Journal of Banking & Finance 33 (2009) 1033–1038

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

The jump component of S&P 500 volatility and the VIX index

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ARTICLE INFO

Article history:
Received 20 February 2008
Accepted 30 October 2008
Available online 7 November 2008

JEL classification:
C12
C22
G00
G14

Keywords:
Implied volatility
VIX
Volatility forecasts
Informational efficiency
Jumps

ABSTRACT

Much research has investigated the differences between option implied volatilities and econometric model-based forecasts. Implied volatility is a market determined forecast, in contrast to model-based forecasts that employ some degree of smoothing of past volatility to generate forecasts. Implied volatility has the potential to reflect information that a model-based forecast could not. This paper considers two issues relating to the informational content of the S&P 500 VIX implied volatility index. First, whether it subsumes information on how historical jump activity contributed to the price volatility, followed by whether the VIX reflects any incremental information pertaining to future jump activity relative to model-based forecasts. It is found that the VIX index both subsumes information relating to past jump contributions to total volatility and reflects incremental information pertaining to future jump activity. This issue has not been examined previously and expands our understanding of how option markets form their volatility forecasts.

1. Introduction

Forecasts of asset return volatility are crucial inputs into numerous investment decisions. Broadly speaking there are two approaches for obtaining forecasts. There are many econometric model-based forecasts (MBF) designed for such purposes along with market determined option implied volatilities (IV). Given the importance of volatility forecasts, the forecast accuracy and informational efficiency of IV relative to MBF has been considered by numerous authors.

Fleming (1998), Jiang and Tian (2003) and Becker et al. (2006), amongst others have examined whether various IV measures subsume historical information (predominantly return data) commonly used when forecasting volatility. While Fleming (1998) and Jiang and Tian (2003) find that IV is efficient with respect to such information, Becker et al. (2006) find that S&P 500 IV does not completely subsume a diverse set of information including MBF. Becker et al. (2007) find that IV contains no information beyond volatility persistence as captured by MBF relevant for forecasting the level of total volatility.

These previous studies considered the relationship between IV and forecasts of the level of total volatility. In doing so, these studies ignored the fact that volatility may be generated from both continuous diffusion and discontinuous jump processes in price (see Barndorff-Nielsen and Sheppard (2004) and Andersen et al. (2007)). Here we extract the component of volatility due to the jump process in price and investigate whether IV contains any information relating to this. Commonly used MBF generate volatility forecasts based on smoothing historical data (often daily squared returns or realized volatility) without any distinction between the diffusion and jump components of volatility.[1] Only very recent developments have sought to redress this issue. In contrast, as IV is market determined, and not constrained to a fixed mapping of such historical data, it may utilize both of the components of total volatility. This may be important as it has been shown to have important implications for volatility forecasting (Andersen et al., 2007).

This article considers two issues relating to the relationship between IV and jump activity. *First*, it will be examined whether IV

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[1] It is important to note that the jumps referred to here are jumps in the price process itself. A different line of research attempts to devise a diffusion process for the process driving volatility. Jumps in such a process are not necessarily the same as jumps in the price process itself (see Dotsis et al., 2007; Branger et al., 2008, as examples for this research).

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doi:10.1016/j.jbankfin.2008.10.015

subsumes historical measures of how jumps contributed to spot market volatility. This will determine how option markets react to, or incorporate jump activity in the S&P 500 price process in their IV forecasts and extends the work of Fleming (1998), Jiang and Tian (2003) and Becker et al. (2006). *Second*, it will be investigated whether IV reflects information beyond that reflected in MBF in relation to future jump activity and extends the work of Becker et al. (2007). In combination, these research questions reveal further insights into the manner in which option markets form their volatility forecasts.

It is found that IV subsumes information relating to historical jump activity meaning that option markets react to volatility due to both the continuous diffusion and discontinuous jump processes in price. It is also shown that IV contains incremental information relative to MBF in relation to future jump activity. This result differs from that of Becker et al. (2007) in that they found that IV contained no information incremental to that of MBF in relation to the total level of volatility.

This paper proceeds as follows. Section 2 presents a description of the required data. Section 3 outlines the estimates of the various volatility components. Section 4 discusses the empirical methodology employed to address each of the research questions. Sections 5 and 6 present the results and concluding comments, respectively.

2. Data

To address the research questions at hand, four different sets of data are required. Equity returns, an estimate of IV, realizations of total equity volatility and the volatility component due to jumps in prices. The study is based on data pertaining to the S&P 500 index, from 2 January 1990 to 17 October 2003 (3481 daily return observations). The implied volatility measure utilized here is that provided by the Chicago Board of Options Exchange, the VIX.[2] The VIX is an implied volatility index derived from a number of put and call options on the S&P 500 index with maturities close to the target of 22 trading days and is derived without reference to a restrictive option pricing model.[3] For technical details relating to the construction of the VIX index see Chicago Board of Options Exchange (2003). The VIX is constructed to be a general measure of the market's estimate of average S&P 500 volatility over the subsequent 22 trading days (Blair et al., 2001; Christensen and Prabhala, 1998).[4]

3. Measuring the components of volatility

This section outlines the methodology used to measure both the diffusion and jump components of total volatility. Following from Barndorff-Nielsen and Sheppard (2004) and Andersen et al. (2007) we start from the premise that returns are generated by the stochastic process

$$dp(\tau) = \mu(\tau)dt + \sigma(\tau)dW(\tau) + \kappa(\tau)dq(\tau) \tag{1}$$

where $p(\tau)$ is the logarithm of the S&P 500 index at time τ, $\mu(\tau)$ the drift, $\sigma(\tau)$ the stochastic volatility process and $W(\tau)$ a standard Brownian motion. The discontinuous jump process is described by the jump size $\kappa(\tau)$ and the counting process $q(\tau)$ where $dq(\tau) = 1$ whenever a jump occurs. The probability of such events is governed by the intensity parameter, $\lambda(\tau)$.

Given the specification in Eq. (1), we now describe how we measure the various components of total volatility of the price process. It is well known (Barndorff-Nielsen and Sheppard, 2004, 2006) that realized volatility

$$\mathrm{RV}_t = \sum_{i=1}^{M} r_{t,i}^2 \quad t-1 < \tau \leqslant t \tag{2}$$

where $r_{t,i}$ is the ith intraday return on day t, captures the continuous and discontinuous components of volatility. On the other hand, bipower variation

$$\begin{aligned} BPV_t &= \mu^{-2}\sum_{i=1}^{M-1}|r_i||r_{i+1}| \\ \mu &= 2^{1/2}\frac{\Gamma(1)}{\Gamma(1/2)} \end{aligned} \tag{3}$$

captures the continuous component of volatility only.[5] As a result, the difference of the two, $J_t = \mathrm{RV}_t - \mathrm{BPV}_t$, is an estimate of the contribution from the jump process to observed price volatility on day t[6]:

$$\sum_{t-1<s\leqslant t} \kappa^2(s). \tag{4}$$

This sum is over the discrete number of jumps observed on day t. As such it captures both the jump size and the intensity with which they occur. Hence, a large value of J_t may be due to either a large number of relatively small jumps, or a small number of relatively large jumps.

To obtain estimates of RV_t and BPV_t from Eqs. (2) and (3) we use 30 min S&P 500 index returns. This choice is guided by the volatility signature plot methodology of Andersen et al. (1999). As J_t is an estimate of the non-negative jump component in (4), all subsequent empirical analysis is based on values for $J_t < 0$ being truncated at 0. Such an adjustment was proposed by Barndorff-Nielsen and Sheppard (2004) and Andersen et al. (2007). The subsequent analysis was repeated with alternative estimates of the jump component, in particular, using the data-dependent truncation proposed by Andersen et al. (2007) for selecting significant jumps. As the results remain qualitatively unchanged they are not reported here.

Fig. 1 plots both the daily returns and the VIX index, where it is clear that the VIX (bottom panel) broadly tracks changes in the level of volatility of the returns. Fig. 2 plots both the daily RV and the estimated jump component of volatility ($J_t < 0$ being truncated at 0). This truncation results in jump activity being observed on 73% of the days in the sample. Of these, half contribute relatively little (less than 30%) to the total volatility measured on that day.[7] Comparing the RV (Fig. 2, upper panel) and VIX (Fig. 1, lower panel) series, it is clear that the daily RV has higher peaks than the VIX. As the VIX is an expectation of average volatility over a 22 day horizon, the increased smoothness of the VIX as compared to the RV series is of little surprise. From Fig. 2, it appears as though the majority of

[2] The VIX index used here is the most recent version of the index, introduced on September 22, 2003. VIX data for this study was downloaded from the CBOE website.

[3] The daily volatility implied by the VIX can be calculated when recognising that the VIX quote is equivalent to 100 times the annualized return standard deviation. Hence $VIX/(100/\sqrt{252}))^2$ represents the daily volatility measure (see Chicago Board of Options Exchange, 2003).

[4] Quoting from the CBOE White paper (2003) on the VIX, "VIX [...] provide[s] a minute-by-minute snapshot of expected stock market volatility over the next 30 calendar days."

[5] The definition of *BPV* presented above is the simplest definition originally proposed by Barndorff-Nielsen and Sheppard (2004, 2006). Here, we implement the definition proposed by Andersen et al. (2007) and Huang and Tauchen (2005) which is robust to the presence of microstructure noise. For specific details (see Andersen et al., 2007, p. 711).

[6] It is, of course, well known that the above arguments are valid in the limit as sampling intervals decrease to 0. The above discussion is meant to convey the general concepts involved. For further details refer to, amongst others, Barndorff-Nielsen and Sheppard (2004, 2006) or Andersen et al. (2007).

[7] The data-dependent truncation methods proposed by Andersen et al. (2007) essentially eliminates such jumps that contribute less than a given amount to the total variance on a given day. As discussed above, utilising such measures of jump activity do not alter the conclusions drawn below. Results are available upon request.

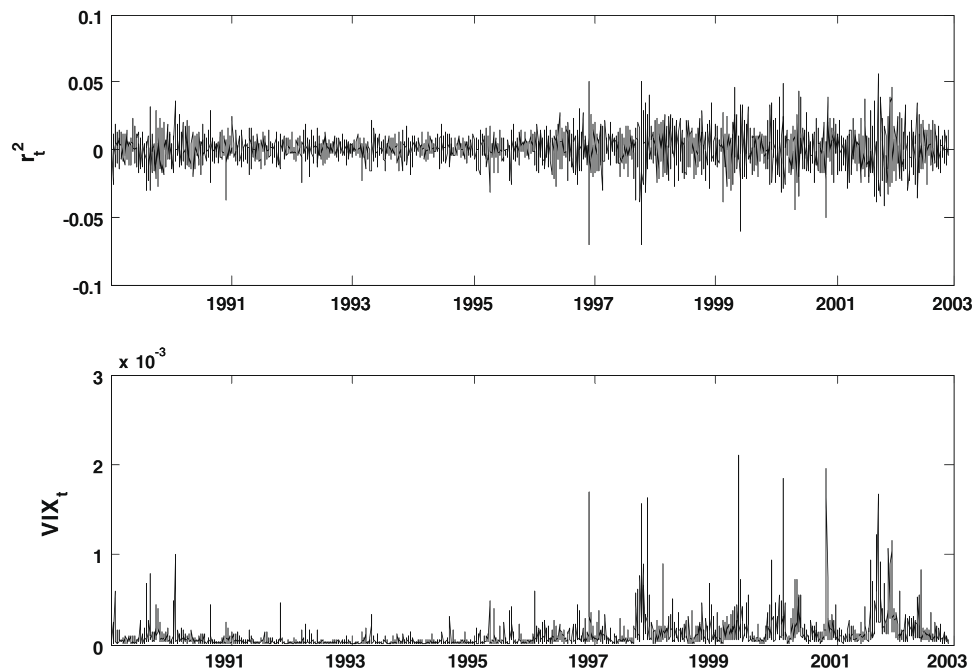

Fig. 1. Daily S&P 500 returns (top panel) and daily VIX index (bottom panel).

jump activity occurs when the overall level of volatility is relatively high. This is to be expected as larger discontinuous jumps in the S&P 500 index usually occur when the market is relatively volatile.

4. Methodology

This section describes the empirical methodology used to address the research questions at hand. We begin by outlining the MBF utilized. The methodology employed to determine whether the VIX subsumes the historical price jump component of volatility is described, followed by that used to ascertain whether it contains any incremental information relevant to future volatility.

4.1. Model-based forecasts

While the true process underlying volatility is not known, we utilize a range of commonly applied econometric models to generate volatility forecasts. In doing so, we adopt those employed by Blair et al. (2001) and Becker et al. (2006, 2007).

The first is the asymmetric GJR–GARCH model of Glosten et al. (1993) where the conditional variance, h_t of returns follows:

$$h_t = \gamma + \beta h_{t-1} + \alpha\varepsilon_{t-1}^2 + \delta D_{t-1}\varepsilon_{t-1}^2 \tag{5}$$

where ε_{t-1}^2 is the lagged squared innovation in returns and D_t is an indicator variable which equals 1 if $\varepsilon_t < 0$, and 0 otherwise. Following Blair et al. (2001) the GJR–GARCH model of Eq. (5) is augmented by the inclusion of realized volatility, RV_t in the following manner and is denoted below as the GJR–RV model

$$\begin{aligned} h_t &= h_{1t} + h_{2t} \\ h_{1t} &= \gamma + \beta h_{1t-1} + \alpha\varepsilon_{t-1}^2 + \delta D_{t-1}\varepsilon_{t-1}^2 \\ h_{2t} &= \lambda h_{2t-1} + \varphi \mathrm{RV}_{t-1}. \end{aligned} \tag{6}$$

A simple stochastic volatility (SV) model given by

$$\begin{aligned} r_t &= \mu + \varepsilon_t \\ \varepsilon_t &= \sigma_t \xi_t \\ \log\sigma_t^2 &= \alpha + \beta\log\sigma_{t-1}^2 + \upsilon_t \end{aligned} \tag{7}$$

where ξ_t is a standard normal innovation to returns and υ_t is the volatility innovation. An SV + RV model

$$\log\sigma_t^2 = \alpha + \beta\log\sigma_{t-1}^2 + \gamma(\log\mathrm{RV}_{t-1} - E_{t-1}[\log\sigma_{t-1}^2]) + \upsilon_t \tag{8}$$

which is augmented with RV in the spirit of the GJR–RV model is included. The RV term enters the equation for the volatility process through the $\log\mathrm{RV}_t - E_{t-1}[\log\sigma_{t-1}^2]$ term. The rationale behind this is that the realized volatility series will inevitably be highly correlated with the stochastic volatility series. Hence, proceeding in the manner above allows the incremental information content of the RV_t series to be incorporated into the model.

Following Pong et al. (2004), Koopman et al. (2004) and Becker et al. (2007), forecasts of volatility based on time series models of RV are also used. Forecasts are generated using ARMA (2,1) and ARFIMA (1,*d*,0) models of RV.

It should be noted that none of the models considered thus far distinguish between the continuous and jump components of volatility. A very recent development attributable to Andersen et al. (2007) allows for forecasts of total volatility to be a function of both components of volatility. This approach utilizes the forecasting framework of Corsi (2003) and will be denoted here as the BPV–J model and takes the following form

$$\begin{aligned} \mathrm{RV}_{t,t+h} = {} & \beta_0 + \beta_1\mathrm{BPV}_t + \beta_2\mathrm{BPV}_{t-5,t} + \beta_3\mathrm{BPV}_{t-22,t} + \beta_4 J_t \\ & + \beta_5 J_{t-5,t} + \beta_6 J_{t-22,t} + \varepsilon_{t,t+h}. \end{aligned} \tag{9}$$

Under the BPV–J model, a forecast of average RV over the ensuing h days (set to 22 in this case) is a function of average BPV and J on the preceding day, week ($t-5$, t) and month ($t-22$, t). The inclusion of this model is important as its forecasts have the potential to reflect information regarding jump activity directly. In essence, it should represent a superior benchmark relative to the models described above that do not utilize jumps directly, given the research question at hand.

The vector ψ_t is denoted to contain the stacked volatility forecasts and thus reflect the information contained in MBF.

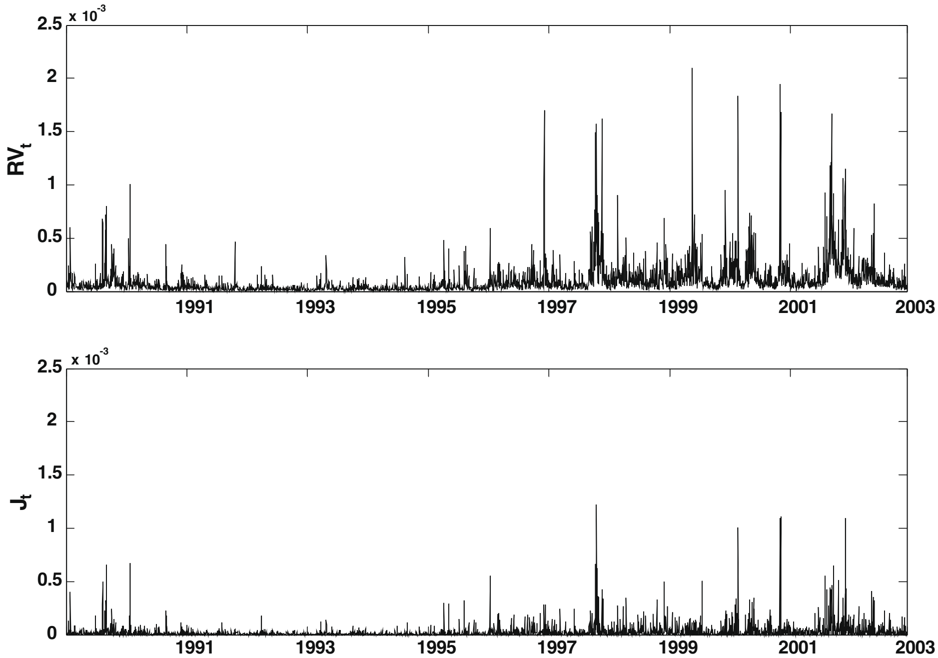

Fig. 2. Daily realized volatility (top panel) and jump component in volatility (bottom panel).

$$\Psi_t = \begin{pmatrix} \mathrm{GJR}_t \\ \mathrm{GJR} + \mathrm{RV}_t \\ \mathrm{SV}_t \\ \mathrm{SV} + \mathrm{RV}_t \\ \mathrm{ARMA}_t \\ \mathrm{ARFIMA}_t \\ \mathrm{BPV} - J_t \end{pmatrix} \tag{10}$$

As the VIX is designed as a fixed 22 day ahead forecast, each of the models are used to produce forecasts of average 22 day ahead volatility. Forecasts are based on parameters estimated from a rolling window of 1000 observations. This procedure results in 2460 22 day ahead forecasts.

4.2. VIX and the historical jump component

To determine whether the VIX subsumes information relating to jumps in the S&P 500 price process, the testing strategy employed by Fleming (1998) and Becker et al. (2006) is used. This entails testing whether the VIX forecast error is orthogonal to a set of available information, z_t. In this instance, the target to be forecast is average realized volatility observed over the ensuing 22 trading days, $\overline{RV}_{t+1\to t+22}$. The forecast error is defined as

$$v_t = \overline{\mathrm{RV}}_{t+1\to t+22} - (\alpha + \beta VIX_t). \tag{11}$$

The incorporation of the parameters, α and β, in the tradition of Mincer-Zarnowitz (1969) regressions, acknowledges that the VIX forecast is not necessarily unbiased. The inclusion of an intercept allows for the presence of a constant volatility risk premium in the VIX. This results in positive estimates of α in Eq. (11). To capture a potentially time-varying volatility risk premium, as suggested by Chernov (2007), Eq. (11) is augmented by the inclusion of RV_t,

$$v_t = \overline{\mathrm{RV}}_{t+1\to t+22} - (\alpha + \beta VIX_t - \gamma \mathrm{RV}_t). \tag{12}$$

Results will be report for both Eqs. (11) and (12).

If the sequence of zero-mean forecast errors $\{\hat{v}_t\}$ are unrelated to any other conditioning information, observations of the jump component of volatility in this case, then the VIX can be said to subsume this information. A direct way of testing the orthogonality of $\{\hat{v}_t\}$ is proposed by Fleming (1998), and used by Becker et al. (2006), which employs the generalized method of moments (GMM) framework. Parameter estimates for Eqs. (11) and (12) are obtained by minimising

$$V = g(\alpha, \beta)' H g(\alpha, \beta), \tag{13}$$

where

$$g(\alpha, \beta) = \frac{1}{T} \sum_{t=1}^{T} v_t z_t. \tag{14}$$

The weighting matrix H is chosen to be the variance–covariance matrix of the moment conditions in $g(\alpha, \beta)$, where allowance is made for residual correlation (see Hansen and Hodrick, 1980).

The instrument vector z_t contains a constant, VIX_t (and RV_t if v_t is defined as in Eq. (12)) as well as information relating to historical observations of the volatility jump component. The analysis is conducted based on the average jump component over the preceeding 1, 2 and 3 days. These will be denoted below as $\overline{J_{t-1}}, \overline{J_{t-2,t-1}}$ and $\overline{J_{t-3,t-1}}$, respectively.

4.3. VIX and the future jump component

To determine whether the VIX contains any incremental information relative to MBF that is relevant for explaining future jump activity, the empirical approach of Becker et al. (2007) is employed.

It is first necessary to extract the information in VIX that cannot simply be attributed to the information contained in the MBF in the vector ψ_t (Eq. (10)). This is achieved by the following regression

$$\mathrm{VIX}_t = \alpha + \beta' \psi_t + \varepsilon_t \tag{15}$$

where ε_t reflects such information. If the $\{\hat{\varepsilon}_t\}$ series is orthogonal to the contents of an instrument vector z_t, it can be concluded that the VIX contains no incremental information relative to MBF relevant for explaining the contents of z_t. Similar to the modification in Eq.

(12) we allow for a time-varying risk premium by adding the current level of volatility to the vector of explanatory variables in Eq. (15), $\tilde{\psi}_t = (\text{RV}_t \psi_t')'$ (see Chernov, 2007). Results using ψ_t and $\tilde{\psi}_t$ will be reported below.

To test this orthogonality condition, the GMM framework is used once again with the moment condition in Eq. (14) redefined as

$$g(\alpha,\beta) = \frac{1}{T}\sum_{t=1}^{T}(VIX_t - \alpha - \beta'\psi_t)z_t. \tag{16}$$

To address the research question, the elements of z_t are defined as a constant, ψ_t (or $\tilde{\psi}_t$) and the average volatility jump component over the subsequent 1, 5, 10 or 22 days. While the VIX forecast horizon is 22 days, it is an interesting issue to consider whether the VIX contains information for near term jumps only.

Following the notation presented in the previous section, these will be denoted as $\overline{J_{t+1}}, \overline{J_{t+1,t+5}}, \overline{J_{t+1,t+10}}, \overline{J_{t+1,t+22}}$. It should be noted, that the above analysis was repeated with alternative definitions of the jump component, namely using the Andersen et. al. (2007) approach to isolate larger jumps only. All results presented below, remain qualitatively unaltered.[8]

5. Results

Section 5.1 presents the empirical results relating to whether the VIX subsumes historical contribution of jumps to historical volatility, with Section 5.2 presenting those relating to whether the VIX contains any incremental information relevant for explaining the future jump activity in volatility.

5.1. VIX and the historical jump component

Table 1 contains results of the test for over-identifying restrictions to test whether the VIX subsumes historical jumps activity in volatility.[9] The tests relate to the moment conditions in Eq. (14) with instrument sets containing various measures of historical jump activity. Results in the top panel of Table 1 relate to Eq. (11) in which allowance is made for the VIX to reflect a constant volatility risk premium, whereas a time-varying volatility risk premium is catered for in the bottom panel. Clearly, the null hypothesis of orthogonality between the forecast errors and historical estimates of the jump component cannot be rejected, irrespective of how the risk premium is catered for.

On the basis of these results, a market determined forecast of volatility, the VIX, is efficient with respect to the degree of price volatility contributed by the jump process. This is a new result that extends the findings of Fleming (1998) and Becker et al. (2006) neither of whom considered jump activity.

5.2. VIX and the future jump component

Table 2 presents results for the over-identifying tests to determine whether the VIX contains information that is incremental to MBF relating to the future jump component in volatility. These tests relate to the moment conditions in Eq. (16). Before interpreting the results it should be reiterated that the jump measure utilized, $\overline{J_{t+h}}$, is an estimator of

$$\frac{1}{\tau}\sum_{t<s\leqslant t+h}\kappa^2(s) \quad \mathit{for} \quad h = 1, 5, 10, 22$$

for $\kappa(s)$ as defined in Eqs. (1) and (4). As discussed previously, this measure captures the intensity of the jump process as well as the average size of the jumps occurring. Any finding relating to the VIX containing information at time t about $\overline{J_{t+h}}$ is clearly information on the parameters of the jump process, jump intensity and average jump size, and not the timing of actual jumps themselves.[10]

Results reported in the top panel of Table 2 indicate whether information in the VIX, not attributable to MBF, is orthogonal to the future volatility jump component when allowing for a constant volatility risk premium. This hypothesis can be rejected at any reasonable level of significance at all forecast horizons (h = 1, 5, 10 and 22). The strength of the rejection increases with the forecast horizon and may be explained in two ways. *First*, the VIX is a volatility forecast for the upcoming 22 business days and, *second*, the jump component is measured with increasing precision as the forecast horizon is increased. These results are mirrored in the bottom panel of Table 2 (allowing for a time-varying volatility risk premium), although the rejection at h = 1 is somewhat weaker.

It is interesting to note the correlations between ε_t and the measure of jump activity over the next h days, $\overline{J_{t+h}}$, which are reported in the last row of the two panels in Table 2. The correlation is always positive and increases in strength as τ increases. Thus, a greater difference between VIX and MBF, on average signals a period with increased jump activity, meaning increased jump intensity and/or average jump size. This result is noteworthy as we have included a model, BPV–J model that explicitly includes jumps. This may be due to the BPV–J model having an inadequate specification in terms of jumps dynamics. A model that goes beyond rel-

Table 1
GMM results of the tests of over-identifying restrictions testing whether the VIX subsumes historical jump information. Results pertain to instrument vectors containing the jump component of volatility. Results in the top panel are for a constant volatility risk premium. Results in the bottom panel allow for a time-varying volatility risk premium.

$v_t = \overline{\text{RV}}_{t+1\to t+22} - (\alpha + \beta VIX_t)$			
z_t	$\{1, VIX_t, \overline{J_{t-1}}\}$	$\{1, VIX_t, \overline{J_{t-2,t-1}}\}$	$\{1, VIX_t, \overline{J_{t-3,t-1}}\}$
J-stat	1.3029	0.9017	0.6728
p-value	0.2537	0.3423	0.4121
R^2	0.7693	0.7693	0.7693
$v_t = \overline{\text{RV}}_{t+1\to t+22} - (\alpha + \beta VIX_t - \gamma \text{RV}_t)$			
z_t	$\{1, VIX_t, \text{RV}_t, \overline{J_{t-1}}\}$	$\{1, VIX_t, \text{RV}_t, \overline{J_{t-2,t-1}}\}$	$\{1, VIX_t, \text{RV}_t, \overline{J_{t-3,t-1}}\}$
J-stat	1.4449	0.8231	0.6833
p-value	0.2293	0.3643	0.4084
R^2	0.7722	0.7723	0.7723

Table 2
GMM results of the tests of over-identifying restrictions testing whether the VIX contains incremental information relevant for explaining future jump activity. Results pertain to instrument vectors containing the jump component of volatility. Results in the top panel are for a constant volatility risk premium. Results in the bottom panel allow for a time-varying volatility risk premium.

$\varepsilon_t = VIX_t - \alpha - \beta'\psi_t$				
z_t	$\{1, \psi_t, \overline{J_{t+1}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+5}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+10}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+22}}\}$
J-stat	14.4723	21.4002	21.5947	19.357
p-value	0.0001	0.0000	0.0000	0.000
R^2	0.3538	0.9368	0.9360	0.9356
Corr $(\varepsilon_t, \overline{J_{t+h}})$	0.0496	0.1524	0.2241	0.2938
$\varepsilon_t = VIX_t - \alpha - \beta'\tilde{\psi}_t$				
z_t	$\{1, \tilde{\psi}_t, \overline{J_{t+1}}\}$	$\{1, \tilde{\psi}_t, \overline{J_{t+1,t+5}}\}$	$\{1, \tilde{\psi}_t, \overline{J_{t+1,t+10}}\}$	$\{1, \tilde{\psi}_t, \overline{J_{t+1,t+22}}\}$
J-stat	6.1008	18.0399	18.9445	17.2860
p-value	0.0135	0.0000	0.0000	0.0000
R^2	0.9388	0.9390	0.9383	0.9380
Corr $(\varepsilon_t, \overline{J_{t+h}})$	0.0287	0.1371	0.2070	0.2742

[8] Results are available upon request.

[9] Individual parameter estimates are not reported as they are not central to the research question at hand.

[10] We thank an anonymous referee for clarifying this.

atively simply linear dependence may be required. Importantly, this result however does not imply that the VIX forecast can predict the timing of jumps, which is consistent with market efficiency.

Considering these results, together with those of the previous section, it is clear that as a market determined forecast, the VIX has the ability to react to and anticipate the impact of non-continuous price movements in the S&P 500 index on overall volatility.

This sheds a new light on the results of Becker et al. (2007) which highlighted that the VIX does not deliver any improvements (relative to MBF) when forecasting total price volatility, as measured by realized variance. However, as established here, it does indeed provide information with regards to the source of future price variation, as differences between MBF and the VIX hint at the importance of jumps relative to continuous price movements.

6. Concluding remarks

The behavior of option implied volatility (IV) has attracted a great deal of research attention. This research has focused on both the forecasting performance and informational content of IV relative to econometric model-based forecasts (MBF). However, as most common MBF simply smooth historical estimates of total volatility when generating forecasts, and IV is a market determined forecast, IV forecasts have the potential to behave differently to MBF when non-smooth price changes (jumps) contribute to the spot market volatility.

This paper has considered two issues relating to the informational content of the S&P 500 VIX implied volatility index. First, whether it subsumes historical information on the contribution of price jumps to volatility. Second, whether the VIX reflects any incremental information relative to model-based forecasts pertaining to future jump activity. This differs from previous studies that have considered these issues in the context of forecasts of the level of future volatility, not considering whether this volatility is caused by continuous or non-continuous price changes.

Results presented here show that the VIX does reflect (or react to) past jump activity in the S&P 500. VIX forecast errors are indeed uncorrelated to past available information relating to jump activity. It has also been shown that the VIX reflects incremental information, relative to MBF, for explaining future jump activity. It appears as if the VIX anticipates jump activity in the S&P 500 share price index, thus an interesting avenue for future research would be to formally incorporate this information into a volatility forecasting model. Overall these results confirm the potential for a market determined forecast to react to volatility changes in a way that standard econometric models, even those that directly incorporate jumps cannot.

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