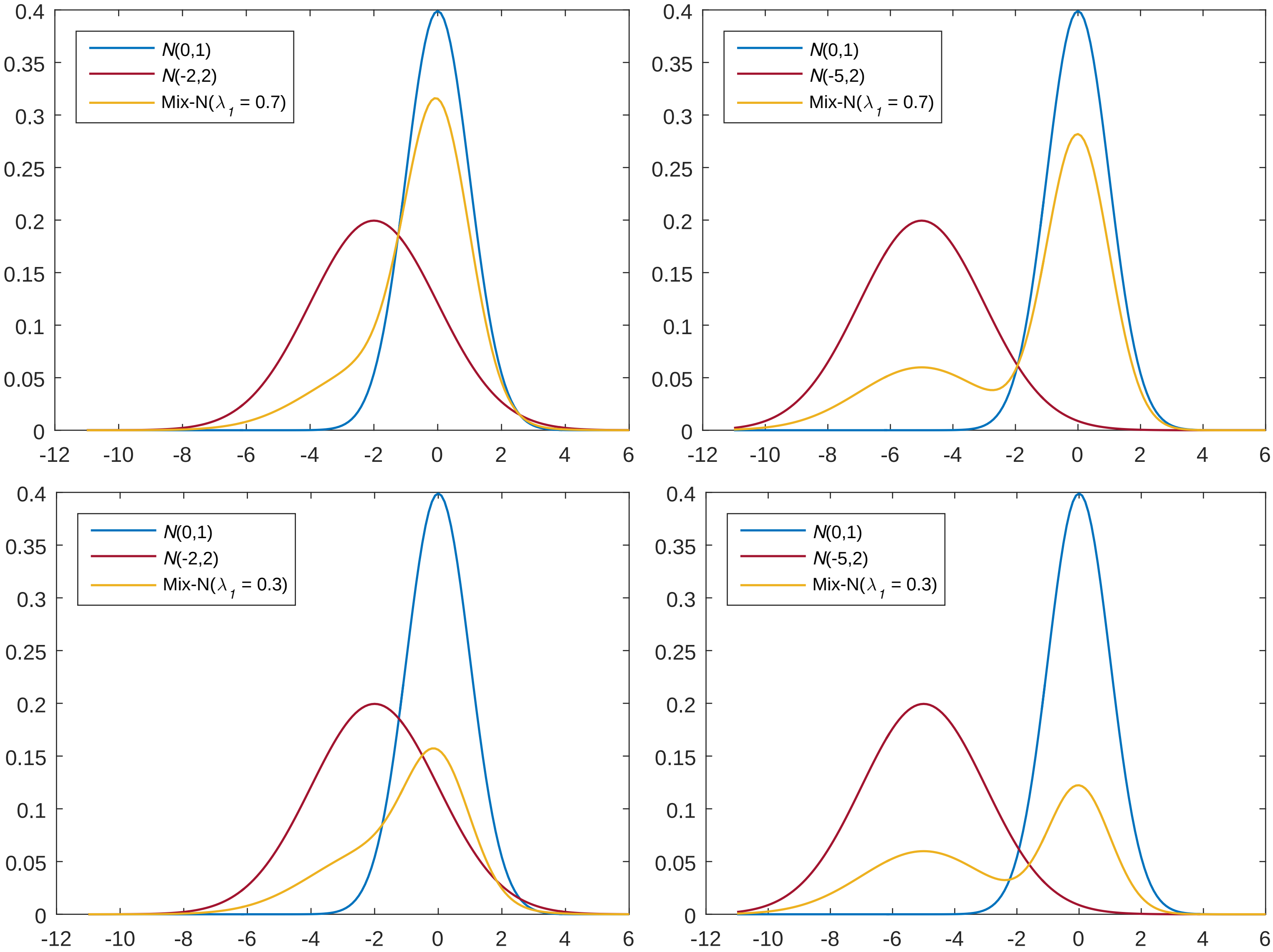

Fig. 2

Volatility of tourism sector stock indices as estimated by the MRS model (in-sample estimates based on the period April 1973–September 2016): aggregate volatility, low and high volatility regime processes.

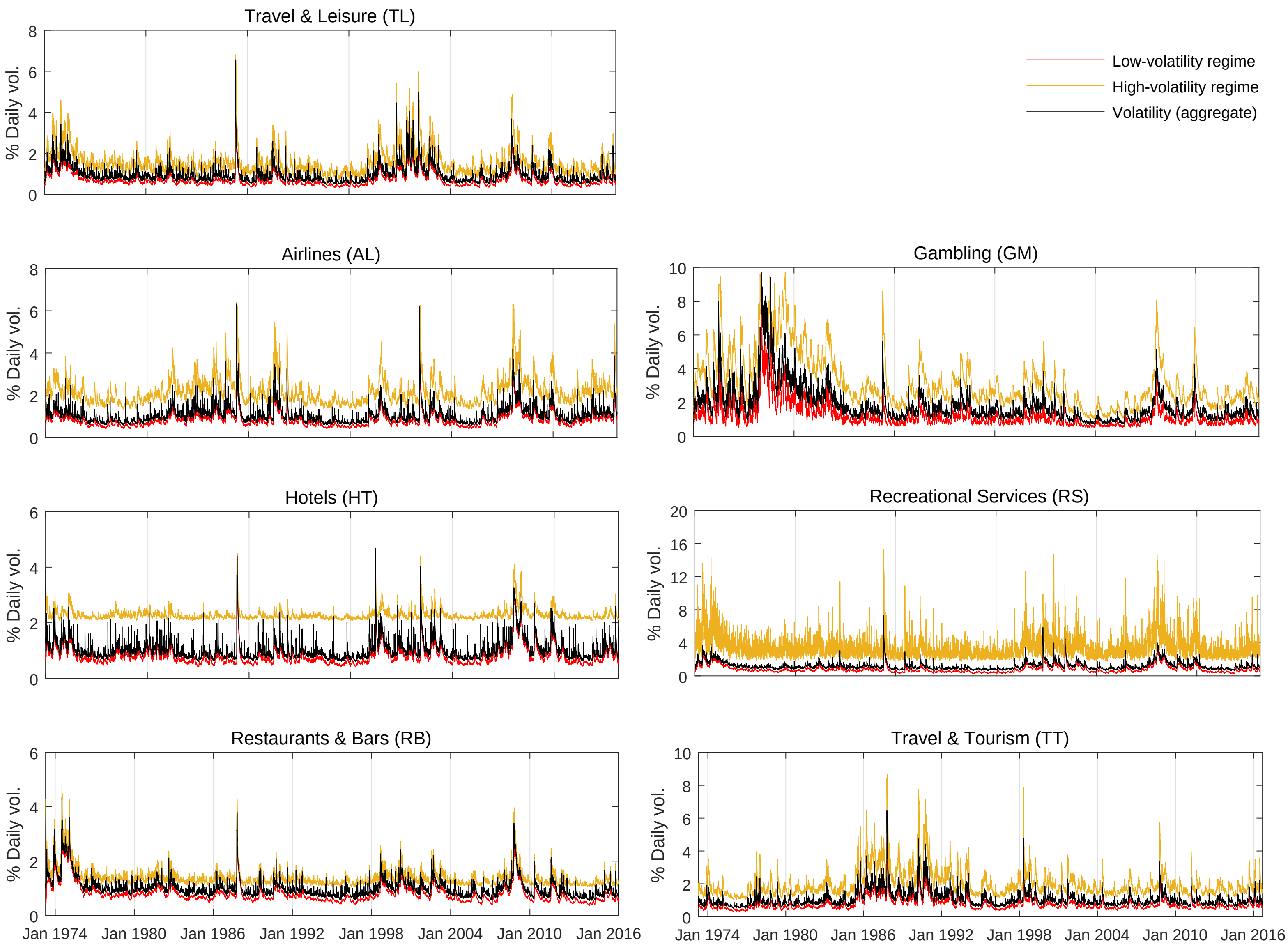

Fig. 3

Tourism & Leisure stock index log-returns against the MRS-based VaR forecasts at the 5% and 95% levels.