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Realized volatility models and alternative Value-at-Risk prediction strategies

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ABSTRACT

We assess the Value-at-Risk (VaR) forecasting performance of recently proposed realized volatility (RV) models combined with alternative parametric and semi-parametric quantile estimation methods. A benchmark inter-daily GJR-GARCH model is also employed. Based on four asset classes, i.e. equity, FOREX, fixed income and commodity, and a turbulent six year out-of-sample period (2007–2013), we find that statistical accuracy and regulatory compliance is essentially improved when we use quantile methods which account for the fat tails and the asymmetry of the innovations distribution. In particular, empirical analysis gives evidence in favor of the skewed student distribution and the Extreme Value Theory (EVT) method. Nonetheless, efficiency of VaR estimates, as defined by the minimization of Basel II capital requirements and its opportunity costs, is reassured only with the use of realized volatility models. Overall, empirical evidence support the use of an asymmetric HAR realized volatility model coupled with the EVT method since it produces statistically accurate VaR forecasts which comply with Basel II accuracy mandates and allows for more efficient capital allocations.

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1. Introduction

The recent 2007–2009 financial crisis demonstrated, if nothing else, that the financial institutions' risk management systems were not as adept as previously thought in tracking and anticipating the extreme price movements witnessed during that highly volatile period. Nearly all financial institutions recorded multiple consecutive exceptions, i.e. days in which the trading book losses exceeded the prescribed Value-at-Risk (VaR).[1] In several instances, the total number of exceptions during the previous trading year exceeded the threshold of ten violations which is the set regulatory maximum (Campel and Chen, 2008).[2] Consequently, much doubt was cast and many questions were raised about the reliability and accuracy of the implemented VaR models, systems and procedures.

However, the criticisms faced by the risk management departments can hardly be attributed to a lack of allocated resources or research efforts. VaR measurement and forecasting have been one of the most vigorously researched areas in quantitative risk management and financial econometrics. It has also enjoyed significant investments both in terms of capex and in human capital within banks and financial institutions. In this context, the evaluation of some recently proposed volatility models which make use of the informational content in high frequency data could reveal some attractive alternative VaR modeling specifications.

The foundations of modern risk management were laid with the seminal work of Engle (1982) who introduced the AutoRegressive Conditional Heteroscedasticity (ARCH) model for modeling the conditional heteroscedasticity in financial assets returns. Since then, a plethora of ARCH-type models have been proposed in the open literature (see Bollerslev, 2010 for a short description for almost all ARCH-type models) and most of them have been included in VaR studies. Giot and Laurent (2003a, 2003b) for example, showed that flexible ARCH specifications combined with fat tailed distributions can provide accurate VaR forecasts for a wide range of assets.

More recently, Andersen and Bollerslev (1998), Andersen et al. (2001a), Andersen et al. (2001b) and Barndorff-Nielsen and Shephard (2002) introduced and promoted the realized volatility as a non-parametric approach for measuring the unobserved volatility. In Andersen et al. (2003), the authors also suggested that standard time series techniques can be used in order to model the “observable” realized volatility. These concrete theoretical foundations coupled with the increased availability of high quality intraday data for a wider range of assets, fuelled the research interest on the use of high frequency data for measuring and forecasting the volatility of financial assets. Several authors demonstrated the superiority of realized volatility models over ARCH models for volatility forecasting (see Koopman et al., 2005; Martens, 2002; Martens et al., 2009 among others), while Giot and Laurent (2004) first utilized high frequency intraday data in a VaR forecasting context.

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[1] Value-at-Risk is the most common measure of downside market risk and is widely adopted by both the financial services industry and the regulators. It reflects an asset's market value loss not be exceeded over a specified holding period, with a specified confidence level (see also Section 4).

[2] A. Campel and X. L. Chen are the authors of a VaR survey article in the “Risk” magazine on July 2008.

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In Table 1, a concise literature review on the use of intraday data for VaR modeling is presented. Eleven out of thirteen studies therein perform a direct or indirect comparison between ARCH-type and realized volatility models (except for Clements et al., 2008; Louzis et al., 2013 who considered only realized volatility models). The findings are mixed as seven out of eleven studies give evidence in favor of the use of high frequency data, while the remaining four provide evidence in favor of ARCH-type models. Almost all of the researchers implement a fully parametric approach for the estimation of the VaR quantiles, i.e. they adopt a specific distributional assumption (e.g. the normal or the skewed student distribution) for the innovation process. The use of alternative assumptions is quite limited (see Kuester et al., 2006 for an excellent review of alternative VaR methods). Finally, the VaR models are almost invariably evaluated in terms of the statistical accuracy of their VaR forecasts (implementing Christoffersen's, 1998 tests for example) and less so by their efficiency with respect to specific regulatory provisions.

Against this background we contribute to this growing literature by complementing and extending previous studies on day ahead VaR forecasting for several aspects. First, this is the first study that empirically investigates the VaR forecasting performance of two classes of realized volatility models combined with three VaR methods: the parametric method using both the normal and the skewed student distributions, the semi-parametric filtered historical simulation (FHS) method and the conditional extreme value theory (EVT) method. The first class of realized volatility models includes the "traditional" time series modeling approach for the "observable" realized volatility employing a recent extension of the Heterogeneous Autoregressive (HAR) model (Corsi, 2009) proposed by Louzis et al. (2012). In the second class, we employ joint GARCH and realized volatility models implementing the recently proposed Realized GARCH model of Hansen et al. (2012). We also include the benchmark GJR-GARCH model of Glosten et al. (1993) implemented in related studies by Martens et al. (2009) and Fuertes and Olmo (2013).

Table 1
Literature review: Value at Risk and realized volatility.

Author(s)	Methodology and VaR evaluation	Data set	Main conclusions
Giot and Laurent (2004)	The RiskMetrics and the skewed student APARCH model are compared with a realized volatility (RV) ARFIMAX-RV model combined with a normal and a skewed student distribution. A two step approach was used to relate the RV dynamics with the returns process. Evaluation: Kupiec's (2005) test and the Dynamic Quantile (DQ) test of Engle and Manganelli (2004).	CAC 40 (1995–1999), SP 500 futures (1989–2000), YEN/USD and DEM/USD (1989–2001)	The RV model did not improve the daily VaR forecasting performance of the APARCH-skst model.
Beltratti and Morana (2005)	An ARFIMA-RV model, an ARFIMA model with a FIGARCH specification for the heteroskedastic errors and a GARCH model were used to generate multi-step VaR forecasts. Evaluation: Christoffersen's (1998) (un)conditional coverage test and Berkowitz (2001) density forecast tests.	YEN and DEM against USD (1986–1999)	The RV ARFIMA-FIGARCH model provided superior VaR forecasts.
Kruse (2006)	GARCH type, RV and stochastic volatility models were used to forecast VaR based on the Normal, GED, skst errors distributions, the Filtered Historical Simulation (FHS) and the EVT methods. Evaluation: (un)conditional coverage tests and the Firm Loss Function (FLF) (Sarma et al., 2003).	SP 500 futures index (the time period is not reported)	The RiskMetrics and the GARCH models were not outperformed by any other model.
Grané and Veiga (2007)	GARCH, EGARCH and GJR-GARCH were augmented with realized volatility as an explanatory variable. Evaluation: the Minimum Capital Risk Requirements (MCRR).	American Express, Coca-Cola, Walt Disney, Pfizer (1997–2007)	RV enhanced the capacity of the models to calculate accurate MCRR.
Angelidis and Degiannakis (2008)	A normal TARCH, a FIAPARCH-skst model and an ARFIMAX-RV model combined with a skst distribution (as in Giot and Laurent, (2004)) were used to forecast daily VaR. Evaluation: (un)conditional coverage tests.	CAC 40, DAX 30 (1995–2003), FTSE 100 (1998–2003).	The TARCH model was the overall best performing model.
Clements et al. (2008)	The authors used AR(5), MIDAS regressions and HAR models combined with normal, t-student (8 degrees of freedom) and the FHS method. Evaluation: A 'tick' or check function assessed with the Diebold and Mariano (1995) test.	AUD, CAD, EUR, GBP, YEN vs USD rates (1999–2003)	The HAR model provided superior forecasts for currencies with volatility shifts.
McMillan et al. (2008)	Intraday GARCH, Component GARCH and EGARCH models were compared with their daily counterparts and RV models (AR-structure) in volatility and VaR forecasting. Evaluation: Kupiec's (2005) and the DQ tests.	EUR against USD, GBP and YEN (2002–2003)	Intraday models provided improved performance wrt daily & RV models
Brownless and Gallo (2010)	RV, bipower RV, two scales RV, realized kernel as well as the daily range are modeled with a P-Spline Multiplicative Error Model. A t-student GARCH was also used. Evaluation: (un)conditional coverage tests, the DQ test and the probability deviation loss functions (Kuester et al., 2006).	3 NYSE stocks: Boeing, General Electric, Johnson and Johnson (2001–2006)	RV measures improved the VaR forecasts with respect to the GARCH model, but not so relative to the range.
Martens et al. (2009)	An AR(22), an ARFI, a HAR and a GJR-GARCH model were extended to incorporate level shifts, leverage effects, day-of the week seasonality and the effect of the macroeconomic announcements. Evaluation: (un)conditional coverage tests, the Quadratic Loss Function (QLF) (Lopez, 1999) and the Basel II Capital Requirements (CR).	SP 500 futures index (1994–2006)	All models failed the coverage tests. The RV models produce less volatile Rs and minimize the QLF.
Shao et al. (2009)	The Realized Range (RR) modeled with a Conditional Autoregressive Range (CARR) model (Chou, 2005) and combined with the skst distribution as in Giot and Laurent (2004). An ARFIMA-RV model, the RiskMetrics, t-student GARCH and the APARCH-skst models were also used. Evaluation: Kupiec's (2005) and the DQ test.	Shanghai Composite and Shenzhen Component Index (2005–2007)	The RV and RR models had similar performance and outperformed the daily ARCH-type models.
Watanabe (2012)	The Realized GARCH model with normal, student t and skewed student innovations is compared with an EGARCH model. Evaluation: Kupiec's (2005) test.	SP 500 stock index (1996–2009)	The Realized GARCH (using either realized volatility or realized kernel) outperforms the EGARCH model
Louzis et al. (2013)	Alternative realized volatility measures, daily range and implied volatility are coupled with Realized GARCH model and a skewed student distribution. Evaluation: Christoffersen's (1998) (un)conditional coverage test, QLF, Basel II Capital Requirements (CR), FLF.	SP 500 stock index (1997–2009)	RV measures immune to microstructure noise and jumps produce capital efficient VaR forecasts.
Fuertes and Olmo (2013)	Optimal combinations of individual (GJR-GARCH and ARFIMAX-RV) VAR models based on quantile regressions. Evaluation: Robust Wald-type conditional quintile encompassing test.	SP 500, Russell, Nasdaq, USDX, 10 yr T-Notes, Gold (1997–2011).	Evidence supports the use of RV in VaR forecasting

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