

Continuous-time VIX dynamics: on the role of stochastic volatility of volatility

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Highlights

Continuous-time VIX dynamics: On the role of stochastic volatility of volatility*International Review of Financial Analysis xxx (2013) xxx – xxx*Andreas Kaeck^a, Carol Alexander^{b,*}^a *Swiss Institute of Banking and Finance, University of St. Gallen, Rosenbergstrasse 52, 9000 St. Gallen, Switzerland*^b *School of Business, Management and Economics, University of Sussex, Falmer, East Sussex, BN1 9QH, UK*

► We examine the performance of affine and non-affine models for the VIX index. ► Standard models are augmented with a stochastic volatility of volatility factor. ► We find that non-affine models significantly outperform their affine counterparts. ► A volatility of volatility factor can explain VIX dynamics over a 20-year period.



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International Review of Financial Analysis



Continuous-time VIX dynamics: On the role of stochastic volatility of volatility

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ABSTRACT

This paper examines the ability of several different continuous-time one- and two-factor jump-diffusion models to capture the dynamics of the VIX volatility index for the period between 1990 and 2010. For the one-factor models we study affine and non-affine specifications, possibly augmented with jumps. Jumps in one-factor models occur frequently, but add surprisingly little to the ability of the models to explain the dynamic of the VIX. We present a stochastic volatility of volatility model that can explain all the time-series characteristics of the VIX studied in this paper. Extensions demonstrate that sudden jumps in the VIX are more likely during tranquil periods and the days when jumps occur coincide with major political or economic events. Using several statistical and operational metrics we find that non-affine one-factor models outperform their affine counterparts and modeling the log of the index is superior to modeling the VIX level directly.

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1. Introduction

As a measure of volatility implied in traded equity index option prices, volatility indices have attracted research for almost a decade. The diverse problems being investigated include: the construction methodology (Carr & Wu, 2006; Jiang & Tian, 2007); their use in constructing trading strategies (Konstantinidi, Skiadopoulos, & Tzagaraki, 2008) and for describing the dynamic behavior of equity return variance (Jones, 2003; Wu, 2011); and their information content regarding future volatility (Jiang & Tian, 2005), volatility and jump risk premia (Duan & Yeh, 2010), and the jump activity of equity returns (Becker, Clements, & McClelland, 2009).

One of the most important strands of the literature focuses on the data generating process of the index itself. This is because a realistic model for volatility index dynamics is crucial for accurate pricing and hedging of volatility derivatives. The liquidity of these contracts has increased dramatically since the international banking crisis of 2008 and a wide range of futures, options and swaps is now available for trading. Market participants use these instruments for diversification, hedging options and pure speculation. To this end, several pricing models have been considered (e.g. Grunbichler & Longstaff, 1996; Whaley, 1993 or

Detemple & Osakwe, 2000; Mencia & Sentana, in press; Psychoyios, Dotsis, & Markellos, 2010).

Empirical evidence regarding the data generating process of volatility indices is, however, still scarce. To date, the only comparative study of alternative data generating processes is Dotsis, Psychoyios, and Skiadopoulos (2007) who investigate the performance of several affine one-factor models using a sample from 1997 to 2004. They find that a Merton-type jump process outperforms other models for a wide range of different volatility indices. Extensions of some of the models are also considered in Psychoyios et al. (2010). In general, there is little disagreement in the literature regarding some important characteristics of volatility, such as the need for a mean-reverting process to account for a long-term equilibrium value.² There is also evidence that volatility jumps constitute a relatively large fraction of the variability of volatility indices. Psychoyios et al. (2010) argue that these jumps are an important feature and show that omitting them from the data generating process can lead to considerable differences in VIX option prices and hedge ratios.

Jumps in volatility may also be important for modeling equity index returns, as for instance in Eraker, Johannes, and Polson (2003). Yet

² Dotsis et al. (2007) point out that this feature is only of second order importance as the best performing model in their study is a Merton-type jump process without a mean-reversion component. Modeling volatility with this process over a long-time horizon is however problematic as in this model volatility tends to either zero or infinity in the long run.

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curiously, there is a large discrepancy between the volatility jump intensities estimated using two-factor models on equity index time series and one-factor models on volatility index time series. The most important example is the difference between the S&P 500 index and its volatility index VIX. Eraker et al. (2003) estimate about 1.5 volatility jumps per year when based on equity index data, yet Dotsis et al. (2007) estimate between 28 to 100 volatility jumps (depending on the model) using the VIX. Although the estimates are not directly comparable due to the different sample periods and the different modeling approaches, their huge differences are still puzzling.

This paper makes several novel contributions to understanding the continuous-time dynamics of volatility indices. In particular, we extend the data and the methodology of other empirical research on volatility index dynamics in four important ways. Firstly, we study the VIX over a long-time horizon of more than 20 years which includes the recent banking and credit crisis. Using a long time series covering several periods of market distress is essential if we are to uncover all dimensions of its historical behavior. Moreover, we have observed several different market regimes over the last two decades, and we shall seek a model that can explain the VIX dynamics during all types of market circumstances. The recent crisis period is of particular importance, as this prolonged period of high volatility revealed vital information regarding the extreme behavior of volatility. Understanding this behavior is particularly important, as it influences numerous aspects of risk and portfolio management.

Secondly, we depart from standard affine model specifications and study the dependence of the diffusion part on the level of the index. Non-affine models have recently attracted much attention, for example Christoffersen, Jacobs, and Mimouni (2010) find that non-affine specifications outperform affine processes in an equity index option pricing framework and Chourdakis and Dotsis (2011) confirm these findings using a joint-time series of the VIX and the underlying S&P 500 index returns. In our context, the chief motivation to study these models is that a stronger dependence of the diffusion term on the VIX level might decrease the jump intensity of the models. Extremely high jump intensities may be problematic because one loses the economic reasoning that jumps cover large, unexpected movements in the time-series. The estimation of non-affine models is, however, more difficult to handle, as discrete-time transition probabilities or characteristic functions are generally unavailable in closed form. Our approach includes the estimation of these processes with a Markov-chain-Monte-Carlo sampler using a data augmentation technique as in Jones (1998). This procedure allows us to study a wide range of processes, affine and otherwise, within the same econometric framework.

The third and perhaps the most important contribution is the extension of existing volatility dynamic models to the case of stochastic volatility (*stochastic vol-of-vol* hereafter). This feature has, to our knowledge, not been studied for the time-series of volatility indices before, but it yields very attractive properties: increasing variability can be modeled as a persistent vol-of-vol component rather than indirectly via an increased activity of the jump part.³ Our results are interesting because this distinction allows for two separate categories of shocks: transient (unexpected) jumps and outliers due to persistent high volatility of the VIX. We find that considering such an extension is of first-order importance and that the estimated variance process for VIX is extremely erratic and mean-reverts very quickly. We further investigate whether both jumps and stochastic vol-of-vol are necessary but our results regarding this issue are mixed.

Fourthly, we provide extensive simulation results that allow us to gauge the absolute performance of all models under consideration. We

use the concept of *predictive p-values* to study a wide range of characteristics of all the processes under consideration. This is crucial, as previous studies focused mainly on the relative performance of the models. We find that the stochastic vol-of-vol model generates dynamics that are, of all the models considered, most closely in line with the observed VIX time series. Finally we provide empirical evidence using a scenario analysis exercise.

The new CBOE volatility index construction methodology provides a close link between instantaneous variance and the VIX index. In pure diffusion models, the squared VIX is the risk-neutral expectation of integrated variance over a 30-day horizon. This fact is very useful not only to establish a theoretical link between the two quantities, but also to model S&P 500 index options and derivatives written on the VIX in a consistent manner (see Sepp, 2008; Zhang & Zhu, 2006 or Zhu & Lian, 2012). In this paper, we model the VIX index directly without explicitly specifying instantaneous variance dynamics. While it would be desirable to model various derivative markets with the same underlying stochastic process, whether standard option pricing models can provide a reasonable fit to several markets at the same time is an open research question. For instance, Broadie, Chernov, and Johannes (2007) report relatively large option pricing errors for the Heston model when time-series consistency is imposed on the structural parameters. Much in the same way it is not evident if equity and VIX derivative markets can be unified with one stable parametric model. In addition, modeling the VIX via the instantaneous variance process would require to specify both the real-world and the risk-neutral dynamics. Our goal is to examine alternative processes for the VIX index directly and to provide evidence regarding the type of process that is needed to explain its empirical characteristics.

We proceed as follows: Section 2 introduces the affine and non-affine one-factor models used; Section 3 describes our econometric estimation methodology. Section 4 provides details on the data set. In Section 5 we provide estimation results for various alternative one-factor processes. Section 6 introduces and presents results for the stochastic vol-of-vol model. We provide a risk management application in Section 7 and Section 8 concludes.

2. Model specifications

Most models proposed for describing volatility or variance dynamics agree on its mean-reverting nature.⁴ This feature reflects the belief that, although volatility can temporarily fluctuate widely, it will never wander away too much from its long-term equilibrium value. The stronger the deviation from this value the stronger the drift of the process pulls the process back toward its long-term mean. Constant and zero drift components have been criticized for ignoring this feature and hence are – at least in the long run – regarded as unrealistic description of volatility. Mean reverting processes are now an accepted starting point for volatility and variance modeling.

The diffusion term of a continuous-time process is often chosen so that the model falls into the class of affine processes. To model the VIX and other volatility indices, Dotsis et al. (2007) rely on the square-root and a Merton-type jump model for volatility and Psychoyios et al. (2010) also consider an Ornstein–Uhlenbeck process to model the log of VIX. In this paper, we study several extensions of these models. For modeling both VIX and its log process, we allow the diffusion function to be proportional to the process. Variants of these models have been successfully applied in other contexts, such as option pricing or spot index modeling (see Chernov, Gallant, Ghysels, & Tauchen, 2003 or Christoffersen et al., 2010). Especially for option pricing applications researchers often favor square-root specifications, as they retain

³ Mencia and Sentana (in press) also find that a stochastic vol-of-vol model has favourable VIX option pricing performance, however their model differs from ours as they model the vol-of-vol process with a Levy process that is independent of the VIX index dynamics.

⁴ Only few exceptions with non-reverting or zero drift components have been proposed in the literature, the SABR model of Hagan, Kumar, Lesniewski, and Woodward (2002) and the Hull and White (1987) model being the most popular.

tractability with analytic pricing formulae for vanilla options, and as such they are relatively easy to calibrate to the market prices of these options.

Another feature that has been found essential in volatility modeling is the inclusion of jumps. Eraker et al. (2003) (using return data) and Broadie et al. (2007) (using both return and option data) find severe misspecifications when jumps in volatility are omitted and document the outperformance of variance specifications with exponential upward jumps. Dotsis et al. (2007) report similar results for volatility indices. Whereas previously-mentioned research is based on the assumption that jumps occur as i.i.d. random variables, there is also evidence that jumps in VIX occur more frequently in high volatility regimes (see Psychoyios et al., 2010).

In order to assess the importance of the characteristics outlined, we employ a general one-factor model in our empirical analysis that accommodates all of the features previously mentioned. Extensions to these models will be considered in Section 6. First we study models that are nested in the following specification:

$$dX_t = \kappa(\theta - X_t)dt + \sigma X_t^b dW_t + Z_t dJ_t \quad (1)$$

where X either denotes the value of the volatility index or its logarithm, κ is the speed of mean reversion, θ determines the long term value of the process and σ is a constant in the diffusion term. The exponent b is set either to one-half or one for the level of the index, and to zero or one for the log process. Note that if $b = 1$ in the log process, VIX is bounded from below by one whereas the lower bound is zero in the other models. As remarked by Chernov et al. (2003), this is a very mild restriction for yearly volatility.⁵

In terms of jump distributions we assume that J is a Poisson process with time varying intensity $\lambda_0 + \lambda_1 X_t$. For the jump sizes we consider two alternatives. Firstly we employ an exponentially distributed jump size, as this assumption is commonly applied to the variance in equity markets. The exponential distribution has support on the positive real axis, so it allows for upward jumps only, which guarantees that the process does not jump to a negative value. The distribution is parsimonious with only one parameter η_j , representing both the expectation and the volatility of the jump size, to estimate. We apply this jump size distribution to all models except for the log volatility model with $b = 0$, for which we use normally distributed jump sizes with mean μ_j and standard deviation σ_j because the support of this model is not restricted to positive numbers and the log volatility may become negative.⁶

3. Econometric methodology

3.1. Estimation of jump-diffusion models

Several estimation techniques for jump-diffusion processes have been proposed in the literature. In the context of volatility indices, Dotsis et al. (2007) use conditional maximum likelihood methods to estimate the structural parameters of several alternative processes for six different volatility indices. Psychoyios et al. (2010) apply the same methodology to the VIX and also include state dependent jump diffusion models. In this paper, we adopt a Bayesian Markov-chain-Monte-Carlo (MCMC) algorithm because this estimation technique has several advantages over other approaches, particularly for the models we consider.⁷ Firstly, it provides estimates not only for structural parameters, but also

⁵ To avoid this one could also model not the VIX directly, but its value minus this lower bound.

⁶ In fact, we have also estimated all models with both normally and exponentially distributed jump size, so that we may gauge the effect of this assumption on the model performance. Since in some models the normal distribution can lead to negative VIX values and we found only little improvements from this more general jump size distribution, we report only results for one distribution in each model. All of our qualitative conclusions are robust with respect to changing this jump size distribution.

⁷ MCMC methods in financial econometrics was pioneered in Jacquier, Polson, and Rossi (1994).

for unobservable latent variables such as the jump times and jump sizes. These latent parameter estimates provide valuable information for testing the model and shed light on whether key assumptions of the model are reflected in our estimates. Secondly, our algorithm allows one to handle non-affine models for which closed-form transition densities or characteristic functions are unavailable.

The center of interest for our analysis is the joint distribution of parameters and latent variables conditional on the observed data. In Bayesian statistics, this distribution is termed the posterior density and is given by

$$p(\theta, Z, J|X) \propto p(X|\theta, Z, J)p(\theta, Z, J)$$

where the first density on the right is the likelihood of the observed data conditional on model parameters and latent state variables and the second density denotes the prior beliefs about parameters and latent state variables, not conditional on the data. The vector θ collects all structural parameters, and Z, J and X collect all jump sizes, jump times and VIX (or log(VIX)) observations respectively.

Knowing the posterior density we can obtain point estimates and standard errors of structural parameters, as well as the probability of jump events and jump size estimates for each day in our sample. Prior distributions are chosen such that they are uninformative, hence our parameter estimates are driven by the information in the data and not the prior.⁸ But there remain two questions to address: how to determine the likelihood, because a closed-form density can only be obtained for some models of the affine class, and how to recover the posterior density.

To obtain a closed-form likelihood we can approximate the evolution of the continuous-time process for the volatility index by a first-order Euler discretization. Therefore between two time steps the process evolves according to

$$X_{t+h} = X_t + \sum_{i=0}^{1/h-1} \left[\kappa(\theta - X_{t+ih})h + \sqrt{h}\sigma X_{t+ih}^b \varepsilon_{t+(i+1)h} + Z_{t+(i+1)h}J_{t+(i+1)h} \right]$$

where h denotes the discretization step, ε_t denotes standard normal variates and the jump process is discretized by assuming that the event $J_{t+h} = 1$ occurs with probability $h(\lambda_0 + \lambda_1 X_t)$. This approximation converges (under some regularity conditions) to the true continuous-time process as h approaches zero. Therefore choosing h to be small should lead to a negligible discretization bias. But in reality the frequency of the observed data cannot be chosen by the researcher. In our case data are recorded daily and so the discretization bias could be substantial, depending on the structural parameters of the model.⁹

A great advantage of the MCMC approach is that it allows one to augment the observed data with unobserved, high-frequency observations, a technique that has been applied to continuous-time diffusion and jump-diffusion models in Jones (1998) and Eraker (2001). This way, we treat data points between two observations as unobserved or missing data. Hence, even if the data set only includes daily values for the VIX, we can estimate the parameters of the continuous-time process accurately by choosing h small and augmenting the observed data. Here there are two practical issues that need addressing. Firstly, decreasing h leads to increasing computational cost and it also increases the parameters to be estimated substantially. And secondly, the inclusion of many data points makes it more difficult for the algorithm to filter out jump times and jump sizes because the signaling effect of a large daily observation becomes weaker. Throughout this paper we use $h = 0.25$. Jones

⁸ Details about these distributions are provided upon request.

⁹ The discretization of the jump part, especially, may lead to a large bias because daily observations allow no more than one jump per day. According to the results in Dotsis et al. (2007) volatility indices can jump far too frequently for this to be negligible. However, if the jump intensity is much lower, as in Eraker et al. (2003), a daily discretization does not introduce any discernible error.

(2003) reports that, for equity index data, taking h to be of this order reduces the discretization bias noticeably.

The posterior for our parameter estimation therefore includes the augmentation of X by unobservable high-frequency observations X^u and yields

$$p(\theta, Z, J, X^u | X) \propto p(X, X^u | \theta, Z, J) p(\theta, Z, J).$$

Note that although we generate a distribution of each augmented data point, we have no interest in the density of X^u itself, it is used only to decrease the discretization bias.

The second question, of recovering the posterior density, is dealt with by applying a Gibbs sampler (Geman & Geman, 1984). This approach achieves the goal of simulating from the multi-dimensional posterior distribution by iteratively drawing from lower-dimensional, so-called complete conditional distributions. Repeated simulation of the posterior allows one to estimate all quantities of interest, such as posterior means and standard deviations for structural parameters and latent state variables. The Gibbs sampler forms a Markov chain whose limiting distribution (under mild regularity conditions) is the posterior density. More precisely, step g in the Markov chain consists of:

1. Draw the latent variables:

$$p(X^{u(g)} | \theta^{(g-1)}, Z^{(g-1)}, J^{(g-1)}, X)$$

$$p(Z^{(g)} | X^{u(g)}, \theta^{(g-1)}, J^{(g-1)}, X)$$

$$p(J^{(g)} | \theta^{(g-1)}, Z^{(g)}, X^{u(g)}, X)$$
2. Draw structural parameters:

$$p(\theta^{(g)} | X^{u(g)}, Z^{(g)}, J^{(g)}, X)$$

The latent state vectors and structural parameters can be further divided into blocks, so that we only need to draw from one dimensional distributions. Some of the univariate distributions are of unknown form and we use a Metropolis algorithm for these.¹⁰

3.2. Model specification tests

In order to test different specifications we employ a simple but powerful test procedure. Taking a random draw of the vector of structural parameters from the posterior distribution, we use this to simulate a trajectory of the same sample size as the original VIX time series. Given this trajectory, we calculate several sample statistics and compare them with the observed sample statistics obtained from the original VIX time series. Applying this procedure several thousand times we obtain a distribution for each statistic and for each model under consideration. Finally, for each statistic and each model, we compute the probability associated with the value of the statistic given by the observed VIX time series under the model's distribution for the statistic. This p -value reveals how likely the observed value of the statistic is, according to the model. Very high or low p -values convey the model's inability to generate the observed data. For more details on this type of model specification testing procedure we refer to Rubin (1984), Meng (1994), Gelman, Meng, and Stern (1996) and Bayarri and Berger (2000).

It is common to use higher order moments to discriminate between alternative specifications. For example, if the estimated models are realistic descriptions of VIX dynamics, then in repeated simulations the models should create kurtosis levels similar to the observed. We shall choose a wide range of statistics that we deem important for modeling volatility indices, including¹¹:

- The descriptive statistics in Table 1 below except for the unconditional mean (because with a mean-reverting process the mean only indicates whether the start value is below or above the last simulated value and this is of no interest). That is we opt for standard deviation (*stdev*), skewness (*skew*) and kurtosis (*kurt*) and the

¹⁰ Details about this algorithm are provided upon request. A standard reference including a wide range of Metropolis algorithms is Robert and Casella (2004).

¹¹ Very similar statistics have also been used for testing equity index dynamics by Kaeck and Alexander (in press).

Table 1 Descriptive statistics. This table reports sample statistics for levels and first differences of the VIX. The sample period for the VIX is from January 1990 until May 2010.

	Mean	Std dev	Skewness	Kurtosis	Min	Max
Level	20.32				9.31	80.86
First difference	0.003	1.512	0.427	21.819	-17.36	16.54

minimum (*min*) and maximum (*max*) of the process. Note that these statistics indicate whether a model can capture the standardized moments up to order four, as well as the extreme movements of the VIX.

- Statistics on the highest positive and negative changes in the index (*minjump* and *maxjump*), the average over the 10 largest positive changes (*avgmax10*) and the average over the 10 largest negative changes (*titavgmin10*). These statistics shed light on whether the model can replicate the observed outliers.¹²
- In order to investigate the clustering of the outliers we use the month (20 trading days) with the highest sum of absolute changes in the process (*absmax20*). Likewise we report the statistic for the month with the least absolute changes (*absmin20*). Taken together these two statistics reflect our belief that the model should be able to reproduce periods of low activity and periods of high uncertainty in the level of the VIX.
- Finally, we report various percentiles of the estimated unconditional distribution of daily changes in the VIX. The percentiles are denoted by *percNUM* where NUM indicates the percentage level, and they indicate whether the model can replicate the observed unconditional density.

To simulate the continuous-time processes we use the same time-discretization as we have employed for the estimation of the processes. Furthermore, we start each simulation at the long-term mean value of the VIX and use 50,000 trajectories to calculate the p -values.

This test procedure has several advantages over simple in-sample fit statistics (most of which do not, in any case, apply to the Bayesian framework we use). Firstly, it allows us to detect exactly which characteristics of the VIX a model struggles to reproduce. Secondly, it allows us to compare the models in both a relative and an absolute sense. That is, as well as comparing the performance of competing models, our procedure also indicates whether each model provides a good or bad description of the observed VIX dynamics. Thirdly, it takes parameter uncertainty into account because it draws the structural parameters randomly from the posterior density.

4. Data

The VIX volatility index is constructed from standard European S&P 500 index options for the two delivery dates straddling 30 days to maturity. These are used to infer a constant 30-days-to-maturity volatility estimate. CBOE publishes this index on a daily basis and makes it publicly available on their website (www.cboe.com). The construction methodology is based on the results in Britten-Jones and Neuberger (2000) and hence it allows one to regard VIX an estimate of volatility that is model free under fairly unrestrictive assumptions on the equity index data generation process. We use daily time series data from January 1990 until May 2010.

VIX and its logarithm are depicted in Fig. 1. As expected, all high volatility periods coincide with either major political events or financial

¹² The label of the first two statistics includes the term 'jump' but this does not imply that they test for the presence of a jump. In fact, all four statistics in this group only capture the ability of a model to explain outliers, without attributing any cause. They could be the result of jumps, or of particularly extreme returns generated by a pure diffusion model.

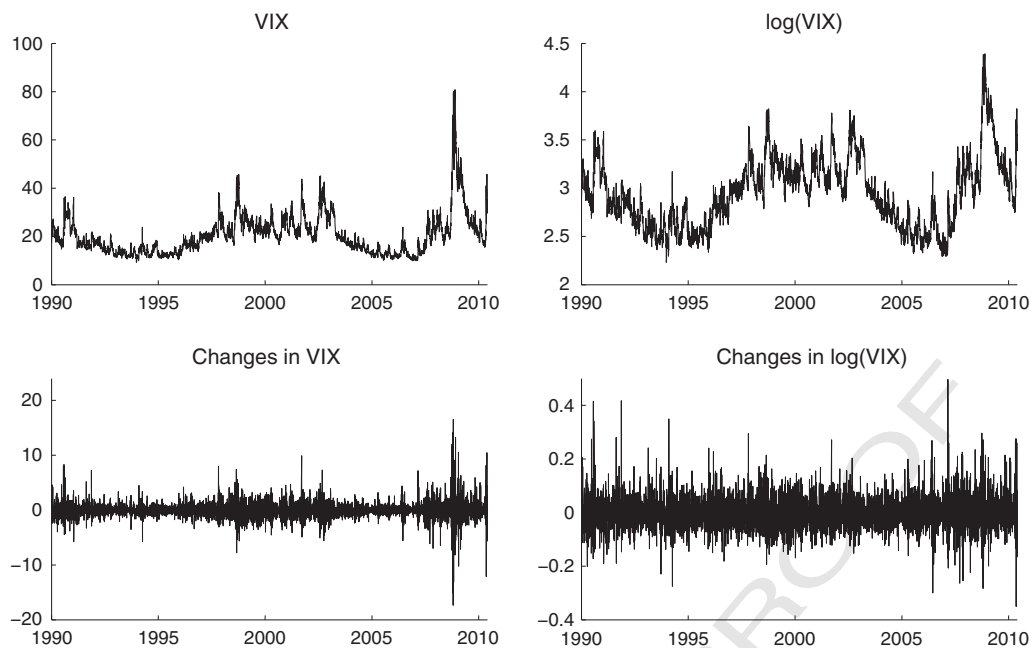


Fig. 1. VIX index. This figure depicts both VIX and its log, as well changes in their values. The sample period for the VIX from January 1990 until end of May 2010.

420 market crises. The first such period in our sample corresponds to the
 421 outbreak of the first Gulf War in August 1990, when the VIX exceeded
 422 30% for several months. Following this, markets stayed calm for a couple
 423 of years until July 1997. During this tranquil volatility regime the VIX
 424 only temporarily exceeded 20%. With the Asian crisis in 1997 we entered
 425 a sustained period of high uncertainty in equity markets. Several
 426 financial and political events contributed to this: the Long Term Capital
 427 Management bailout in 1998, the bursting of the Dot-Com bubble in
 428 2000 and the 9/11 terror attacks leading to the second Gulf War in
 429 2001. In 2003 VIX levels begin a long downward trend as equity markets
 430 entered another tranquil period which prevailed until 2007.
 431 Then, after the first signs of a looming economic crisis surfaced, VIX
 432 rose again. Following the Lehman Brothers collapse in September
 433 2008 it appeared to jump up, to an all-time high of over 80%. Before
 434 this such high levels of implied volatility had only been observed during
 435 the global equity market crash of 1987, which was before the VIX
 436 existed. Equity markets returned to around 20% volatility in 2009, but
 437 then with the Greek crisis in May 2010, at the end of the sample, the
 438 VIX again appeared to jump up, to around 40%.

439 Table 1 reports descriptive statistics for the VIX. From a modeling
 440 perspective the most interesting and challenging characteristic are
 441 some huge jumps in the index, indicated by the very large min and
 442 max values of the first difference. Movements of about 15% per day
 443 (about 10 standard deviations!) will pose a challenge to any model trying
 444 to describe the evolution of the indices. Interestingly downward
 445 jumps can be of an even higher magnitude and we will discuss this
 446 issue further below.

447 5. Estimation results

448 5.1. Jump-diffusion models on the VIX level

449 First we focus on the jump-diffusion models for the VIX level with
 450 $b = 0.5$, which are reported in the left section of Table 2. Starting with
 451 the pure diffusion model in the first column, we estimate a speed of
 452 mean reversion κ of 0.016 which corresponds to a characteristic time
 453 to mean revert of $1/0.016 = 63$ days. One minus this parameter is approximately
 454 the first-order autocorrelation of the time series, hence our results imply that
 455 volatility is highly persistent. The long-term

volatility value θ is about 20.5% which is close to the unconditional
 mean of the process in Table 1. Our parameter estimate for σ is 0.289.

456 Several interesting features arise when considering the exponential
 457 jump models in columns 2, where $\lambda_1 = 0$ so that jump intensities are in-
 458 dependent of the level of the VIX, and column 3 where $\lambda_0 = 0$ but jump
 459 intensities depend on the level of the VIX.¹⁴ Firstly, the inclusion of
 460 jumps increases the speed of mean reversion considerably, to 0.037
 461 when $\lambda_1 = 0$ and 0.051 when $\lambda_0 = 0$. A possible explanation is that the
 462 drift of the process tries to compensate for omitted downward jumps,
 463 so that when volatility is exceptionally high the process can create larger
 464 downward moves with an increased κ estimate. Furthermore, in the
 465 jump models the estimates for the second drift parameter θ drop to
 466 about 12–14%, a result that is expected because θ carries a different in-
 467 terpretation once jumps are included. To obtain the long-term volatility
 468 we have to adjust θ by the effect of jumps and our estimation results
 469 imply long-term volatility levels of approximately 21%, similar to the
 470 pure diffusion model. As expected the parameter σ decreases in all
 471 jump models since part of the variation in the VIX is now explained
 472 by the jump component.

473 When jump probabilities are assumed to be independent of the VIX
 474 level, a jump occurs with a likelihood of 0.107 per day. A parameter of
 475 this magnitude implies about 27 jumps per year, hence such events
 476 may be far more frequent than for many other financial variables such
 477 as stock prices or interest rates. An average-sized jump is 2.38 VIX
 478 points. Jump occurrence in the models with state-dependent jumps is
 479 higher, with average jump probabilities of about 26%.¹⁵ As we estimate
 480 more jumps in this case, the average jump size decreases to only 1.58
 481 VIX points.
 482
 483

¹³ Note that this model was previously studied in Dotsis et al. (2007) but these authors used VIX data from the generally volatile period from October 1997 to March 2004 so our results are not directly comparable. Not surprisingly, the parameter estimates in Dotsis et al. (2007) imply more rapidly moving processes than ours: they estimate a (yearly) speed of mean reversion of 9.02 (whereas our yearly equivalent is 4.03) and a long-term volatility level of 24.54%.

¹⁴ We have also estimated all models with λ_0 and λ_1 being simultaneously different from zero but these results are omitted for expositional clarity. The parameter estimates for these models reveal that jump probabilities are mainly driven by the state-dependent jump part as λ_0 is close to zero. Therefore, the evidence appears to point toward state-dependent jumps. We return to this observation later on.

¹⁵ This estimate is based on an average VIX level of about 20%.

Table 2 Parameter estimates (level models). This table reports the estimates for the structural parameters. The posterior mean is reported as the point estimate, posterior standard deviations and 5%–95% posterior intervals are reported in brackets.

	Models on VIX with $b = 0.5$			Models on VIX with $b = 1$		
κ	0.016 (0.003) [0.011, 0.02]	0.037 (0.003) [0.033, 0.041]	0.051 (0.003) [0.047, 0.055]	0.014 (0.003) [0.01, 0.019]	0.029 (0.003) [0.024, 0.034]	0.039 (0.003) [0.034, 0.044]
θ	20.496 (1.187) [18.667, 22.544]	13.747 (0.567) [12.806, 14.665]	12.311 (0.473) [11.525, 13.076]	20.510 (1.357) [18.566, 22.951]	13.294 (0.561) [12.358, 14.207]	13.033 (0.427) [12.337, 13.739]
σ	0.289 (0.004) [0.283, 0.296]	0.229 (0.003) [0.223, 0.234]	0.214 (0.003) [0.209, 0.219]	0.062 (0.001) [0.06, 0.063]	0.050 (0.001) [0.049, 0.051]	0.048 (0.001) [0.047, 0.049]
λ_0		0.107 (0.016) [0.082, 0.134]			0.082 (0.012) [0.063, 0.102]	
λ_1			0.013 (0.002) [0.01, 0.016]			0.007 (0.001) [0.005, 0.008]
η_j		2.376 (0.185) [2.104, 2.706]	1.584 (0.102) [1.428, 1.759]		2.708 (0.21) [2.399, 3.074]	2.299 (0.161) [2.057, 2.584]

We now turn to the non-affine models with $b = 1$ in the right half of Table 2. There are several interesting results. Firstly the speed of mean reversion κ is smaller than in the square-root models. This possibly stems from the fact that the diffusion term, through its stronger dependence on the level of the VIX during high-volatility regimes, can create larger downward jumps and this requires a less rapid mean-reverting process. The long-term level of the VIX is, as in the square-root model, consistent with its unconditional mean. The diffusion parameter σ , however, is not comparable with previously studied models and its estimates range from 0.048 to 0.062. State-independent exponentially distributed jumps occur with a likelihood of 0.082 per day and state-dependent jumps are again more likely than state-independent jumps, but they occur only about half as often as in the square-root model class. This has an effect on estimated jump-sizes, where we find that jumps in the non-affine models are more rare events, but their impact is greater and all jump size estimates are larger than in the square-root models. Overall, the jump intensities in non-affine models are still relatively high.

Table 3 provides results from our simulation experiments. These show that the square-root diffusion model is fundamentally incapable of producing realistic data as it fails to generate statistics similar to the observed values for almost every statistic we use. Some of the results are improved when jumps are added, for example using state-independent

Table 3 Simulation results (level models). This table reports the p -values for all the statistics described in Section 3. The closer these values are to 1 or 0 the greater the degree of model misspecification.

Jump distribution	Data	VIX with $b = 0.5$		VIX with $b = 1$	
		No	Exp	No	Exp
Jump type		λ_0	λ_1	λ_0	λ_1
stadev	1.512	0.9988	0.6276	0.6248	0.8644
skew	0.427	1.0000	0.0000	0.0000	0.9991
kurt	21.819	1.0000	0.8474	0.9985	0.9972
avgmax10	11.556	1.0000	0.4029	0.9587	0.9916
avgmin10	-10.663	0.0000	0.0000	0.0000	0.0153
perc1	3.673	0.0026	0.0000	0.0000	0.3545
perc5	2.004	0.9294	0.1149	0.3068	0.7652
perc95	2.160	0.6397	0.5043	0.0050	0.5909
perc99	4.642	1.0000	0.0051	0.0108	0.9687
absmax20	149.620	1.0000	1.0000	1.0000	0.9922
absmin20	3.810	0.0000	0.0000	0.0000	0.0016
maxjump	16.540	1.0000	0.5571	0.9122	0.9884
minjump	-17.360	0.0000	0.0000	0.0000	0.0110
max	80.860	0.9984	1.0000	0.9998	0.8521
min	9.310	0.9998	0.9514	0.9592	0.9906

jumps the standard deviation and the kurtosis of the data yield more realistic values. Nevertheless, overall the square-root model with or without jumps does a very poor job of explaining the characteristics of the VIX. The results for the non-affine specification are more encouraging. Whereas several statistics could not even be produced once in our 50,000 simulations for the square-root diffusion, the non-affine specification does a far better job of matching the observed characteristics of the VIX. However, in absolute terms the non-affine models, with or without jumps, are still severely misspecified. Again, there appears to be little benefit from introducing jumps into the models as the models especially fail to reproduce the statistics that are linked to the jump behavior of the VIX.

5.2. Jump-diffusion models on the log of the VIX level

Structural parameter estimates for the log-VIX models are reported in Table 4. We consider the models with $b = 0$ first, shown in the left side of the table. The mean reversion speed κ is more consistent across models with and without jumps, taking values between 0.014 and 0.029. The long-term level θ for the log process is estimated to be 20.51 in the pure diffusion model, a value that implies a long-term volatility level of about 19%. The value for this parameter is again dependent on the estimated jump parameters and hence it drops in the jump models. The implied long-term volatility level however hardly changes, for example our results in the state-independent and exponential jump model implies a similar long-term volatility level of 19.9%. Estimates for σ vary across models, between 0.04 and 0.06. The jump likelihood in the log volatility model is again very high, with daily jump probabilities of 20% or more, which implies more than 50 jumps per year. The average jump probability for the time-varying jump intensity model is of larger magnitude. The normally distributed jump sizes have mean 0.03 with a standard deviation of around 0.08. Parameter estimates for the log model with additional dependence of the diffusion term on the level of the VIX are reported in the right half of Table 4. The only noteworthy feature of our estimates here is that jump sizes are higher, with an estimated mean of about 0.08 for both models.

Simulation results for the log models are presented in Table 5. Models with $b = 1$ perform quite well in producing samples with similar characteristics as the observed VIX time series. The only characteristic that can be rejected at a 5% significance level is the skewness. The observed statistic is 0.427, but the simulations imply a smaller statistic in 97.96% of the cases. Apart from this, the pure diffusion model produces realistic samples. This is true in particular of the large jumps in the VIX. For example the large negative and positive jumps of more than -17 and 16 VIX points respectively, creates no obstacle for the model. Including jumps into the processes can improve some of the

t4.1 **Table 4**

t4.2 **Parameter** estimates (log models). This table reports the estimates for the structural parameters. The posterior mean is reported as the point estimate, posterior standard deviations
 t4.3 and 5%–95% posterior intervals are reported in brackets.

t4.4	Models on log(VIX) with $b = 0$			Models on log(VIX) with $b = 1$		
t4.5	κ	0.014	0.016	0.017	0.014	0.019
t4.6		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
t4.7		[0.01, 0.018]	[0.012, 0.019]	[0.013, 0.02]	[0.01, 0.018]	[0.015, 0.023]
t4.8	θ	2.951	2.562	2.534	2.955	2.098
t4.9		(0.064)	(0.076)	(0.077)	(0.063)	(0.115)
t4.10		[2.848, 3.055]	[2.431, 2.673]	[2.403, 2.649]	[2.858, 3.064]	[1.898, 2.274]
t4.11	σ	0.060	0.043	0.040	0.020	0.016
t4.12		(0.001)	(0.001)	(0.002)	(0)	(0)
t4.13		[0.059, 0.062]	[0.041, 0.045]	[0.037, 0.044]	[0.02, 0.021]	[0.016, 0.017]
t4.14	λ_0		0.229			0.215
t4.15			(0.044)			(0.045)
t4.16			[0.164, 0.303]			[0.154, 0.296]
t4.17	λ_1			0.111		0.084
t4.18				(0.027)		(0.017)
t4.19				[0.069, 0.156]		[0.06, 0.114]
t4.20	μ_j		0.027	0.022		
t4.21			(0.005)	(0.005)		
t4.22			[0.019, 0.036]	[0.015, 0.031]		
t4.23	σ_j		0.082	0.074		
t4.24			(0.006)	(0.007)		
t4.25			[0.074, 0.092]	[0.065, 0.085]		
t4.26	η_j				0.078	0.074
t4.27					(0.006)	(0.006)
t4.28					[0.068, 0.088]	[0.065, 0.084]

567 statistics we use, but overall the inclusion of jumps is, at least as far as
 568 these test statistics are concerned, of no benefit. Interestingly, the
 569 jump models still struggle to capture the observed skewness of the
 570 VIX, but now the models tend to underestimate this statistic as the in-
 571 clusion of jumps decreases the skewness in the models. Using $b = 0$
 572 on the other hand, leads to significant misspecification.

573 **6. Stochastic volatility of volatility**

574 Having shown that the log-VIX models perform better than models
 575 for the VIX level, we now extend the log volatility specification a sto-
 576 chastic volatility-of-volatility (SVV) model as follows:

$$d \log(VIX_t) = \kappa[\theta - \log(VIX_t)]dt + \sqrt{V_t}dW_t + Z_t dJ_t$$

$$dV_t = \kappa_v[\theta_v - V_t]dt + \sigma_v \sqrt{V_t}dW_t^v$$

578 where the correlation ρ between the two Brownian motions is assumed
 579 constant, but possibly non-zero. Considering a non-zero correlation
 580 case is essential in this set-up, as previous evidence points toward a

t5.1 **Table 5**

t5.2 Simulation results (log models). This table reports the p -values for all the statistics de-
 t5.3 scribed in Section 3.

t5.4	Jump distribution	Data	log(VIX) with $b = 0$			log(VIX) with $b = 1$	
t5.5			No	Normal	No	Exp	
t5.6	Jump type		λ_0	λ_1	λ_0	λ_1	
t5.7	stadev	1.512	0.9250	0.9455	0.8545	0.6069	0.1484
t5.8	skew	0.427	0.9997	0.0110	0.0257	0.9796	0.0001
t5.9	kurt	21.819	0.9999	0.9880	0.9764	0.9426	0.5219
t5.10	avgmax10	11.556	0.9996	0.9804	0.9450	0.8881	0.1114
t5.11	avgmin10	-10.663	0.0009	0.0002	0.0048	0.1601	0.0747
t5.12	perc1	-3.673	0.2352	0.0664	0.2159	0.6917	0.6236
t5.13	perc5	-2.004	0.6930	0.2017	0.3245	0.7873	0.7829
t5.14	perc95	2.160	0.6189	0.7076	0.5310	0.4228	0.0554
t5.15	perc99	4.642	0.9907	0.8342	0.7257	0.7814	0.0165
t5.16	absmax20	149.620	0.9997	0.9995	0.9951	0.8903	0.8846
t5.17	absmin20	3.810	0.0367	0.0545	0.0893	0.0906	0.1295
t5.18	maxjump	16.540	0.9985	0.9309	0.8881	0.8572	0.1603
t5.19	minjump	-17.360	0.0010	0.0016	0.0096	0.1253	0.0633
t5.20	max	80.860	0.9452	0.9635	0.8961	0.6763	0.6506
t5.21	min	9.310	0.9929	0.9770	0.9742	0.9466	0.9315

strong dependence between the VIX and its volatility level. In addition
 to a stochastically moving volatility, we allow for normally distributed
 jumps as before.

The results presented in Section 5 gave no indication that including
 jumps necessarily improves the modelling of the VIX index. However,
 the SVV model differs substantially from previously studied specifica-
 tions. For this reason we shall retain the possibility of jumps in the sec-
 tion and study whether the inclusion of a stochastic vol-of-vol factor
 alters our previous conclusions. Also note that the model presented
 here is affine, and contrary to the one-dimensional log model with
 $b = 1$, this implies that the VIX index is bounded by zero from below. Es-
 timation of this model is, as before, by MCMC.¹⁶

There are several motivations for considering this model. Firstly, the
 empirical results in the previous section motivate a more detailed study
 of the diffusion part of the process. Considering a stochastic volatility
 component is a natural extension for one-dimensional models and
 this approach has been successfully applied to other financial variables.
 Secondly, in the one-dimensional SDEs studied so far the jump proba-
 bility is extremely high, so jumps cannot be interpreted as rare and ex-
 treme events, which is the main economic motivation for incorporating
 jumps into a diffusion model. The diffusion part is designed to create
 normal movements, whereas jumps contribute occasional shocks that
 are – because of their magnitude – unlikely to come from a pure diffu-
 sion process. If jumps were to occur very frequently these models may
 be poorly specified, or at least not compatible with their usual inter-
 pretation. A third motivation for considering the SVV specification is to
 capture the clustering in volatility of index changes that is evident
 from Fig. 1. As opposed to a transient shock, this feature is commonly
 modeled with a stochastic volatility component.

Table 6 reports the estimated parameters of the SVV model, first
 without jumps and then with normally distributed jumps. The
 speed of mean reversion parameter κ is lower than in any previously
 reported model, with an estimate of 0.011 and 0.012. As mentioned
 above, κ is likely to be distorted upward when a model cannot capture
 large negative outliers, so this result indicates that SVV models are
 more consistent with large downward moves than models without
 stochastic volatility. Furthermore, both models imply a long-term

¹⁶ We provide details on the algorithm used here upon request.

Table 6
 Parameter estimates (log vol-of-vol models). This table reports the estimates for the structural parameters. The posterior mean is reported as the point estimate, posterior standard deviations are given in parenthesis.

	κ	θ	κ_v	$\theta_v \times 100$	$\sigma_v \times 10$	ρ	λ_0	μ_j	σ_j
Mean	0.011	3.073	0.110	0.349	0.183	0.653			
Standard dev	(0.002)	(0.086)	(0.013)	(0.016)	(0.01)	(0.038)			
Mean	0.012	2.983	0.097	0.330	0.162	0.659	0.009	0.136	0.103
Standard dev	(0.002)	(0.072)	(0.015)	(0.035)	(0.016)	(0.039)	(0.004)	(0.054)	(0.027)

volatility level, of between 21% and 22%. The correlation is, as expected, positive with high (and again virtually identical) estimates of 0.653 and 0.659.

The characteristics of the variance equation are very interesting, because this process differs somewhat from variance processes estimated from other financial variables. The speed of mean-reversion in the variance equation κ_v is very high, at 0.11 for the diffusion model. This implies a very rapidly reverting process with an estimated value 10 times larger than for the VIX itself. Including a further jump component decreases this parameter only marginally, to a value of 0.097. The mean-reversion level for the variance θ is consistent with the estimate from the one-dimensional diffusion model. The estimate of 0.06 in the log volatility diffusion model reported in Table 4 is approximately equal to the average volatility level implied by our estimate for θ_v . In order to visualize the variance V over the sample period, we provide the estimated sample path of this latent variable in Fig. 2.

We have seen that including (state-independent) jumps into the SVV model changes parameter estimates only marginally, and this is probably because jumps occur only every six months, on average. Now, as desired, jump events concentrate only on exceptional outliers that cannot be explained with a more persistent stochastic vol-of-vol process. This is also reflected in the estimated jump sizes as, for all specifications, we obtain higher estimated jump sizes with a mean of 0.136 and a standard deviation of 0.103. This adds further evidence that jumps are now covering only the more extreme events. Also modelling

negative jumps are of no major importance, as depicted by the estimated jump sizes depicted in Fig. 3.

These results pose an interesting question: *Are jumps necessary at all once we account for stochastic vol-of-vol?* To answer this consider the 5% percentile of the posterior distribution of λ_0 , which is 0.003. This provides some statistical evidence in favor of including jumps, although they occur very infrequently. However, there is no evidence from our simulation results in Table 7 that including jumps improves the model. With or without jumps, the SVV model is capable of reproducing all the characteristics of the VIX that we consider. For both models it is the lower percentiles that are most difficult to reproduce, but still, the p -values for all models are between 0.05 and 0.95 so neither model can be rejected.

The rare occurrence of jumps is now similar to those found in the equity index market (Eraker et al., 2003). However, there is an important difference, because including jumps seems less important for volatility than it is for the index itself. The variance process of the VIX is much more quickly mean reverting and rapidly moving than the variance process of the S&P 500 index, omitting jumps from the specification has a lesser impact than it would have when variance is more persistent.

It is instructive to investigate the jumps in log-VIX events depicted in Fig. 3. Interestingly, the biggest estimated jump in the sample period is not obtained during the highly turbulent period of the banking crisis. This is because most of the movements are now captured by the stochastic vol-of-vol component. Instead there is an increased intensity

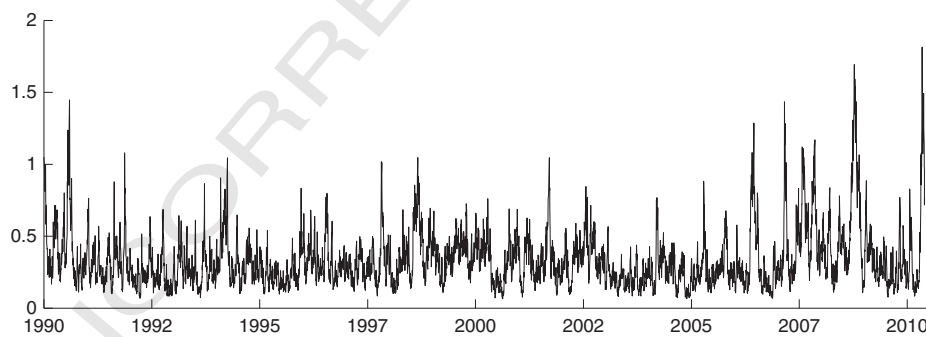


Fig. 2. Estimated variance paths. This figure depicts the estimated variance path (multiplied by 100) for the log(VIX) for the diffusion case.

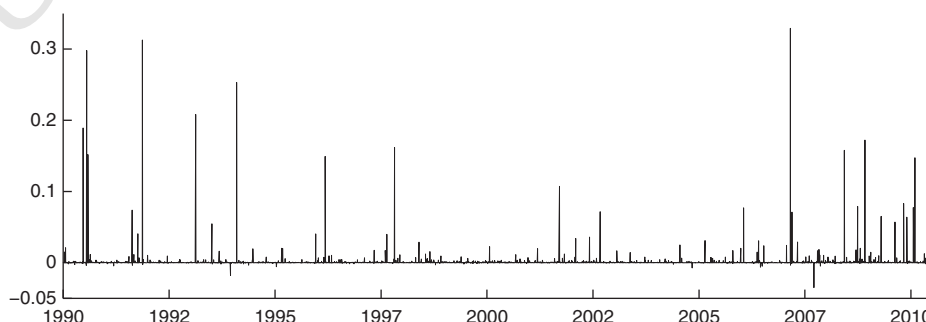


Fig. 3. Estimated jumps. This figure depicts the average jump distribution for the model with normally distributed jumps.

Table 7

Simulation results (stochastic vol-of-vol models).

Jump distribution	Data	p-values	
		no	normal
stadev	1.512	0.260	0.245
skew	0.427	0.713	0.338
kurt	21.819	0.829	0.791
avgmax10	11.556	0.607	0.505
avgmin10	−10.663	0.382	0.342
perc1	−3.673	0.924	0.911
perc5	−2.004	0.922	0.913
perc95	2.160	0.129	0.133
perc99	4.642	0.353	0.289
absmax20	149.620	0.728	0.748
absmin20	3.810	0.294	0.308
maxjump	16.540	0.563	0.457
minjump	−17.360	0.310	0.275
max	80.860	0.369	0.381
min	9.310	0.777	0.762

of smaller jumps, so the vol-of-vol could adjust to capture even large outliers in the data. In other words, the clustering of large movements was best captured with a stochastic vol-of-vol component. One of the largest jumps in our sample was in November 1991, when the VIX jumped from less than 14 to over 21 in one day. This jump was preceded by several tranquil months with little movements in the VIX. The same applies to the jumps in February 1993 and in February 1994. Another large jump is estimated in February 2007. Prior to this, volatility was bounded between about 10 and 13% for many months. Then a slump in the Chinese stock market created a knock-on effect for Europe, Asia and North America with substantial losses for all major equity indices on 27 February. This left financial markets in doubt over economic prospects, and the VIX jumped up by more than 7 points. This jump is difficult to create with a stochastic vol-of-vol component because its arrival came as a total surprise and thus required a substantial upward jump. Based on these observations we conclude that volatility jumps are required, but only for surprising events triggered by totally unexpected political or financial news. Note also, that the jumps estimated by the model occur during periods of low VIX levels thus there is no evidence in this model that suggests that jumps are more likely when VIX levels are high.

7. Applications to risk management

A standard task in risk management is to explore the effect of potential shocks in economic variables. The evolution of VIX can affect bank portfolios for many reasons, either indirectly as a measure of volatility, or more directly as the underlying of several derivative products such as futures, swaps and options. In this section, we take the most drastic scenario observed in our sample period and investigate the probability assigned to this scenario under different models for the VIX. To this end, we consider the evolution of VIX during the outburst of the banking crisis in autumn 2008, when VIX increased from 21.99 on September 2, to reach its all-time high of 80.06 only few weeks later on October 27. Preceding this peak, the index was increasing almost continually from the beginning of September, with only minor and very temporary corrections.¹⁷

A possible strategy is to re-estimate the models using data until September 2008, as this would allow us to access the predictability of

¹⁷ Another application of VIX index processes, to pricing VIX futures and options, has been removed for brevity. Details about these findings (which show that, consistent with Mencia and Sentana (in press), a stochastic vol-of-vol model has a marked impact on VIX derivatives) are provided upon request.

such a scenario. However, it is very unlikely that a pure statistical model based on our data could have predicted this scenario because since its inception the most extreme value of the VIX before October 2008 was 45.74, far away from the highs that were witnessed during the banking crisis. This is a deficiency of the data set, as even higher volatility levels were recorded during the global market crash of 1987, when the old volatility index VXO reached levels of more than 100%. For any risk management application it would be therefore crucial to take this pre-sample data into account, or to use parameter estimates from shocked data.

The question we address here is not the predictability of the banking crisis but whether the models, after observing such an extreme event (and incorporating it into the estimated parameters) are capable of generating such scenario, or whether they still consider it impossible. Put differently, we ask how plausible is such a scenario under the different models, with parameters estimated after the event. For each model, we use the VIX value on September 2, 2008 (before the crisis) as our starting value and simulate the process until October 27, 2008 according to the parameter estimates presented in the two previous sections.¹⁸ Then, after simulating 100,000 paths, we gage the likely range of values produced by the models by calculating percentiles for the two-month period. In each simulation the parameter values are drawn randomly from the posterior distribution, so that the analysis takes account of the uncertainty in estimated parameters.

Fig. 4 illustrates the results of this exercise for six of the models. For the one-factor models we consider the most general specifications, with time-varying jump probabilities. Other assumptions on the jump part of the processes lead to virtually identical conclusions and so we omit these for expositional clarity. In both affine and non-affine models of the VIX itself the index ends up far beyond the 99.9%-percentile. Log models fare better but still assign only a tiny probability to the likelihood of the observed path. The best among the one-factor models is the log model with additional dependence of the diffusion coefficient on the VIX level. This finding confirms our previous evidence that such a modeling approach yields the most realistic results, among all the one-factor models considered. SVV models also do a good job, as for both processes the actual time series ends between the 99% and 99.9% percentiles. Indeed, given that our sample consists of almost 150 such two month periods, we would hope that such a one-off scenario is predicted in less than 1% of the cases. We conclude that only the one-factor log model with $b = 1$ and the stochastic volatility-of-volatility models provide accurate assessments of the likelihood of the banking crisis scenario.

8. Conclusion

This paper has studied alternative jump-diffusion models for the VIX volatility index, considering two broad modeling approaches, i.e. to model the VIX directly or its log value. Our models include one-factor affine and non-affine diffusion and jump-diffusion models, and two-factor stochastic volatility models. We evaluate these models using probability values for a wide range of statistics and assess their performance for a risk management application.

As in Dotsis et al. (2007) we find that modeling the VIX log returns (equivalently, the log value of VIX) is superior to modeling its level. Beyond this we present a variety of novel contributions to the literature. First, we find that non-affine models, in which the diffusion term is proportional to the VIX level or log respectively, are far superior to their affine counterparts. The main reason for this is that non-affine models accommodate a more rapidly moving VIX during high volatility levels. Not only are affine models unable to reproduce the observed characteristics of the VIX, they also assign too great an intensity to the jump processes. This is problematic, since the intuition of introducing jumps is

¹⁸ In addition, for the SVV models we use the estimated variance on September 2 as a starting value.

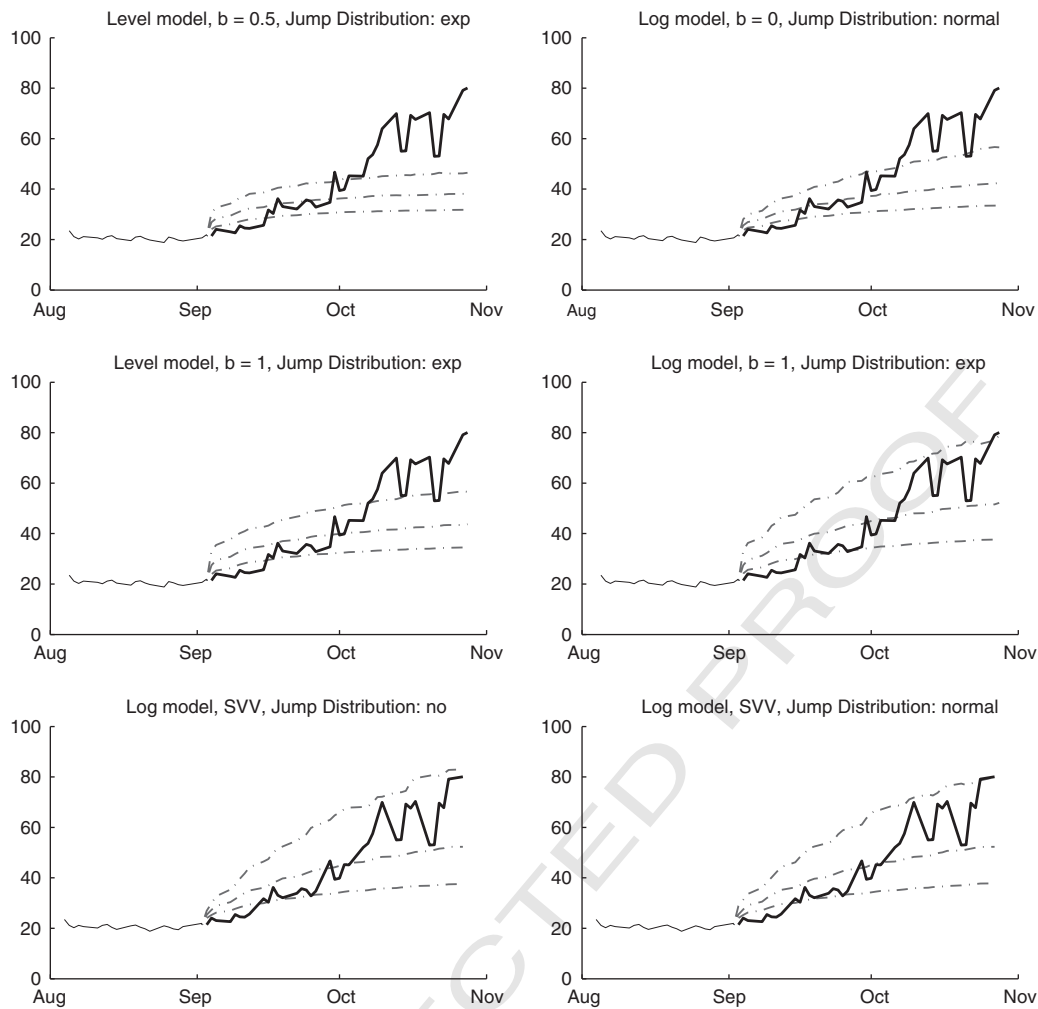


Fig. 4. Simulated VIX 2008. This figure depicts the true evolution of the VIX during the beginning of the banking crisis in 2008. In addition, we plot 95%, 99% and 99.9% percentiles.

766 that they cover rare and extreme events. There is also strong statistical
767 evidence in favor of time-varying jump intensities in these models.
768 However since one-factor models are misspecified, it is likely that re-
sults for these models are distorted. Our simulation experiments show
that the absolute benefit from the addition of jumps to one-factor
models can be fairly small.

771
772 The only one-factor model that can explain a multitude of facets of
773 the VIX is the non-affine log model. A yet more promising approach to
774 capturing the extreme behavior of the VIX is the inclusion of a stochastic,
775 mean-reverting variance process. This model passes all the specification
776 hurdles and yields superior results in our scenario analysis. It is also ap-
777 pealing because jumps are rare and extreme events, which only occur
778 on days that can be linked to major political or financial news.

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