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Realizing smiles: Options pricing with realized volatility[☆]

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We develop a discrete-time stochastic volatility option pricing model exploiting the information contained in the Realized Volatility (RV), which is used as a proxy of the unobservable log-return volatility. We model the RV dynamics by a simple and effective long-memory process, whose parameters can be easily estimated using historical data. Assuming an exponentially affine stochastic discount factor, we obtain a fully analytic change of measure. An empirical analysis of Standard and Poor's 500 index options illustrates that our model outperforms competing time-varying and stochastic volatility option pricing models.

1. Introduction

It is well established that proper use of intraday price observations leads to precise and accurate measurement and forecast of the unobservable asset volatility. At the same time, volatility is the primary ingredient of every option pricing model. In this paper, combining both these aspects, we develop a new option pricing model that effectively incorporates the information contained in high-frequency data, as summarized by the Realized Volatility (RV) measure.[1]

The RV is an easy-to-compute nonparametric measure of the asset variability, and it is typically constructed from the intraday price movements. This allows the RV to change rapidly according to the market's movements. We show that such a reliable volatility measure yields accurate pricing of short-term options. Moreover, we show that our model is able to mimic the long-memory characterizing the volatility process,[2] leading also to

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[1] The idea of RV measures goes back to the seminal work of Merton (1980), which shows that the integrated variance of a Brownian motion can be approximated by the sum of a large number of intraday squared returns. This original intuition has been recently formalized and generalized by Andersen, Bollerslev, Diebold, and Labys (2001, 2003), Barndorff-Nielsen and Shephard (2001, 2002a, 2002b, 2005), and Comte and Renault (1998).

[2] See, e.g., Andersen, Bollerslev, Diebold, and Labys (2001, 2003) and Andersen, Bollerslev, Diebold, and Ebens (2001).

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accurate pricing of long-term options. Thus, both the fast-changing dynamics inherent in the RV and the simple long-memory structure allow our model to reproduce a realistic Implied Volatility (IV) term structure under different market conditions (e.g., different volatility regimes). The improvements on the pricing performances yielded by GARCH-type option pricing models, that rely on the volatility filtered solely from daily returns, are remarkable. Indeed, in terms of Root Mean Square Error on IV ($RMSE_{IV}$), the overall improvements on the extension of the Heston and Nandi (2000) GARCH recently proposed by Christoffersen, Jacobs, and Heston (2011) and the Component GARCH of Christoffersen, Jacobs, Ornthanalai, and Wang (2008) are 14% and 26%, respectively. Finally, the use of RV as a proxy for the unobservable volatility simplifies the estimation considerably: filtering procedures are no longer required, and the model can be estimated directly using the observed RV, as obtained from high-frequency data.

Surprisingly, to the best of our knowledge, little work has been devoted to combining RV literature with that on option pricing to construct RV option pricing models. Notable exceptions are the work of Stentoft (2008) and Christoffersen, Feunou, Jacobs, and Meddahi (2010). In Stentoft (2008), an Inverse Gaussian model of a 30-minute returns RV measure is applied to price options on some individual stocks. However, this work does not provide a formal change of measure for the RV process, since it only considers the case in which the risk-neutral and physical dynamics of RV are identical (i.e., when the volatility risk is not priced). In a concurrent paper, Christoffersen, Feunou, Jacobs, and Meddahi (2010) generalize the GARCH option pricing approach by extending the Heston and Nandi (2000) GARCH model to include RV measures. However, they focus mainly on the RV's contribution to short- and medium-term option pricing.

Indeed, so far, only marginal attention has been devoted to the long-term part of the IV surface, where the persistence of the volatility process plays a crucial role. Two exceptions are Comte, Coutin, and Renault (2012), who employ a fractional stochastic volatility model, and Carr and Wu (2003), who apply alpha-stable processes to slow down the central limit theorem and obtain negative skewness and excess kurtosis for long-maturity options.

Moreover, a growing strand of literature advocates the presence of a multi-components volatility structure. For instance, Li and Zhang (2010), using nonlinear principal components analysis, find that two factors are needed to explain the variation in the IV surface. Christoffersen, Jacobs, Ornthanalai, and Wang (2008) employ a modified version of the two-factor component GARCH in Engle and Lee (1999) for options pricing in discrete-time, while Bates (2000) proposes a two-factor jump-diffusion model to fit the implicit distribution in futures options. In addition, Adrian and Rosenberg (2008) show that a multi-components volatility model substantially improves the cross-sectional pricing of volatility risk.

In this paper, we combine all these streams of literature and we introduce a new class of models that rely on the RV, featuring long-memory, multi-components structure, and analytical tractability. We model the conditional mean of the volatility process by the Heterogeneous Autoregressive (HAR) multi-components model (see Corsi, 2009). The HAR specification can be considered as an acceptable compromise between parameter parsimony and multi-components specification. Despite the fact that the HAR model does not formally belong to the class of long-memory processes, it is able to produce the same memory persistence observed in financial data. Moreover, its multi-component specification is important in providing the necessary smoothing of the otherwise too noisy (for option pricing purposes) RV measure. For these reasons the HAR has become one of the standard models for describing and forecasting the dynamics of RV.[3] The HAR model provides only the first conditional moment of the RV. In order to specify the whole transition density and complete the probabilistic description of the RV process, we assume that the conditional distribution of the HAR is a noncentral gamma. The noncentral gamma is the same transition density implied by the Cox, Ingersoll, and Ross (1985) (CIR) model, widely applied to describe the dynamics of the volatility process. The resulting model belongs to the family of autoregressive gamma processes, a class of discrete-time affine processes introduced by Gourieroux and Jasiak (2006). Due to this combination, our new model features both long-memory and affine structure. The latter feature is particularly attractive for option pricing purposes since, as with the affine processes, it leads to a fully analytic conditional Laplace transform. In order to capture the asymmetric shape of the IV smile for S&P 500 options, we include the leverage effect. The resulting model is extremely flexible for option pricing purposes. Moreover, considering restricted versions of this general model, we are able to disentangle the contribution of the different model ingredients (i.e., long-memory and leverage) to the overall pricing performance.

The paper is organized as follows. Section 2 defines our model for log-return and RV under both the historical and risk-neutral probability measures. Section 3 describes the estimation of the model, and then analyses its dynamic features. In Section 4, we present the option pricing performances, compare them with option pricing benchmarks, and perform several robustness checks. Finally, Section 5 summarizes the results.

2. The model

2.1. Dynamics under physical probability

2.1.1. Log-return dynamics

A well-established result in financial econometrics literature is that the marginal distribution of daily log-return

[3] Andersen, Bollerslev, and Diebold (2007a), Aït-Sahalia and Mancini (2008), McAleer and Medeiros (2008), Busch, Christensen, and Nielsen (2011), and Andersen, Bollerslev, and Huang (2011) use this model (and its extensions) to forecast the RV; Clements, Galvão, and Kim (2008) and Maheu and McCurdy (2011) implement it for risk management; Bollerslev, Tauchen, and Zhou (2009) use it to analyze the risk-return trade-off; Andersen and Benzoni (2010) employ it to test whether bond yields span volatility risk; and Bollerslev and Todorov (2011) adopt it for modeling the expected Integrated Volatility to compute the Investor Fear Index.