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Modeling the daily electricity price volatility with realized measures[☆]

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ABSTRACT

We propose using Realized GARCH-type models to estimate the daily price volatility in the EPEX power markets. The model specifications extract the volatility-related information from realized measures, which improves the in-sample fit of the data. More importantly, evidence on the out-of-sample predictability reinforces the value of the specifications, as the forecast quality is improved over the benchmark EGARCH model under eight conventional criteria. In particular, we show that the benefit of including intraday range as a realized measure is more substantial than realized variance. All the key findings are robust under rolling-window and recursive estimation schemes, Gaussian and skewed *t*-distribution assumptions on the innovation process, and alternative specifications on the predictable price component.

1. Introduction

Reliably forecasting asset price volatility is rewarding per se as it has vast implications in portfolio management, asset pricing, risk management, policy making and even derivatives trading (Poon and Granger, 2003). Besides this general interest that applies to all financial markets there is a particular interest in modeling price volatility in the electricity market, since reliable volatility estimates will significantly improve the interval predictions of the spot price given the unique structure presented in conditional mean and variance of the electricity prices (García-Martos et al., 2011). Despite its relevance, the bulk of the literature has focused on modeling the first moment of the electricity prices, leaving behind the needs of estimating the price volatility in the electricity market as a separate, not fully resolved task.[1] This makes our work crucial as we address this issue directly by providing a simple, yet highly effective approach to more accurately forecast the daily price variation in the EPEX spot market.

The deregulated electricity markets have led to huge price risks for market participants, which are not known from other commodity or financial markets (Seifert and Uhrig-Homburg, 2007). Electricity is a non-storable commodity, of which the demand and supply need to be balanced on a knife-edge in real time (Bierbrauer et al., 2007). Stylized facts of daily (and intraday) electricity spot prices include at least the following: multiple seasonality, a high degree of mean reversion, large volatility and high volatility persistence, frequent price jumps and short-lived spikes, an inverse leverage effect, stationarity at both the price and the squared price level, and (possibly) long memory at the price level (Bierbrauer et al., 2007; Byström, 2005; Crespo Cuaresma et al., 2004; Haldrup and Nielsen, 2006; Higgs and Worthington, 2008; Huisman et al., 2007; Knittel and Roberts, 2005; Seifert and Uhrig-Homburg, 2007; Weron and Misiorek, 2008).[2]

Given the enormous market risk and the complexity of the price process mentioned above, it is important yet challenging to model the price dynamics in the electricity markets. Various approaches have been used

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[1] Recent efforts of modeling the electricity price volatility include Chan et al. (2008), Ullrich (2012), Haugom et al. (2010), and Hickey et al. (2012).

[2] As we will show in Section 2, extreme price spikes occasionally result in even negative electricity prices in our sample period, for negative electricity prices see also Fanone et al. (2013).

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in the empirical literature to (partially) address this issue: neural networks, wavelets, structural equations, and time series techniques, just to name a few. In practice, time series techniques remain the most widely used method for short-term spot price forecasting (Conejo et al., 2005; Hickey et al., 2012; Weron and Misiorek, 2008; among others). Earlier publications such as Pilipovic (1998) and Lucia and Schwartz (2002) focus exclusively on the mean-reverting and seasonal pattern by approximating the price process by AR processes. Other specifications such as ARMA or ARIMA models are also used in empirical work (Bowden and Payne, 2008). The failure of ARMA-type models to account for frequently observed extreme jumps and spikes, which characterize the power market, has triggered various modifications including the use of spike pre-processed models, p-AR, or threshold autoregressive models, TAR (see e.g. Weron and Misiorek, 2008). Furthermore, alternative estimation methods for modeling the jump component directly have recently been suggested: One competing method is the jump diffusion model, which adds a mean-reverting jump-component to the mean process (see Bierbrauer et al., 2007; Clewlow and Strickland, 2000; Deng, 2000; Knittel and Roberts, 2005; Seifert and Uhrig-Homburg, 2007; among others). Another popular approach is the Markov regime-switching model with 2 regimes (normal and jump regimes) or 3 regimes (normal, jump and reverse jump regimes) as applied in Huisman and Mahieu (2003) and Bierbrauer et al. (2007). A few extensions of the regime-switching model have been proposed in the literature to incorporate more characteristics of the empirical data (De Jong and Huisman, 2002; Haldrup and Nielsen, 2006). For example, Haldrup and Nielsen (2006) use a Markov switching fractional integration model to account for the long memory in the price series in each separate regime. Recently a number of studies also stressed the potential gains in forecasting accuracy by incorporating exogenous variables, such as temperature forecasts or market fundamentals, into the forecasting model (e.g. Karakatsani and Bunn, 2008; Weron and Misiorek, 2008). Summing up, the vast majority of the empirical literature has focused on modeling and forecasting the level of the electricity prices.

Explicitly modeling the volatility process of electricity prices for daily or higher frequencies has also gained much attention by researchers, a flouring field in the recent empirical literature. A number of empirical works apply GARCH-type models including Bollerslev's (1986) GARCH, Nelson's (1991) EGARCH and EGARCH-M, Engle and Lee's (1999) CGARCH, and Ding et al. (1993) APARCH to model the volatility structure of *hourly* prices of the power markets (Bowden and Payne, 2008; Hickey et al., 2012; Higgs and Worthington, 2005; Knittel and Roberts, 2005; Liu and Shi, 2013). Within this class of models it seems that the ability to capture both, the volatility persistence and the inverse leverage effect present in the power markets, makes the EGARCH model the superior specification (Bowden and Payne, 2008; Hickey et al., 2012). Another related line of research has focused on estimating the *daily* realized volatility and jump occurrence with realized measures constructed from high frequency data. Chan et al. (2008) applies the quadratic variation theory to disentangle the realized volatility into a continuous component and a jump component for the Australian power markets and find prevalent jumps. This result is further confirmed by Ullrich (2012) who refines the jump detection technique to account for the immediate price reversals following jumps observed in the electricity price series. More interestingly, Chan et al. (2008) employ an augmented HAR-type model with two realized measures (the continuous and the jump component) to estimate the one-day ahead price volatility. However, there is no strong evidence in their work that the HAR-type model outperforms the EGARCH model, which contradicts the findings by Haugom et al. (2010).[3] The inconclusive results drawn from the literature, coupled with relatively few published works on this topic, render more in-depth empirical analysis on the price volatility in the electricity markets (see Hickey et al., 2012 for similar notions). Our work clearly contributes to this line of research.

This paper is closely related to Chan et al. (2008), Ullrich (2012), and Haugom et al. (2010) as we also attempt to extract volatility signals from multiple realized measures such as realized variance and incorporate these realized measures into the volatility model to enhance the forecast quality.

However, we substantially differ from these works. First, we propose a new approach in modeling the one-day ahead electricity price volatility by applying two recently suggested Realized GARCH-type models (Hansen and Huang, 2012; Hansen et al., 2012) to the electricity market. One important feature of Realized GARCH-type models is that both the squared return and a realized volatility measure are employed in the variance equation to form the expectation about the next period's volatility. The advantage of using multiple volatility signals instead of one signal is straightforward: The Realized GARCH-type models are 'fast' at catching up the current level of the conditional variance, which is more suitable for the electricity market with frequent price spikes. Another key feature of the Realized GARCH-type models is that it augments the naïve GARCH-X models with a measurement equation, which estimates the joint dependence between the ex post realized measures and the ex ante conditional variance. The inclusion of the measurement equation implies a very parsimonious, short memory, ARMA structure for the conditional variance and the realized measure, which well fits the fact that most of the price jumps and spikes are short-lived in the power market. In contrast, the HAR model (and long memory model in general) implies a fairly 'slow' decay rate of the volatility process due to the long-lasting influence of lagged volatility shocks (e.g. the jump occurred one week/month ago). It is counterintuitive to assume a price jump that occurred one week ago would still have a huge impact on the current and future conditional volatility in the electricity market. As we show later in the empirical section, the Realized GARCH-type models are more suitable for the electricity market where daily volatility moves rapidly.

Second, to the best of our knowledge, we are the first to use the intraday range as a valid volatility signal to estimate the daily price volatility in the power market. The benefits of using range-based volatility measure are well established in the financial literature and there is a large amount of financial literature devoted to the properties of range-based measures (see Alizadeh et al., 2002; Brandt and Jones, 2006; Garman and Klass, 1980; Parkinson, 1980; Rogers and Satchell, 1991; Rogers et al., 1994; Yang and Zhang, 2000). Given the unique microstructure of the electricity market, we take no position as to which range-based measure is the better proxy, but employ the squared intraday high-minus-low measure as a volatility signal, whose efficiency is demonstrated in the application by Hansen and Huang (2012). Our evidence is compelling: Under both the rolling-window and the recursive estimation scheme the use of our intraday range as the realized measure in the Realized GARCH-type models increases the out-of-sample forecasting ability more than the use of realized variance. We attribute this to the facts that 1). realized variance in the context of electricity market can (only) be built from hourly (or half-hourly) data, a sampling frequency which makes it virtually indistinguishable from intraday range.[4] 2). the range-based measures have certain appeals such as robustness against microstructure noise bias (see Louzis et al., 2013; among others), which results in higher "signal-to-noise" ratio as is confirmed in our estimation results.

[3] In principle, the inclusion of realized measures in the volatility model should lead to increased forecast quality as more volatility-related information can be extracted from these realized measures. However, volatility forecasts are sensitive to the specification of the volatility model, which could be one of the possible explanations for the inability of HAR model to outperform EGARCH in the Australian electricity markets.

[4] It is known in the financial literature, the accuracy of intraday range is equivalent to realized variance sampling at 2 to 4 h. In stock or FX markets, realized variance can be constructed from 5-min or even finer frequency, which makes it a superior volatility measure over intraday range. This, however, is not the case in the electricity market.