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The Volatility of Realized Volatility

Fulvio Corsi, Stefan Mittnik, Christian Pigorsch & Uta Pigorsch

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Abstract

In recent years, with the availability of high-frequency financial market data modeling realized volatility has become a new and innovative research direction. The construction of "observable" or realized volatility series from intra-day transaction data and the use of standard time-series techniques has lead to promising strategies for modeling and predicting (daily) volatility. In this article, we show that the residuals of commonly used time-series models for realized volatility and logarithmic realized variance exhibit non-Gaussianity and volatility clustering. We propose extensions to explicitly ... ing and forecast ... futures we show tha ... thmic realiz ... ance. Furth ... in density forecast

Keywor...
Realized quarticity Realized volatility

JEL Classification: C22 C51 C52 C53

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Notes

[1]We disregard the overnight trading of contracts at GLOBEX, the CME overnight trading platform, which started in 1994.

[2]The impact of market-microstructure effects on the realized-variance measures as well as possible data-adjustment and prefiltering procedures, allowing the full use of the tick-by-t ... 2002), Bandi and Russ ... and Corsi (2003), ...

[3]Simi ... ansaction price ...

Reporte ... ized variance ... or as defined in Eqs. (13)–(15), as well as the measures of the volatility of the logarithmic realized variance as defined in Eqs. (17)–(19). reports the Geweke-Porter-Hudak estimates of the fractional integration parameter.

[4]The Kolmogorov–Smirnov test rejects the null of Gaussianity (p-value=0.0087). Our results differ from those reported in Thomakos and Wang (2003), who also perform tests on Gaussianity but use a much shorter sample period.

[5]In fact, there exists a large number of different approaches to explain long memory. Historically, the first class of long-memory models has been the fractionally integrated process proposed by Granger and Joyeux (1980) and Hosking (1981) (for comprehensive surveys see Beran, 1994; Robinson, 2003). With another seminal article showing the link between long memory and the aggregation of an infinite number of stationary processes, Granger (1980) also started an alternative strand of literature, which tries to approximate long-memory dependence through a multicomponent approach, as in Andersen and Bollerslev (1997), Barndorff-Nielsen and Shephard (2001), Engle and Lee (1999), Gallant et al. (1999), Lux and Marchesi (1999), and Müller et al. (1997). A profoundly different view on the source of long memory is instead offered by, among others, Diebold and Inoue (2001), Gourieroux and Jasiak (2001), Granger and Hyung (2004), Granger and Teräsvirta (1999), and Mikosch and Starica (2004), who provide theoretical justification and Monte Carlo evidence that models with structural breaks and regime-shifting may exhibit spurious long memory. In addition, other approaches for reproducing long-memory dependence, such as the multifractals and cascade models of Calvet and Fisher (2002, 2004) and Mandelbrot et al. (1997), or the error duration model of Parke (1999), have been proposed (see also Banerjee and Urga, 2005; Davidson and Teräsvirta, 2002 for recent reviews on long-memory models).

[6]See, for example, Andersen et al. (2003), Koopman et al. (2005), Martens et al. (2004), Martens … and Wang (2003), a…

[7]Note th… xactly be inter… r, our defi… lso, when employi… fined by the square r… al results.

[8]As a consequence the logarithmic realized-variance components cannot be directly interpreted as the logarithm of the multiperiod realized variance.

[9]Agiakloglou et al. (1993) report poor small-sample properties of the Geweke–Porter–Hudak estimator.

[10]See Doornik and Ooms (2003) for a recent review on this topic.

The different HAR-model specifications are as follows: I is a standard HAR model with Gaussian innovations; II also includes GARCH effects; III is a standard HAR model with (standardized) NIG innovations; and IV corresponds to the HAR–GARCH model with (standardized) NIG innovations. The indices S and L denote the HAR models formulated for realized volatility and logarithmic realized variance, respectively. The numbers in parentheses are the standard errors. The AIC = − 2L + k, and BIC= − 2L + klog T, where L denotes the log likelihood, k the number of parameters in the model, and T is the number of observations.

[11]For brevity we do not present the corresponding figures here.

All entries report the root mean square error of parameter estimates for the different models. They are based on 1, 000 simulations from the HAR–GARCH–NIG model as given in Table 2. "Obs." denotes the number of simulated observations of each simulation run and "Model" corresponds to the different models: I is a standard HAR model with Gaussian innovations; II also includes GARCH effects; III is a standard HAR model with (standardized) NIG innovations; and IV corresponds to the HAR–GARCH model with (standardized) NIG innovations.

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[12]Note, … st for unbiase … ession coefficie …

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[13]Since the density forecasting performance is also evaluated in terms of realized volatility, the logarithmic scores of the logarithmic-realized-variance models are given by .

[14]Much less is known about the effects of model parsimony on the accuracy of density forecasts. A small simulation study comparing the point and density forecast accuracy of the pure Gaussian–HAR model and the HAR–NIG model, with the latter being the correct data generating process corroborate our empirical observation. In particular, we find strong superiority of the HAR–NIG model in density forecasting, but slightly less accurate point forecasts than those produced by the Gaussian–HAR model.