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# Forecasting spikes in electricity return innovations

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ABSTRACT

This paper evaluates the accuracy of several hundred one-day-ahead value at risk (VaR) forecasts for predicting Australian electricity returns. We propose a class of observation-driven time series models referred to as asymmetric exponential generalised autoregressive score (AEGAS) models. The mechanism to update the parameters over time is provided by the scaled score of the likelihood function in the AEGAS model. Based on this new approach, the results provide a unified and consistent framework for introducing time-varying parameters in a wide class of non-linear models. The Australian energy markets is known as one of the most volatile and, when compared to some well-known models in the recent literature as benchmarks the fitting and forecasting results demonstrate the superior performance and considerable flexibility of proposed model for electricity markets.



## 1. Introduction

In this paper we examine the distributional properties of electricity returns in Australia. The Australian electricity market is one of the most volatile energy markets in the world, [58]. It is not unusual to observe annualised volatilities of more than 1000% on daily spot prices. Additionally, spot prices exhibit positive price spikes. In contrast to the jumps observed in the financial markets, spot price spikes are normally quite short-lived, and as soon as the weather phenomenon or outage is over, prices fall back to a normal level. These are both intriguing and challenging from the statistical and risk-management points of view.

Trading in electricity markets is challenging because spot prices are highly volatile and exhibit occasional extreme price movements of magnitudes rarely seen in markets for traditional financial assets (cf. [14,44,52]). These extreme movements are attributable to several distinctive features of electricity markets: (1) electricity cannot be stored effectively through time and space [1]; and (2) electricity prices have inelastic demand curves and kinked supply curves ([16,67]).

As a result, energy industry participants often self-impose trading limits to prevent extreme price fluctuations from adversely affecting firm profitability. Indeed the operation of the entire industry require optimal trading limits to allocate capital to cover potential losses should the trading limits be violated. Obviously, over-capitalisation implies idle capital and compromises profitability. On the other hand, under-capitalisation may cause financial distress should the firm be unable to honour its trading contracts. From a trader's point of view, it is important to prevent such extreme price fluctuations from affecting their firm's profitability. As evidence in this concern, risk management measures need to be at hand in order to prepare for extreme events, whether defining trading limits of operation or estimating savings requirements on a given period. One of the most common of these measures is the Value at Risk (VaR), which is frequently used to establish trading limits, estimating the amount that a firm may lose in a certain horizon given a statistical probability.

The above definition involves two quantitative factors: the horizon and the given confidence level. In the early stage, a certain amount of past returns were assumed to follow either some empirical or normal distributions, from which tail quantiles are computed for VaR forecasting. Later, Gaussian mixtures and

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[1] This issue has been particularly problematic in South Australia, where over 55% of the electricity generation is from renewable sources ([63]). Consequently, the SA government has commissioned Tesla to provide a 100 MW/129 MWh Powerpack system to be paired with global renewable energy provider Neoens Hornsdale Wind Farm near Jamestown, South Australia. Tesla was awarded the entire energy storage system component of the project (cf. [69]).

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Students *t*-distributions were also considered to deal with high excessive kurtosis of financial time series [53]. Although convenient, all the above-mentioned methods did not gain much popularity in practice since they failed to capture the prominent characteristics of financial time series data such as dependence among data and volatility clustering (cf. [65]). Accordingly, practitioners have desired to develop more efficient VaR forecasting methodologies.

Generalised autoregressive conditional heteroskedastic (GARCH) models, proposed by Ref. [9], have long been popular due to their capability to effectively capture high excessive kurtosis, dependence, and volatility clustering. Suitable surveys of GARCH modelling in the spot electricity markets may be found in Refs. [19,36,50]. GARCH models are often combined with autoregressive (AR) models to provide a better fit to financial time series, and conventionally, are assumed to have Gaussian innovations; such GARCH models are referred to as normal AR–GARCH models. These models seemingly outperform conventional normal GARCH models in terms of VaR forecasts (cf. [3,48]).

The main contribution of this paper is to apply a framework for time-varying parameters which is based on the score function of the predictive model density at time *t*. We will argue that the score function is an effective choice for introducing a driving mechanism for time-varying parameters, which in turn provides us with a more accurate estimates of VaR. We refer to our observation-driven model based on the score function as the (asymmetric) exponential generalized autoregressive score or AEGAS model, which is a variation of the generalised autoregressive score (GAS) model of [26]. The GAS class of models has the advantages of other observation-driven models. Likelihood evaluation is straightforward. Since the AEGAS model is based on the score, it exploits the complete density structure rather than means and higher moments only. It differentiates the AEGAS model from other observation-driven models in the literature, such as the generalized autoregressive moving average models of [6] and the vector multiplicative error models of [23].

Due to the stylised features of electricity returns, we only use (skewed) Student-*t* for the distribution of innovations. This class of GAS models was also discussed in Ref. [46], as the generalised form of GARCH models with Beta distribution. The authors also considered the logarithmic form of the volatility process, which they termed, Beta-t-EGARCH, as a generalised form of EGARCH models. In principle, Beta-t-EGARCH is the same model as EGAS, except for some minor specifications, which we discuss in Section 4. Throughout this paper, we will refer to the model as 'asymmetric', whenever the skewed Student-*t* fits the innovation process better than the Student-*t* distribution. We adopt the skewing method proposed by Ref. [39], for the clarity and convenience in presentation.

While it is important to have a well-specified model that describes the data, most of the time we are interested in utilising the model in predictions. For this reason, we conduct an out-of-sample evaluation of the proposed models. A comparison of volatility models should therefore include alternatives that account for empirical features such as jumps and fat-tails of electricity returns. Although [10], includes more than 100 GARCH specifications in his glossary, it is necessary to be selective in comparing these models. In addition, some models are special cases of others. There are three main time-series approaches in electricity modelling, namely, (1) univariate conditional volatility models [30], (2) multi-variate conditional volatility models [49], and (3) extreme value (EV) conditional volatility models [13,59]. The model proposed in this paper, AEGAS, falls within the first group, but we will show that it outperforms every other model.

A crucial issue that arises in this context is how to evaluate the performance of a VaR model. According to [42], when several risk forecasts are available it is desirable to have formal testing procedures for comparison. These do not necessarily require knowledge of the underlying model, or if the model is known, do not restrict attention to a specific estimation procedure [55]. pioneered an approach to detect systematic errors of models in predicting one-step-ahead VaR, which he termed *violations* [22]. points out that the problem of determining the accuracy of a VaR model can be reduced to the problem of determining whether the sequence of violations satisfies two properties; namely, *Unconditional Coverage Property* and the *Independence Property*. When both hypotheses are simultaneously valid, VaR forecasts are said to have a correct *conditional coverage*, and the VaR violation process is a martingale difference.

We evaluate the forecasting performance of our model and compare it with the set of competing models, through by conducting the Kupiec test of [55] and the Dynamic Quantile test of [27,33]. We hasten to add that the sort of omnibus backtesting procedures suggested here are the statistical diagnostic tests carried out on various aspects of the risk model in the model estimation stage (cf. [20]), we avoided experimenting with very recent developments in the back-testing literature.

The remainder of this paper is structured as follows: Section 2 briefly presents the Australian power market data set studied here. Section 3 provides a discussion on the methods used to model the drift of the returns time-series, as well as to capture the periodicity in the data. In Section 4, the theoretical framework and the model setting are described at length. Section 5 provides the definition of VaR and entails the back-testing procedures used in the paper. A comprehensive discussion of the empirical results is provided in Section 6. Section 7 concludes the paper.

## 2. Data description

In this study we use daily spot prices from the five state electricity markets in Australia: New South Wales (NSW), Queensland (Qld), South Australia (SA), Tasmania (Tas.) and Victoria (Vic.) For each market the sample of 1823 daily observations covers the time period from January 1, 2011 to December 30, 2015. In a similar manner to [47], all data is obtained from the National Electricity Market (NEM) Management Company, originally on a half-hourly basis representing 48 trading intervals in each 24-h period. A series of daily arithmetic means is calculated from the 48 trading interval data, from which we calculate the daily logarithmic return.

By way of comparison [35], employ daily spot prices in their respective analyses of the western United States, United Kingdom, Scandinavian and Australian electricity markets. Importantly, the use of daily prices may lead to the loss of at least some information impounded in the more frequent trading interval data. The Australian NEM is considered as the most volatile market featuring the largest and most frequent number of price spikes. This can be attributed to two reasons:

1. Unlike other markets, the Australian spot electricity market is not a day-ahead market but electricity is traded in a constrained real time spot market where prices are set each 5 min by Australian energy market operator. Therefore, generators submit offers every 5 min. The final price is determined every half-hour for each of the regions as an average over the 5-min spot prices for each trading interval [1]. This places balancing demand and supply at a knife-edge as very small changes in amount of electricity generated or change in demand can catapult into large changes in electricity prices (aka *jumps* or *spikes*).