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Abstract

Much research has investigated the differences between option implied volatilities and econometric model-based forecasts in terms of forecast accuracy and relative informational content. Implied volatility is a market determined forecast, in contrast to model-based forecasts that employ some degree of smoothing to generate forecasts. Therefore, implied volatility has the potential to reflect information that a model-based forecast could not. Specifically, 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 relative to model based forecasts pertaining to future jumps. It is found that the VIX index both subsumes information relating to past jump contributions to volatility and reflects incremental information pertaining to future jump activity, relative to model-based forecasts. This is an issue that has not been examined previously in the literature and expands our understanding of how option markets form their volatility forecasts.

Keywords: Implied volatility, VIX, volatility forecasts, informational efficiency, jumps.

JEL Classification: C12, C22, G00, G14

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, Clements and White (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, Clements and White (2006) find that S&P 500 IV does not completely subsume a diverse set of information including MBF. Becker, Clements and White (2007) find that IV contains no information beyond volatility persistence as captured by MBF relevant for forecasting the level of volatility.

These previous studies considered the relationship between IV and forecasts of the level of volatility whereas this article investigates the relationship between IV and jump activity contributing to the volatility of the price process. Given that MBF generate forecasts based on smoothing historical data and that IV is market determined, IV has the potential to react to (or forecast) the component of spot market volatility that is due to jumps in the price process. This article considers two issues relating to the relationship between IV and jumps in the price process. *First*, it will be examined whether IV 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&P500 price process in their IV forecasts and extends the work of Fleming (1998), Jiang and Tian (2003) and Becker, Clements and White (2006). *Second*, it will be investigated whether IV reflects information beyond MBF in relation to jump activity and extends the work of Becker, Clements and White (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 does in fact subsume information on historical jump activity meaning that option markets react not only to price volatility generated by the continuous price process when forming their volatility forecasts, but also to discontinuous price jumps. This result leads to the finding that IV contains incremental information relative to MBF in relation to future jump activity contributing to price volatility. This result differs from that of Becker, Clements and White (2007) in that they found that IV contained no information incremental to that of MBF in relation to the overall level of volatility (due to the continuous and jump price processes). The reason for the difference in results is due to the fact that the overall level of volatility is dominated by volatility due to the continuous price process.

This paper proceeds as follows. Section 2 presents the required data. Section 3 outlines the empirical methodology employed to address each of the research questions. Sections 4 and 5 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, and realisations of equity volatility and the 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 utilised here is that provided by the Chicago Board of Options Exchange, the VIX¹. 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 days². It is derived without reference to a restrictive option pricing model. 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, Poon and Taylor 2001, and Christensen and Prabhala, 1998)³. As highlighted by Jiang and Tian (2003), the advantages of such a model-free approach to computing implied volatility are two-fold⁴. Relative to a model-based IV estimate (e.g. IV based on assuming the validity of the Black-Scholes option pricing model), a model-free estimate incorporates more information from a range of observed option prices. In the current context, utilising model-free estimates avoids a joint test of both the option pricing model and market efficiency.

The measure of volatility used here is realised volatility (RV), constructed from intra-day S&P 500 index data (see Andersen, Bollerslev, Diebold and Labys 2001, 2003 for a discussion of RV)⁵. In dealing with practical issues such as intra-day sampling frequency when constructing daily RV_t , the signature plot methodology of Andersen *et al.* (1999) is followed. Given this approach, daily RV_t estimates are constructed using 30 minute S&P 500 index returns in the following manner

$$RV_t = \sum_{i=1}^M r_i^2 \quad (1)$$

where r_i , $1, \dots, M$ are returns from the M discrete intervals within each trading day.

The component of S&P 500 volatility attributable to price jumps was recovered using the bi-power variation (BPV) methodology of Barndorff-Nielsen and Sheppard (2004). The BPV is given by

¹The 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.

²The daily volatility implied by the VIX can be calculated when recognising that the VIX quote is equivalent to 100 times the annualised return standard deviation. Hence $(VIX / (100\sqrt{252}))^2$ represents the daily volatility measure (see CBOE, 2003).

³Quoting 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."

⁴They utilise a different approach to that embodied into the calculation of the VIX.

⁵Intraday S&P 500 index data were purchased from Tick Data, Inc.

$$BPV_t = \mu^{-2} \sum_{i=1}^{M-1} |r_i| |r_{i+1}| \quad (2)$$

where

$$\mu = 2^{1/2} \frac{\Gamma(1)}{\Gamma(1/2)}$$

is the expected absolute value of a standard normally distributed random variable. This allows for the jump component to the realized volatilities to be recovered as

$$J_t = RV_t - BPV_t. \quad (3)$$

Both RV_t and BPV_t broadly capture the volatility of the underlying price process. It has been demonstrated (see e.g. Barndorff-Nielsen and Sheppard, 2004) that RV_t captures volatility due to both the continuous price movements and discontinuous price jumps. In contrast, BPV_t can be shown to only capture price volatility resulting from price changes of the continuous diffusion process, such that the difference between the two measures proxies the volatility contribution made by jumps in the price process.

Figure 1 plots both the daily returns and the VIX index. It is clear that the VIX (bottom panel) broadly tracks changes in the level of volatility of the returns. Comparing the RV (top panel) and VIX from Figure 1, it is clear that the daily RV has higher peaks than the VIX. As the VIX is an expectation of average volatility over the 22 day horizon, the comparable smoothness of the VIX, as compared to the RV series, is of little surprise.

Figure 2 plots both the daily RV and the jump component of volatility. A number of interesting observations can be gleaned from a comparison of the RV (top panel) and the jump component (bottom panel). Conceptually, jumps can only contribute positively to the integrated variance of a price process. However, Figure 2 shows that, when estimating J_t from equation (3), $J_t < 0$ for some t . As discussed in Barndorff-Nielsen and Sheppard (2004) an alternative, albeit biased, estimator is available by introducing a floor of zero into equation (3). The following empirical analysis will make allowance for this issue by singling out the positive values of the J_t series. The mean of J_t is $7.66e^{-6}$ with $J_t < 0$ in 25% of observations. The mean of $J_t < 0$ is an order of magnitude smaller than that of $J_t > 0$ as negative values are simply due to estimation error and such observations would indicate no jump activity. It appears as though the majority of jump activity occurs when the overall level of volatility is relatively high. This is of little surprise, as larger discontinuous jumps in the S&P500 index usually occur when the market is relatively volatile.

INSERT FIGURES 1 and 2 ABOUT HERE

3 Methodology

This section describes the empirical methodology used to address the research

questions at hand. We begin by outlining the MBF utilised. 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.

3.1 Model Based Forecasts

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

The first is the asymmetric GJR-GARCH model of Jagannathan and Runkle (1993) where the conditional variance, h_t of returns follows

$$h_t = \gamma + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \delta D_{t-1} \varepsilon_{t-1}^2 \quad (4)$$

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, Poon and Taylor (2001) the GJR-GARCH model of equation 4 is augmented by the inclusion of realised volatility, RV_t in the following manner and is denoted below as the GJR-RV model,

$$h_t = h_{1t} + h_{2t} \quad (5)$$

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

$$h_{2t} = \lambda h_{2t-1} + \varphi RV_{t-1}.$$

A simple stochastic volatility (SV) model given by

$$r_t = \mu + \varepsilon_t \quad (6)$$

$$\varepsilon_t = \sigma_t \xi_t$$

$$\log \sigma_t^2 = \alpha + \beta \log \sigma_{t-1}^2 + \nu_t$$

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

$$\log \sigma_t^2 = \alpha + \beta \log \sigma_{t-1}^2 + \gamma (\log RV_{t-1} - E_{t-1}[\log \sigma_{t-1}^2]) + \nu_t \quad (7)$$

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 $\log RV_t - E_{t-1}[\log \sigma_{t-1}^2]$ term. The rationale behind this is that the realised 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 Koopman, Jungbacker and Hol (2005) and Becker, Clements and White (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.

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

$$\Psi_t = \begin{pmatrix} GJR_t \\ GJR + RV_t \\ SV_t \\ SV + RV_t \\ ARMA_t \\ ARFIMA_t \end{pmatrix} \quad (8)$$

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.

3.2 VIX and the historical jump component

Logically, a market determined estimate of future volatility such as the VIX can accommodate information that relates to the jump component of the volatility process, whereas standard model based forecasts, be they based on either filtering squared returns or $\{RV_t\}$, are unable to make allowance for such information. 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, Clements and White (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 realised volatility observed over the ensuing 22 trading days, $\overline{RV}_{t+1 \rightarrow t+22}$. The forecast error is defined as

$$\varepsilon_t = \overline{RV}_{t+1 \rightarrow t+22} - (\alpha + \beta VIX_t) \quad (9)$$

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 a potential volatility risk premium in the VIX.

If the sequence of zero-mean forecast errors $\{\hat{\varepsilon}_t\}$ are unrelated to any other conditioning information, observations of the jump component to volatility in this case, then the VIX can be said to subsume this information. A direct way of testing the orthogonality of $\{\hat{\varepsilon}_t\}$ is proposed by Fleming (1998), and used by Becker, Clements and White (2006), which employs the *Generalized Method of Moments*

(GMM) framework. Parameter estimates of equation (9) are obtained by minimising

$$V = g(\alpha, \beta)' H g(\alpha, \beta), \quad (10)$$

where

$$g(\alpha, \beta) = \frac{1}{T} \sum_{t=1}^T (\overline{RV}_{t+1 \rightarrow t+22} - \alpha - \beta VIX_t) z_t. \quad (11)$$

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 information relating to historical observations of the volatility jump component. The analysis is conducted based on the average jump component over the preceding 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. As discussed previously the analysis is also undertaken by replacing the average jump component measures with the averages across the positive jump components only, J_{t-1}^+ , $J_{t-2,t-1}^+$ and $J_{t-3,t-1}^+$. In total six sets of results are presented. The traditional test of overidentifying restrictions in the GMM framework is then a test of whether the VIX subsumes the jump information.

3.2 VIX and the future jump component

To determine whether the VIX contains any incremental information relative to MBF that is relevant for predicting future price volatility, or more precisely the volatility component contributed by price jumps, the empirical approach of Becker, Clements and White (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 (equation 8). This is achieved by the following regression

$$VIX_t = \alpha + \beta' \psi_t + \varepsilon_t \quad (11)$$

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 .

To test this orthogonality condition, the GMM framework is used once again with the moment condition in equation 11 redefined as

$$g(\alpha, \beta) = \frac{1}{T} \sum_{t=1}^T (VIX_t - \alpha - \beta' \psi_t) z_t \quad (12)$$

To address the research question, the elements of z_t are defined as a constant, ψ_t and the average volatility jump 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. Again, the analysis is repeated for measures of positive volatility jump components only. Following the notation presented in the previous section, these will be denoted as $\overline{J_{t+1}}$, $\overline{J_{t+1,t+5}}$, $\overline{J_{t+1,t+10}}$, $\overline{J_{t+1,t+22}}$ and J_{t+1}^+ , $J_{t+1,t+5}^+$, $J_{t+1,t+10}^+$, $J_{t+1,t+22}^+$. For each of the four forecast horizons, the incremental information reflected in the VIX in relation to future jump activity will be examined. Thus in total, eight sets of results will be presented.

4 Results

Section 4.1 presents the empirical result relating to whether the VIX subsumes historical jumps in volatility, with Section 4.2 presenting those relating to whether the VIX contains any incremental information relevant for explaining the future jump activity in volatility.

4.1 VIX and the historical jump component

Table 1 contains results of the test for overidentifying restrictions to test whether the VIX subsumes historical jumps in volatility⁶. The tests relate to the moment conditions in equation 11 with instrument sets containing various measures of historical jump activity.

Results in the top panel of Table 1 relate to whether the VIX subsumes all jumps (irrespective of sign). It is clear that at a p -value of 0.0051 the null hypothesis of orthogonality between the VIX forecast errors and the jump component, $\overline{J_{t-1}}$, is rejected. This indicates the VIX does not subsume jumps that occurred on the preceding trading day. Conversely, the average jump component of volatility is subsumed by the VIX over the preceding 2 or 3 trading days. This pattern is confirmed when restricting the analysis to jump volatility components that are measured to be positive.

These results indicate that, as a market determined forecast of volatility, the VIX does react to the effect of jumps in price on S&P 500 volatility. Interestingly, it seems as though a jump on a single day is not sufficient for option markets to significantly alter their forecasts. It appears as though jump activity across successive days influences the option market. One may conjecture that it takes jumps in prices over a number of days for the options market to believe this is simply not a one-off transitory shock to volatility and their forecasts are finally revised. This is a new result that extends the findings of Fleming (1998) and Becker, Clements and White (2006) neither of whom considered jump information.

⁶ Individual parameter estimates are not reported as they are not central to the research question at hand.

INSERT TABLE 1 ABOUT HERE

4.2 VIX and the future jump component

Table 2 presents results for the overidentifying 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 equation 12.

Results reported in the top panel of Table 2 indicate whether the null hypothesis that information in the VIX, not attributable to MBF, is orthogonal to the future volatility jump component. This hypothesis can be rejected at a 5% level of significance. This finding implies that the VIX does contain information incremental to that in MBF relevant to future jumps in prices. This finding is again confirmed when examining the panel which relates to the results obtained when using the jump component series constrained to be non-negative.

This result can be interpreted in the following way. In Becker, Clements and White (2007), it was shown that the VIX contained no information incremental to MBF in relation to the future level of volatility. Thus, it was conjectured that the VIX could be viewed as some combination of model based volatility forecasts. However, according the results of this paper, if one focuses on the component of volatility due to non-smooth jumps in prices the VIX does contain information incremental to MBF. Therefore, whenever the VIX appears to produce a forecast higher than MBF, the options market is expecting a price process that will exhibit jumps.

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&P500 index on overall volatility. This sheds a new light on the results of Becker, Clements and White (2007) which highlighted that the VIX does not deliver any improvements (relative to MBF) when forecasting 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 discrepancies between MBF and the VIX hint at the importance of jumps relative to continuous price movements.

INSERT TABLE 2 ABOUT HERE

5 Concluding remarks

The behaviour 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 MBF employ a degree of smoothing 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, it is investigated 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. It appears as though the S&P 500 options market does not react to price jumps on a single day but requires jump activity on successive days to alter their forecasts. 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 positive jump activity in the S&P500 share price index although, does not deliver forecast improvements of overall price volatility. This would be due to the fact that the majority of movement in the overall level of volatility is due to the continuous price component and the not the jump process.

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 econometric models cannot.

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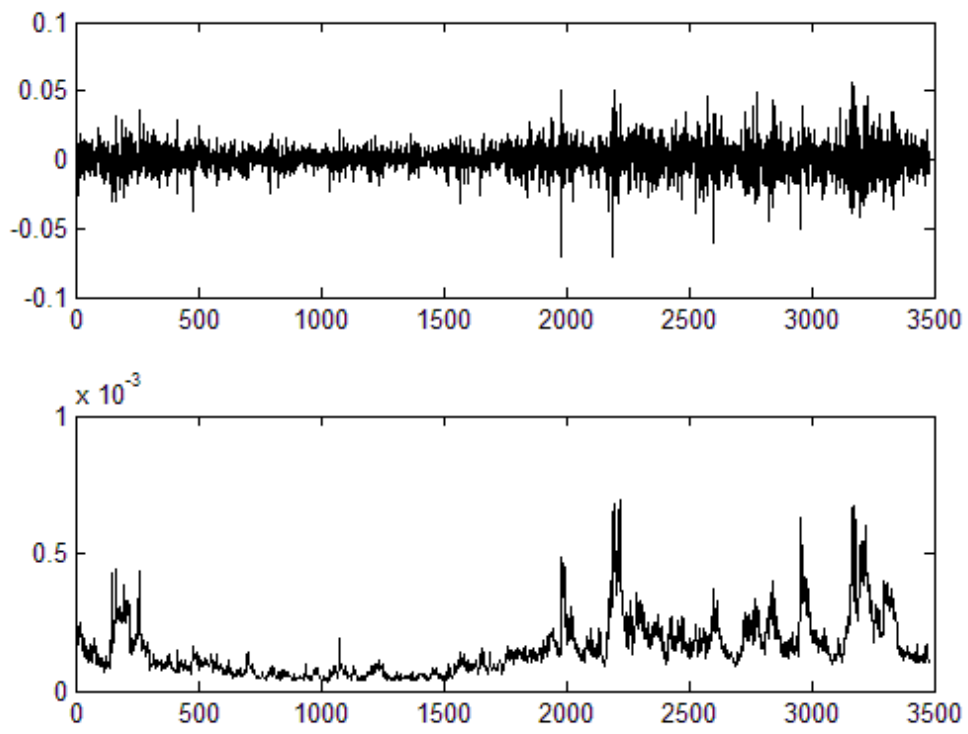


Figure 1: Daily S&P 500 returns (top panel) and daily VIX index (bottom panel).

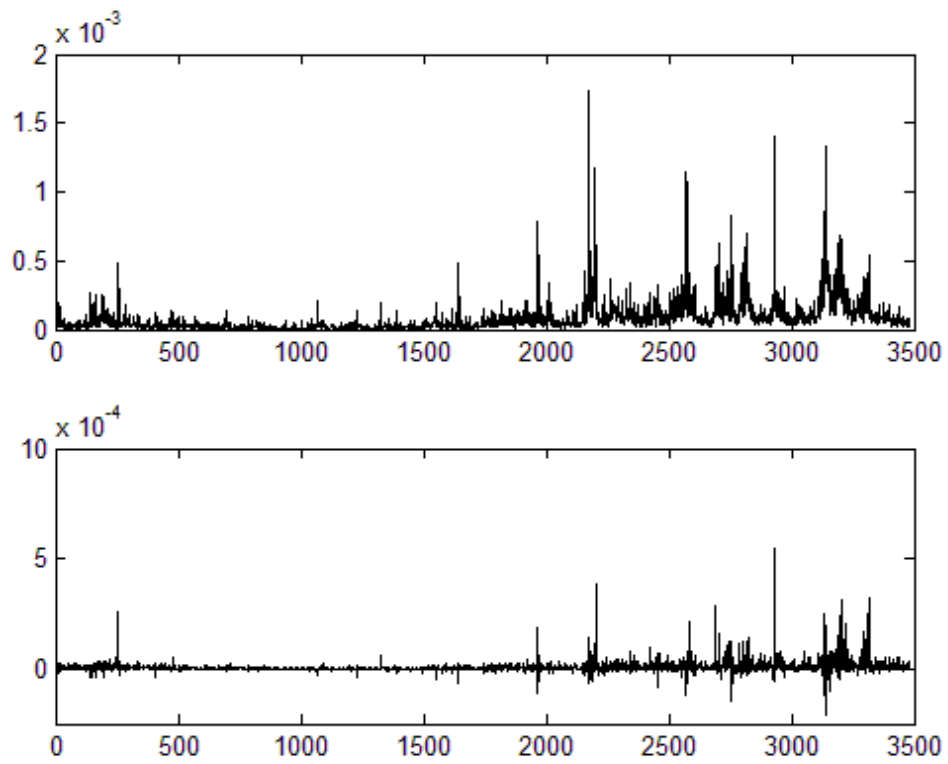


Figure 2: Daily realised volatility (top panel) and jump component in volatility (bottom panel).

z_t	$\{1, VIX_t, \overline{J_{t-1}}\}$	$\{1, VIX_t, \overline{J_{t-2,t-1}}\}$	$\{1, VIX_t, \overline{J_{t-3,t-1}}\}$
<i>J-stat</i>	7.8436	1.4864	0.0087
<i>p-value</i>	0.0051	0.2228	0.9254
<i>R-squared</i>	0.6753	0.6755	0.6755
z_t	$\{1, VIX_t, \overline{J_{t-1}^+}\}$	$\{1, VIX_t, \overline{J_{t-2,t-1}^+}\}$	$\{1, VIX_t, \overline{J_{t-3,t-1}^+}\}$
<i>J-stat</i>	7.4341	1.2630	0.0103
<i>p-value</i>	0.0064	0.2611	0.9192
<i>R-squared</i>	0.6735	0.6755	0.6755

Table 1: GMM results of the tests of over-identifying restrictions testing whether the VIX subsumes historical jump observations. Results pertain to instrument vectors containing total jumps (top panel) along with only positive (middle panel) and negative (bottom panel) jumps.

z_t	$\{1, \psi_t, \overline{J_{t+1}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+5}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+10}}\}$	$\{1, \psi_t, \overline{J_{t+1,t+22}}\}$
<i>J-stat</i>	4.4050	6.1932	5.9492	4.2605
<i>p-value</i>	0.0358	0.0128	0.0147	0.0390
<i>R-squared</i>	0.9300	0.9300	0.9301	0.9300
z_t	$\{1, \psi_t, \overline{J_{t+1}^+}\}$	$\{1, \psi_t, \overline{J_{t+1,t+5}^+}\}$	$\{1, \psi_t, \overline{J_{t+1,t+10}^+}\}$	$\{1, \psi_t, \overline{J_{t+1,t+22}^+}\}$
<i>J-stat</i>	4.4050	6.1933	5.9492	4.2606
<i>p-value</i>	0.0358	0.0129	0.0147	0.0390
<i>R-squared</i>	0.9300	0.9301	0.9300	0.9300

Table 2: GMM results of the tests of over-identifying restrictions testing whether the VIX contains incremental information relevant for explaining future jumps. Results pertain to instrument vectors containing total jumps (top panel) along with only positive (middle panel) and negative (bottom panel) jumps.