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Forecasting realized volatility in electricity markets using logistic smooth transition heterogeneous autoregressive models

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ABSTRACT

We apply the non-parametric realized volatility technique and the associated jump detection test to measure volatility and jumps in electricity prices. Then, we propose a group of logistic smooth transition heterogeneous autoregressive (LSTHAR) models of realized volatility. The models can simultaneously approximate long memory behavior and describe sign and size asymmetries. They differ in the underlying heterogeneous autoregressive structure and the transition variable specification. The out-of-sample forecast accuracy of the LSTHAR models is evaluated through the Diebold–Mariano test and the superior predictive ability test, in terms of the mean square error and the mean absolute error. Using high-frequency prices from the Australian New South Wales (NSW) electricity market as empirical data, we draw the following conclusions. 1) Introducing the logistic smooth transition structure with appropriate transition variable specification to the heterogeneous autoregressive models improves volatility forecasts. 2) Overall, the LSTHAR model that uses the sum of Beta function weighted past returns as the transition variable and includes past daily jumps as a predictor is the superior model for predicting volatility in the NSW market. This model significantly outperforms the others.

1. Introduction

In recent years, electricity markets in many countries have been deregulated to introduce competition in supply and demand activities. The supply and demand activities force the market to reach an equilibrium price so that trading can occur. However, due to unexpected weather conditions and social/economic activities, the demand of electricity exhibits seasonal fluctuations as well as sudden, dramatic shocks. The supply of electricity also fluctuates as a result of plant outages. Furthermore, the fact that electricity cannot be stored prevents the use of inventory to smooth out supply and demand shocks. Accordingly, electricity prices have become much more volatile, with abrupt jumps that can be several orders of magnitude greater than the mean. Therefore, the ability to accurately forecast electricity price volatility is crucial for policy makers and for anyone who participates in the competitive electricity markets.

Early research uses the generalized autoregressive conditional heteroskedastic (GARCH) model (Bollerslev, 1986) and its various extensions to model electricity price volatility.[1] However, jumps are generally not taken into consideration with these models, as they would be difficult to identify.

Recent developments in econometric literature have enabled the non-parametric estimation of price volatility and jumps. First, the realized volatility (RV) (Andersen and Bollerslev, 1998), which is constructed by aggregating squared intraday returns estimates total price variation, making volatility "observable" for the first time.[2] The realized bipower variation (BPV) (Barndorff-Nielsen and Shephard, 2004) that is constructed from the summation of appropriately scaled cross-products of adjacent absolute intraday returns is a robust estimate of the non-jump component of volatility. Tests for statistically significant jumps can be constructed using the statistics proposed by Huang and Tauchen (2005). Inspired by the heterogeneous market hypothesis (Müller et al., 1993) and the HARCH model (Müller et al., 1997), Corsi (2009) proposes the heterogeneous autoregressive model of realized volatility (HAR-RV). The model parameterizes realized volatility as a linear function of lagged realized volatilities over different investment horizons and reproduces its long memory property. Andersen et al. (2007) further propose the HAR-RV-J model and the HAR-RV-CJ model, respectively. The former uses past daily jumps, along with the lagged realized volatilities, as predictors of volatility. The latter separates the contributions to volatility forecasting of jump and non-jump components.

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[1] For a complete review of the GARCH specifications that have been explored in the electricity price volatility modeling literature, see the papers by Hickey et al. (2012) and Liu and Shi (2013). These two papers also conduct comprehensive forecast performance comparisons among various GARCH specifications.

[2] Footnote 10 in Chan et al. (2008) points out that since electricity is not storable, there is no such thing as a "return" in the traditional sense. However, the word "return" is still used to represent log price difference.

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These three HAR models achieve superior fit and forecast performance compared to the ARCH/GARCH models; thus, they have been widely employed and extended in modeling financial return volatility.[3]

For electricity price data, Chan et al. (2008) apply the HAR-RV model and the HAR-RV-CJ model to forecast the realized volatility of spot prices in five Australian wholesale electricity markets. Haugom et al. (2011) apply the HAR-RV model and the HAR-RV-CJ model with various market measures as predictors to forecast realized volatility in the Nord Pool electricity forward market and discover forecast improvements from the inclusion of exogenous effects. Haugom and Ullrich (2012) propose the HAR-RV-F and HAR-RV-CJ-F models by including forward realized volatility as a predictor and improve spot price volatility forecasts in the Pennsylvania–New Jersey–Maryland wholesale electricity market. These studies utilize the HAR structure to characterize the long memory property of realized volatility, and introduce additional predictors under the guidance of financial theories for improved forecast performance. It is also worth mentioning that the latter two studies confirm the value of considering jumps in forecasting electricity price volatility.

On the other hand, a separate line of literature has provided evidence of the presence of asymmetric volatility dynamics; for examples, see Hadsell et al. (2004), Bowden and Payne (2008), Knittel and Roberts (2005), Hickey et al. (2012), and Liu and Shi (2013), among others. It is empirically confirmed that positive shocks increase electricity price volatility more than negative shocks, a condition known as the inverse leverage effect. The aforementioned studies use the TARCH, EGARCH, and APARCH models to capture the asymmetric response to positive and negative shocks, which all assume that the volatility response to price shocks does not depend on the current volatility level. However, as noted by Anderson et al. (1999), the volatility can "response more strongly to news which strikes when the market is nervous and volatility is already high, than when such news reaches a calm and quiet market". Therefore, the current models that imply a single news impact curve are too restrictive. Further, these latent volatility models do not consider the impacts of jumps, and they are unable to describe the long memory property.

To describe both the long memory property and the inverse leverage effect simultaneously, as well as allow the asymmetric news impact curve to change shape with the variance in volatility, we propose a group of logistic smooth transition heterogeneous autoregressive (LSTHAR) models in this research. They are inspired by McAleer and Medeiros (2008), who combine ingredients from the HAR-RV model and the logistic smooth transition autoregressive models (Teräsvirta, 1994). The underlying heterogeneous autoregressive structure ensures that the long memory property is reproduced. Sign and size asymmetries are captured by setting the transition variable to a function of past returns.[4] Since incorporating jumps improves the forecast accuracy of electricity price volatility, we not only use the HAR-RV model as the underlying structure, but also use the HAR-RV-J and HAR-RV-CJ models, respectively. The in-sample fit and out-of-sample forecast performance of these LSTHAR models are then empirically evaluated using high frequency spot prices from the Australian New South Wales electricity market. This is the basis upon which we provide volatility modeling suggestions.

We make several contributions. First, this is the first paper to introduce the logistic smooth transition structure in modeling the realized volatility of electricity prices. We show that introducing the logistic smooth transition structure with appropriate transition variable specification to the heterogeneous autoregressive models improves volatility forecasts in the NSW electricity market.

Second, we consider a large variety of new and existing LSTHAR models. Specifically, we not only use the HAR-RV model as the underlying structure (McAleer and Medeiros, 2008), but we also use the HAR-RV-J and HAR-RV-CJ models. Thus, we can explore the benefits of incorporating jumps into the volatility model. Furthermore, besides using past daily, weekly, and monthly returns as transition variables (McAleer and Medeiros, 2008), we propose the use of a linear combination of weighted past returns as a transition variable, with the Beta function (Ghysels et al., 2006) as the weighting scheme. Such design offers a richer variety of transition variable choices while only incurring two more parameters to estimate. Empirical results show that the LSTHAR model with the sum of Beta function weighted past returns as the transition variable and the HAR-RV-J model as the underlying structure is the superior volatility model in the NSW market, significantly outperforming the others.

Finally, we not only use the pairwise Diebold–Mariano (DM) test (Diebold and Mariano, 1995) to evaluate the value of introducing the logistic smooth transition structure in terms of volatility forecast accuracy, but we also use the superior predictive ability (SPA) test of Hansen (2005). The SPA test can provide robust comparison of the forecasts of multiple models. Therefore, it is able to suggest the most appropriate transition variable specification for each underlying HAR structure, as well as the overall best LSTHAR model.

The remainder of this paper is organized as follows. Section 2 reviews the calculation of realized volatility and jump detection. Section 3 introduces the HAR models and the LSTHAR models. Section 4 describes the data and provides descriptive statistics. Section 5 describes the forecast comparison methods and presents the comparison results. Section 6 contains concluding remarks.

2. Realized volatility and jump detection

Assume that the logarithmic price p_t of a given asset follows the following continuous-time jump-diffusion process:

$$dp_t = \mu_t dt + \sigma_t dw_t + k_t dq_t, \tag{1}$$

where μ_t is the drift, σ_t is the instantaneous volatility, w_t is a standard Brownian motion, q_t is a counting process with intensity λ_t, and k_t is the size of the corresponding discrete jumps in the logarithmic price process.

The volatility of the price process over day t is measured by the quadratic variation:

$$QV_t = \int_{t-1}^{t} {\sigma_s}^2 ds + \sum\nolimits_{t-1<s\le t} {k_s}^2. \tag{2}$$

The first integrated variance term represents the contribution from the continuous sample path, while $\sum_{t-1<s\le t} {k_s}^2$ accounts for the contribution from the jumps.

Suppose that the price is observed at discrete times $j = 1,2,\ldots, M$ within each day $t = 1,2,\ldots$, and let $r_{t,j} = p_{t,j} - p_{t,j-1}$ be the jth intraday return of day t. The realized volatility for day t is defined as:

$$RV_t = \sum\nolimits_{j=1}^{M} r_{t,j}^2. \tag{3}$$

The theory of quadratic variation indicates that the realized volatility converges uniformly in probability to the quadratic variation as the sampling frequency increases, that is: $RV_t \to QV_t$ for $M \to \infty$.[5]

[3] For extensions of the HAR models, see the papers by McAleer and Medeiros (2008), Bollerslev et al. (2009), Andersen et al. (2011), Louzis et al. (2012), Corsi and Renò (2012), Huang et al. (2013), and Qu and Ji (2014), among others.

[4] Logistic smooth transition function is defined as: $G(z_t, \gamma, c) = 1/(1 + e^{-\gamma(z_t - c)})$, where z_t is the transition variable.

[5] In reality, market microstructure noise will eventually render the realized volatility inconsistent as a measure of the quadratic variation as the sampling frequency increases. Five-minute sampling frequency is often chosen for active financial markets as a bias-variance tradeoff. As for the NSW electricity market, we only have half-hourly prices. This sampling frequency is relatively low; thus, the impact of market microstructure noise is well controlled.