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Forecasting gains of robust realized variance estimators: evidence from European stock markets

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Abstract

The classical realized variance (RV) estimator is biased due to microstructure effects and asset price jumps. Robust realized variance (RRV) estimators adjust for these biases, and make more efficient of use of the intraday data. This article examines the benefits of using RRV estimators instead of the RV estimator, in the context of volatility forecasting. The recently proposed Realized GARCH framework is used to generate daily forecasts of the conditional variance for eight European stock indices. The out-of-sample comparisons indicate that the RRV estimators improve upon the RV estimator on efficiency and bias criteria.

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1. INTRODUCTION

Forecasting volatility of financial assets has applications in portfolio design, option valuation and risk management. Since the volatility is unobservable (latent), it has to be estimated. The realized variance (RV) estimator, calculated as the sum of squared intradaily returns, provides an asymptotically consistent estimator of the latent integrated variance (Andersen et al. 2001; Andersen and Bollerslev 1998; Barndorff-Nielsen 2002; Barndorff-Nielsen and Shephard 2002). In practice, the RV estimator is biased due to the microstructure effects, caused by bid-ask bounce, price rounding, among other reasons. As the sampling frequency is increased, the bias due to microstructure effects gets progressively worse (Bandi and Russell 2006; Bandi and Russell 2008; Zhou 1996). The early attempts to mitigate the microstructure bias in the RV measure were heuristic in nature. One popular approach is to select a lower sampling frequency, typically 5 to 30 minutes. The most commonly used realized estimator is the 5-minute RV, i.e., the sum of squared 5-minute returns. However, using a lower sampling frequency, also known as sparse sampling, has two drawbacks. First, it leads to a loss of a vast number of price observations. Discarding a large number of observations is undesirable as it reduces the efficiency of the RV estimate. Second, the RV estimator converges to the latent integrated variance only under the assumption of nearly infinite sampling. This asymptotic approximation becomes questionable with lower sampling frequencies. Another problem with the RV estimator is that in the presence of price jumps, it measures the true integrated variance plus a contribution equal to the cumulative squared jumps (Andersen et al. 2012; Barndorff-Nielsen and Shephard 2004a; Barndorff-Nielsen and Shephard 2004b). Therefore, price jumps induce an upward bias in the RV estimator.

Recent literature has proposed alternative realized estimators that are robust to the bias caused due to microstructure noise and price jumps, and make efficient use of the available data. In this study, we use the RV as the benchmark realized estimator, and compare it with three robust realized variance (RRV) estimators: the two time scale realized variance (TSRV) estimator (Zhang et al. 2005), the realized kernel (RK) estimator (Barndorff-Nielsen et al. 2008) and the realized bipower variance (BV) estimator (Barndorff-Nielsen and Shephard 2004a). The TSRV and RK estimators are robust to the microstructure noise bias, whereas the BV estimator is robust to price jumps. Each of these realized estimators are used in the novel Realized GARCH framework of Hansen et al. (2012), to construct daily variance forecasts for eight European stock indices. We compare the out-of-sample performance of the RRV based models with that of the RV based model using bias and efficiency criteria. The sample period for this analysis extends from 1 January 2000 to 12 September 2014.

This article contributes to the existing literature in a number of ways. First, it is one the earliest implementation of the Realized GARCH model in the European stock markets. Other notable implementations include Hansen et al. (2012), Louzis et al. (2013) and Watanabe (2012), all of which are based on the U.S. equity market. Second, it contrasts the out-of-sample performance of various RRV estimators. Several studies report that incorporating realized estimators in volatility models provides large statistical and economic benefits across a range of forecasting applications (Christoffersen et al. 2012; Fleming et al. 2003; Koopman et al. 2005; Pong et al. 2004; Vortelinos 2013; Vortelinos and Thomakos 2012). Nonetheless, the literature that compares the forecasting benefits of robust realized variance estimators remains sparse. Third, it uses a data set with a reasonably large sample dimension in the context of realized volatility forecasting studies. The full sample period is around 14 years, comprising of eight

European stock indices. Hence, the key results are likely to be widely applicable, and robust to data snooping bias.

2. METHODOLOGY

2.1 Realized variance estimators

We use the RV estimator as the benchmark, and three RRV estimators, namely, the TSRV estimator, the RK estimator and the BV estimator. Next, some notations are provided for defining the realized estimators. Let $\{p_i\}_{i=0}^{M}$ denote the time-series of intraday prices. To standardize the notations we define a function $\gamma_{h,q}(k)$ as

$$\gamma_{h,q}(k) = \sum_{i=1}^{m} \left(p_{iq+h} - p_{(i-1)q+h}\right)\left(p_{(i+k)q+h} - p_{(i-1+k)q+h}\right) \tag{1}$$

where $m = \lfloor (M - h + 1)/q \rfloor - k$. The RV estimator (benchmark) is calculated as

$$\mathrm{RV} = \gamma_{0,q}(0) \tag{2}$$

The highest sampling frequency is denoted by $q = 1$, i.e., $\gamma_{0,1}(0)$ provides the RV estimate using all intraday returns. The 5-minute RV (benchmark) is calculated using $= M/\, l$, where l is the number of 5-minute intervals in the trading day. The use of sparse sampling (5-minute returns) reduces the microstructure bias in the RV estimate; however, it leads to a loss of a large number of intraday price observations. For instance, if price observations are available for each second, sampling at 5-minute intervals discards over 99% of the data. The TSRV and RK estimators make more efficient use of the available data, and provide separate adjustments for the microstructure noise bias.

The TSRV approach estimates the realized variance using two different sampling frequencies, a high-frequency RV estimate and a low-frequency RV estimate. Zhang et al. (2005) show that by taking a suitable linear combination of these two RV estimates, the TSRV estimator is able to cancel out the bias induced by the microstructure noise[1]. The TSRV estimator also makes use of the subsampling approach, which makes a more efficient use of the available data. In this approach, the price process is sampled at a given frequency, using a variety of non-overlapping sub-grids. A collection of the realized estimates is obtained using these subsamples, which are then averaged to yield the subsampled realized estimate. We use the full grid of all intraday returns for the high-frequency RV estimate, and subsampled 5-minute returns for the low frequency RV estimate. The TSRV is calculated as

$$\mathrm{TSRV} = \left(1 - \bar{M}/M\right)^{-1}\left(\frac{1}{q}\sum_{h=0}^{q-1}\gamma_{h,q}(0) - \frac{\bar{M}}{M}\gamma_{0,1}(0)\right) \tag{3}$$

where $\bar{M} = (M - q + 1)/\,q$ and $q = M/\,l$. The first term in the bracket, $\frac{1}{q}\sum_{h=0}^{q-1}\gamma_{h,q}(0)$, is the subsampled 5-minute RV estimate. The second term, $\gamma_{0,1}(0)$, is the RV estimate that uses all intraday returns.

The second RRV estimator used in this study is the RK estimator of Barndorff-Nielsen et al. (2008). The RK is robust to microstructure noise, and makes use of all the intraday data.

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[1] Under the assumption that the microstructure noise process is independent of the true price process.

Essentially, it adjusts the realized variance estimate for the serial correlation induced by the microstructure effects. The RK is measured as

$$\mathrm{RK} = \gamma_{0,1}(0) + 2\sum_{h=1}^{H} \kappa\left(\frac{h-1}{H}\right)\gamma_{0,1}(h) \tag{4}$$

where $\kappa(x)$ is a kernel weight function and the optimal bandwidth parameter H is calculated using the procedure of Barndorff-Nielsen et al. (2009). Barndorff-Nielsen et al. (2008) compute the RK measure with several alternative kernels, namely, the Bartlett kernel, the cubic kernel, the Tukey-Hanning$_2$ kernel and the Parzen kernel. We use the "non-flat-top" Parzen kernel function as it ensures a positive variance estimate, while allowing for dependence or endogeneity in the microstructure noise process (Barndorff-Nielsen et al. 2011). The Parzen kernel function is defined as

$$\kappa(x) = \begin{cases} 1 - 6x^2 + 6x^3 & 0 \le x \le 1/2 \\ 2(1-x)^3 & 0 \le x \le 1/2 \\ 0 & x > 1 \end{cases}$$

Finally, we use the BV estimator of Barndorff-Nielsen and Shephard (2004a), which is robust to price jumps. To avoid microstructure noise bias, the BV estimator is calculated using 5-minute returns. Following Barndorff-Nielsen and Shephard (2004a), the BV is calculated as

$$\mathrm{BV} = \frac{\pi}{2}\sum_{i=1}^{m} \left|p_{iq} - p_{(i-1)q}\right| \left|p_{(i+1)q} - p_{iq}\right| \tag{5}$$

For 5-minute sampling frequency we use $= M/\,l$, where l is the number of 5-minute intervals in the trading day. We use a subsampled BV estimate, BVS, which uses 5-minute returns with 1-minute subsampling. The calculation of the BVS estimate is as follows. Suppose the BV estimate is calculated using the prices sampled at the time points 9:30, 9:35, 9:40 ..., etc. Another BV estimate is calculated using the prices at the time points 9:31, 9:36, 9:41 ..., etc. In this manner, for each day, five values of BV are computed using five non-overlapping subsamples. Since the start and end times of the subsamples may not coincide with those of the trading session, these BV estimates may omit a small number of observations of the trading day. To adjust for the loss of observations, the BV estimates are proportionally inflated to account for the missing part of the trading day. The BVS is then calculated as the average of these five BV estimates. Since, the RK and TSRV estimators make use of all available intraday observations; subsampled versions of these estimators are not included in the analysis.

2.2 Forecasting Methodology

For each sample index, we generate daily (one-step-ahead) forecasts of the conditional variance using the Realized GARCH model. Following Louzis et al.(2013), we use an AR(1) specification for modeling the conditional mean of the Realized GARCH model[2]. The conditional mean equation is given by

$$r_t = c + \phi_1 r_{t-1} + \varepsilon_t, \qquad \varepsilon_t = \sigma_t z_t, \qquad z_t \sim i.i.d.\ N(0,1) \tag{6}$$

[2] We tested three alternative conditional mean specifications: zero mean, constant mean and GARCH-in-mean. The key results of this analysis remain robust under different specifications of the conditional mean.

where $r_t = \ln(P_t/P_{t-1})$ and P_t is the closing price on day *t*.

In a comparison of 330 ARCH-type models, Hansen and Lunde (2005) found that a model with higher lags (for the ARCH and GARCH terms) rarely provides better forecasting performance than the same model with fewer lags. Based on their findings, we restrict our Realized GARCH model to the simplest lag specification, i.e., we use the Realized GARCH(1,1) model. It is defined as

$$\text{Realized GARCH(1,1)}: \log \sigma_t^2 = \omega + \beta \log \sigma_{t-1}^2 + \gamma \log x_{t-1} \quad (7)$$

$$\log x_t = \xi + \varphi \log \sigma_t^2 + \delta(z_t) + u_t,\ u_t \sim i.i.d.\ N(0, \sigma_u^2) \quad (8)$$

Here, α, ω, β, τ_1, τ_2, γ ,ξ, φ, δ_1, δ_2 are the model parameters. Equation (7) models the conditional variance, σ_t^2. Equation (8) is the measurement equation used for modeling the realized variance, x_t. For each sample index, we implement the Realized GARCH model with five realized estimators defined earlier, i.e., x_t = RV, TSRV, RK, BV or BVS. $\delta(\cdot)$ is the leverage function given by $\delta(z_t) = \delta_1 z_t + \delta_2(z_t^2 - 1)$. The leverage function captures the asymmetric effect of negative return shocks on the volatility process. All models are estimated using the method of maximum likelihood. Following Hansen et al. (2012) and Frommel et al. (2014), we assume Gaussian specification for the log-likelihood functions. We use a rolling window of the most recent 2000 daily observations for the estimation of GARCH models. The estimate of the variance at the end of day *t*, σ_{t+1}^2, is used as the one-step-ahead variance forecast, $\hat{\sigma}_{t+1}^2$, for the day *t*+1.

2.3 Forecast evaluation

The evaluation of variance forecasts is non-trivial as the true integrated variance is latent and must be estimated. In this study, we use the RK as the estimate for true integrated variance. The choice is motivated by theoretical strengths of the RK estimator; it is robust to microstructure noise and makes efficient use of the intraday data. Moreover, in a comparison of nineteen realized variance estimators, Gatheral and Oomen (2010) found that the RK is one of the best estimators in terms of efficiency and robustness to time varying parameters. We use bias and efficiency criteria for comparing the out-of-sample performance of the RRV based models with that of RV based model. The efficiency is measured using the mean squared error (MSE) and quasi likelihood (QLIKE) loss functions. As the true volatility is latent, the forecast error is calculated with respect to a proxy of true volatility. The estimation error in the volatility proxy may distort the ranking of competing volatility forecasts. Patton (2011) examined a class of loss functions for their robustness to the estimation error in the volatility proxy. Comparing nine widely used loss functions, he demonstrated that only the mean squared error (MSE) and quasi-likelihood (QLIKE) loss functions are robust to an imperfection in the volatility proxy. Finally, we use the expected forecast error as measure of bias. These loss functions are defined as

$$\text{MSE} = E(\hat{\sigma}_t^2 - \sigma_t^2)^2 \quad (9)$$

$$\text{QLIKE} = E(\log(\hat{\sigma}_t^2) + \sigma_t^2\, \hat{\sigma}_t^{-2}) \quad (10)$$

$$\text{BIAS} = E(\hat{\sigma}_t^2 - \sigma_t^2) \quad (11)$$

3. DATA

The study uses daily and intradaily price data of eight European stock indices, for the period 1 January 2000 to 12 September 2014. All data are sourced from the Thomson Reuters DataScope Tick History (RDTH) database. Table 1 provides the list of sample indices and their descriptive statistics. As the number of trading days varies across different exchanges, the total number of daily observations *T*, in Table 1, differs across the sample indices. For each index, we generate *N* variance forecasts, where *N* = *T*- 2000.

Table 1 Descriptive statistics

Ticker	Index	Country	*T*	*N*	r_t		r_t^2	
					μ	σ	μ	σ
FTSE	FTSE 100	United Kingdom	3687	1687	0.000	1.193	1.422	4.175
DAX	DAX	Germany	3721	1721	0.010	1.538	2.364	6.635
CAC	CAC 40	France	3740	1740	-0.008	1.481	2.194	5.655
AEX	AEX	Netherlands	3739	1739	-0.013	1.469	2.158	6.167
SMI	SMI	Switzerland	3676	1676	0.005	1.217	1.482	4.463
IBEX	IBEX 35	Spain	3705	1705	-0.002	1.500	2.250	5.813
STOXX	STOXX 50	Euro zone	3717	1717	-0.011	1.510	2.280	5.870
FTMIB	FTSE MIB	Italy	3702	1702	-0.018	1.533	2.349	6.148

Notes: This table provides descriptive statistics for the time-series of daily returns and daily squared returns from 1 January 2000 to 12 September 2014. μ and σ denote the mean and standard deviation, respectively. *T* is the total number of daily observations in the sample period. *N* is the number of variance forecasts generated for a particular index.

4. RESULTS

Table 2-4 compare the out-of-sample performance of the RRV based models with that of the RV based model. Table 2 compares the forecasting performance of various models using the MSE criterion. For each index, the models are ranked from one to five, with one indicating the best model and five indicating the worst model in terms of the MSE loss criterion. The Mean Rank metric is the average of these eight ranks. The Ranked Best (Worst) metric is the number of times a forecasting model is ranked as the best (worst) model. In most comparisons, the RRV estimators provide better out-of-sample performance than that of the RV estimator. The RV based model has the highest MSE for five out of eight sample indices, and it is never ranked as the best model. In terms of the Mean Rank metric, RV is the worst estimator with a mean rank of 4.5, whereas BVS is the best estimator with a mean rank of 1.875. The RK and TSRV are ranked as second and third best estimators, with a mean rank of 2.625 and 2.750 respectively. The comparison between the BV and BVS estimators indicate that there is a considerable gain in efficiency due to subsampling. With the exception of the AEX index, the BVS estimator always performs better than the BV estimator.

Table 3 compares the forecasting performance of various models using the QLIKE loss criterion. We can observe a similar pattern in the relative forecasting performance. The RRV estimators generally outperform the RV estimator. The RV estimator ranks as the worst estimator for seven out of eight sample indices. The BVS and RK are the best performing estimators with mean ranks of 2.125 and 2.375 respectively. The BVS estimator outperforms the BV estimator for six out of eight indices. As earlier, this indicates that subsampling improves the forecasting performance. Among the RRV estimators, the TSRV estimator performs the worst with a mean rank 3.167. However, with the exception of the CAC index, it always outperforms the RV estimator.

Table 2 Forecasting performance comparison using the MSE loss criterion

Index	RV	TSRV	BV	BVS	RK
FTSE	3.510	3.440	3.500	3.490	3.430
DAX	9.980	9.390	9.580	9.340	9.690
CAC	7.750	7.490	7.770	7.480	7.590
AEX	6.330	6.420	6.320	6.380	6.240
SMI	3.410	3.210	3.370	3.230	3.600
IBEX	7.240	7.200	7.150	7.080	7.210
STOXX	15.580	14.980	15.160	14.530	14.760
FTMIB	7.120	7.090	7.070	6.920	6.540
Mean Rank	4.500	2.750	3.250	1.875	2.625
Ranked Best	0	1	0	4	3
Ranked Worst	5	1	1	0	1

Notes: This table reports the MSE for the various forecasting models. Each row corresponds to a particular sample stock index, and the column headings indicate the realized variance estimator used in the Realized GARCH model.

Table 3 Forecasting performance comparison using the QLIKE loss criterion

Index	RV	TSRV	BV	BVS	RK
FTSE	0.863	0.858	0.861	0.859	0.853
GDAXI	1.392	1.391	1.389	1.388	1.390
CAC	1.505	1.510	1.503	1.505	1.506
AEX	1.320	1.254	1.257	1.255	1.253
SMI	0.941	0.939	0.931	0.928	0.934
IBEX	1.779	1.772	1.773	1.770	1.773
STOXX	1.509	1.497	1.488	1.504	1.471
FTMIB	1.614	1.612	1.613	1.602	1.605
Mean Rank	4.625	3.125	2.750	2.125	2.375
Ranked Best	0	0	1	4	3
Ranked Worst	7	1	0	0	0

Notes: This table reports the QLIKE for the various forecasting models. Each row corresponds to a particular sample stock index, and the column headings indicate the realized variance estimator used in the Realized GARCH model.

Table 4 compares various forecasting models using the BIAS criteria. Overall, the RV estimator performs worst with a mean rank of 4.125. Moreover, the RV based forecasts have the highest bias for five out of eight sample indices. The BVS, RK and TSRV estimators perform the best, with mean ranks of 2.125, 2.5 and 2.625 respectively. With the exception of the SMI index, in all comparisons the BVS based forecasts are less biased than the BV based forecasts.

Table 4 Forecasting performance comparison using the BIAS criterion

Index	RV	TSRV	BV	BVS	RK
FTSE	0.198	0.050	0.242	0.183	0.029
GDAXI	0.035	0.047	0.041	0.021	0.036
CAC	0.121	0.094	0.112	0.077	0.105
AEX	0.356	0.328	0.352	0.336	0.329
SMI	0.246	0.258	0.237	0.251	0.341
IBEX	0.416	0.385	0.397	0.366	0.416
STOXX	0.366	0.265	0.337	0.333	0.236
FTMIB	0.589	0.557	0.560	0.524	0.514
Mean Rank	4.125	2.625	3.625	2.125	2.500
Ranked Best	0	1	1	3	3
Ranked Worst	5	1	1	0	1

Notes: This table reports the BIAS for the various forecasting models. Each row corresponds to a particular sample stock index, and the column headings indicate the realized variance estimator used in the Realized GARCH model.

5. CONCLUSION

This article examines the benefits of using RRV estimators instead of the RV estimator, in the context of volatility forecasting. We find that RRV estimators improve upon the RV estimator in terms of the bias and efficiency criteria. Among the RRV estimators, the BVS estimator generally provides the best out-of-sample of performance. This results is consistent with Andersen et al. (2007), who found that filtering the jump component from the realized variance estimates provides a significant improvement in the volatility forecasts. Additionally, we find that subsampling improves the forecasting performance of the sparse-sampled BV estimator, regardless of the choice of the forecast evaluation criterion.

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