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# A Stochastic Latent Moment Model for Electricity Price Formation

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## Abstract

The wide range of models needed to support the various short-term operations for electricity generation demonstrates the importance of accurate specifications for the uncertainty in market prices. This is becoming increasingly challenging, since electricity hourly price densities exhibit a variety of shapes, with their characteristic features changing substantially within the day and over time, and the influx of renewable power, wind and solar in particular, has amplified these effects. A general-purpose, analytically tractable representation of the stochastic price formation process would have considerable value for operations control and trading, but existing empirical approaches or the application of standard density functions are unsatisfactory. We develop a general four parameter stochastic model for hourly prices, in which the four moments of the density function are dynamically estimated as latent state variables and furthermore modelled as functions of several plausible exogenous drivers. This provides a transparent and credible model that is sufficiently flexible to capture the shape-shifting effects, particularly with respect to the wind and solar output variations causing dynamic switches in the upside and downside risks. Extensive testing on German wholesale price data, benchmarked against quantile regression and other models in out-of-sample backtesting, validated the approach and its analytical appeal.

*Keywords:* Electricity Prices, Density Estimation, Skewness, Quantiles, Risk

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## 1. Introduction

Price formation in wholesale electricity spot markets is known to be a complex function of many fundamental drivers, interactions, time-varying specifications and stochastic shocks. Various factors characterise the idiosyncratic dynamics, and the reasons why the stochastic models for price formation may be challenging to formulate have invited many explanations, see Lucia and Schwartz (2002), Knittel and Roberts (2005), Chen and Bunn (2010), Panagiotelis and Smith (2008), Benth et al. (2013), Aïd et al. (2013) and Weron (2014) among others.

In particular, power markets are local and resource-dependent. In some markets, the production of electricity may be a commodity spread between gas, oil or coal; in others it may be a result of infrastructure investments in nuclear facilities or large reservoirs, whilst elsewhere, and increasingly, it relates to the use of renewable resources such as wind, solar,

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hydro, biomass, geothermal or tidal currents. Furthermore electricity is produced to meet demand instantaneously; it is not easily storable, and in responding to inelastic consumers, the prices are prone to exhibit substantial volatility. And, with liberalised power markets being far from perfectly competitive, often composed of a small oligopoly of generators, at times of scarcity market power effects can result in price spikes substantially above fundamental levels. In contrast and increasingly, with some producers of electricity having inflexible production facilities, eg district heating facilities or nuclear plants, their aversion to shut down/start-up costs may incentivise them to make negative offers to the market during transient periods of oversupply (particularly from wind), resulting in “downspikes”.

Thus, to the extent that the underlying commodity properties dominate the price formation and these may be nonstationary, power prices will accordingly follow them as random walks; but if the natural renewables dominate, mean reversion will emerge from the dynamics of weather or transient supply outages. Unsurprisingly, therefore, specification tests on daily power series for mean reversion, unit roots, fractional cointegration or trend stationarity have varied in their indications over time, between locations and according to whether spikes have been trimmed out of the data (eg Haldrup and Nielsen (2006); Escribano et al. (2011); De Vany and Walls (1999); Koopman et al. (2007); Bunn and Gianfreda (2010); Nan et al. (2014)). Furthermore, with many markets being in structural transition, as governments seek to incentivise the replacement of fossil fuels with renewables, price formation will veer between different processes as wind, solar and hydro availabilities fluctuate. Finally, the granularity of power markets is fine and, because of the lack of storage, arbitrage between price formation at different times of the day or year is very restricted; thus we see quite different price distributions at offpeak hours during the night from those in the morning, midday or evening peaks. In the context of all of this, therefore, it is easily understandable why attempts to model the power price processes have led to different models for different times of the day and seasons, with regime switching and time varying specifications, nonlinear formulations as well as skewed and fat-tailed distributions all having been applied.

The complexity and evolutionary nature of these various influences on power price formation is well illustrated by the changing shapes of the German price densities since 2007. The German power market provides the main reference for European prices and, having also been at the forefront with its high penetration of renewable energy, is the most attentively observed in the region. In Figure 1 we display three selected daily time series for hours 3, 12 and 19 in 2007, and contrast these with the same series only four years later in 2011. The 2007 series exhibit the conventional patterns of a fossil fuel dominated power system, mostly coal and some gas at that time, with periods of volatility clustering and positive spikes. In contrast, 2011 shows the situation after some substantial penetration by wind and solar facilities. The price distributions are remarkably different. The predominantly positive skewness has transformed to negative skewness. In the supplementary Appendix 6.1, we display the series for all 24 hours and these fully demonstrate the diversity and rapid evolution in time series properties. The penetration of solar facilities in particular, by residential and commercial end-users, is continuing to diminish the midday need for conventional generation and eroding what used to be a daily peak, see Moody’s (2012). Thus, there is complexity in evolution, which materialises annually, as well as the time of day distinctiveness becoming increasingly sensitive to changes in the weather. It is therefore a research question of considerable practical relevance to evaluate if the various hourly price densities can be deter-

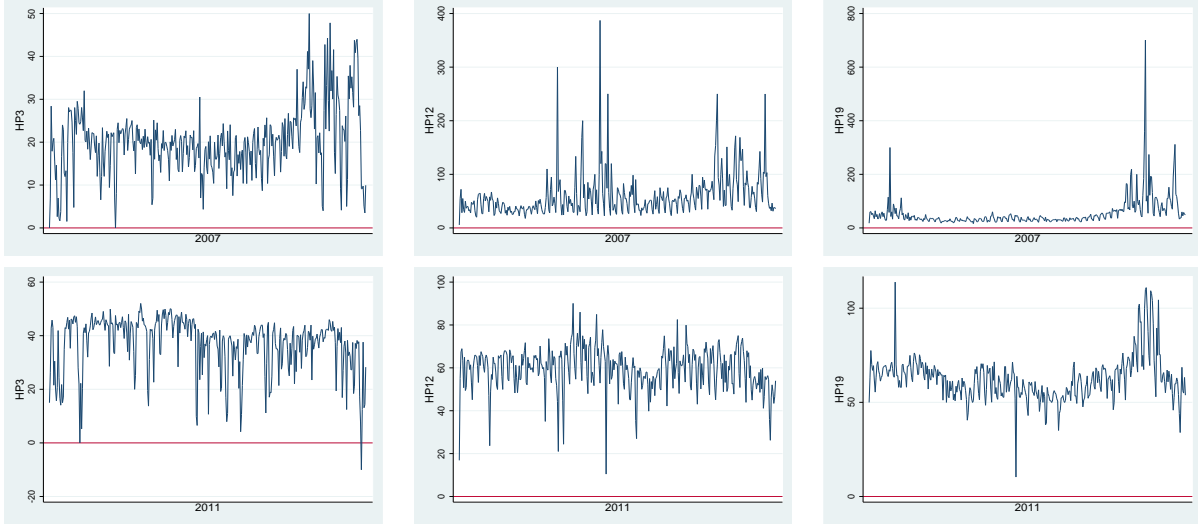


Figure 1: Daily time series for electricity prices (in €/MWh) for hours 3, 12 and 19 in 2007 (first row) and in 2011 (second row). Data source: EPEX ([www.epexspot.com](http://www.epexspot.com))

mined, not apparently as empirical idiosyncracies, but as variations of a general parametric stochastic process, the parameters of which drive the appropriate changes in shape through their dependence upon the evolution of fundamental exogenous factors. That is the aim of this study.

To pursue this, we have searched for a general three or four parameter density specification with special stochastic and analytical features. From a large selection of distribution functions, we identified a few that are sufficiently flexible to provide adequate fit to the wide range of shapes displayed in the German hourly prices over 2006–2016. Furthermore, using generalized linear multivariate estimation for the four moments, sufficient to define the distributions, we were able to relate these moments to several key fundamental dynamic drivers in a plausible way, as well as to an autoregressive representation of the latent estimates to capture behavioural persistence. With respect to the latter feature, the formulation thereby represents to some extent the widely used conditional heteroscedasticity approach for volatility estimation and generalises it to the higher moments as well; the persistence of stochastic skewness being the particular new feature of power prices that we wish to capture. Overall, the latent four moment dynamic modelling within a Skewed  $t$  density representation was considered most appropriate on the balance of its empirical performance and closed form analytical properties. Day ahead predictive densities were then recursively estimated out-of-sample and benchmarked successfully against analogous quantile regression and other methods.

In the next section we consider the practical relevance of more accurate hourly price formation modelling for short-term electricity operations and then review some of the related background research on electricity price modelling, forecasting and density estimation. In Section 3, we discuss the case of Germany and present key results from the distributional analysis of power prices and fundamental drivers. The multifactor modelling approach is described in Section 4, with the empirical support and the dependence of higher moments on fundamental drivers in Section 4.1, and the relative performance in forecasting density quan-

tiles compared with other benchmarking techniques in Section 4.2. Finally, we summarise the research contributions in Section 5.

## 2. Operational Contexts of Power Price Density Modelling

Modelling the day-ahead electricity price formation process at hourly resolution has attracted extensive research (see Weron (2014), for a review) motivated by the practical considerations of a wide range of operational decisions for which these models provide support. Typically, in most wholesale power markets worldwide, the main-market, day-ahead prices emerge as a vector for all 24 hours of a particular day from auctions held around midday of the previous day. Whilst there are usually some demand and supply responses in the subsequent intra-day trading and real-time balancing, substantial operational commitments in practice need to be planned in advance of the day ahead auction, but with outcomes contingent upon those prices. Forecasts or simulations based upon the price formation models of the day-ahead auction prices are therefore essential to such short-term advance planning.

For example, unit commitment decisions for production facilities are often done days in advance, especially if single or two shift daily schedules are being considered (Hobbs et al., 2001; Tseng and Barz, 2002). From a risk management perspective, Stoft (2002) argues that day ahead hourly price forecasts are crucial for generators making offers to the day ahead auction in a way that recovers start-up costs over their expected dispatched periods. With the relative attractiveness of the intra-day and balancing markets, many generators face the decision problem of how much capacity to offer to the day ahead auction and how much to retain for the intra day and balancing opportunities (Soares et al., 2017; Ding et al., 2017). This will depend upon the relative price risks. The economic operation of gas-fired plants require positive spark spreads and the forecasts of power prices will therefore influence not only the offer strategy to the electricity auctions, but also planning the linked activities in the day ahead gas market, pipeline commitments and/or calls upon any swing option contracts for variable gas off-takes (Eydeland and Wolyniec, 2003; Harris, 2006, Jaillet et al., 2004). Similarly, when trading across interconnectors, transmission capacity may have to be acquired in advance of the day ahead auctions, the value of which will be a real option on the anticipated locational spreads across the day-ahead auction prices (Deng et al., 2001; Carmona and Durreleman, 2003; Bunn and Martoccia, 2010). All of these operational decisions are made in advance of the day-ahead auction prices, often with an element of optionality, and as a consequence, their valuations depend upon the probability densities of the hourly prices. The specifications of the stochastic hourly price-formation in the models that have been presented to support these decisions are often, however, quite simple mean-reverting (Ornstein-Uhlenbeck) or seasonal autoregressive processes, suitable for long-term analysis, but without any conditional dependence upon the exogenous factors such as weather and demand forecasts, as well as fuel prices, that are highly informative in the short term.

We expand on three specific illustrative contexts that are currently being actively researched and where short term conditional models of price formation would appear to be crucial for model adequacy:

- *Optimal Battery Storage and Electric Vehicle Charging Operations:* The operation of an electricity pumped storage facility on a daily cycle, based upon day ahead prices, is

a well-established textbook example of optimised operational planning (Sioshansi and Conejo, 2017). Recently the linking of batteries to wind facilities has engaged various researchers in the application of stochastic optimisation techniques (Kim and Powell, 2011, Li et al., 2011, Jiang et al., 2013, Ding et al., 2016, Abdullah et al., 2017). The two stage models of Ding et al. (2016) and Abdullah et al. (2017) make use of the 24 day-ahead forecasts, but these forecasts are derived simply as historical densities. Many papers related to operating electric vehicle charging facilities have similar properties. Typical formulations have been as optimal stopping rules for charging and discharging as a function of mean reverting Gaussian spot prices (Jiang and Powell, 2016). In practice, decision making is likely to be more episodic, as with storage, based upon daily expectations for prices (Sioshansi, 2011). The day-ahead storage optimisation is particularly challenging because valuation depends upon a spread for charging and discharging and the agent has to decide upon both bid and offer hourly quantities for the auction. Accurate price risk modelling is clearly important to operate profitably across these short-term spreads.

- *Risk Management by Renewable Energy Producers:* In the absence of a link to storage, wind or solar producers can face considerable short term revenue risk from both prices and output volumes. This can be managed by means of a financial product that has payoffs to cover low volumes and low prices. Such an option contract is an example of an energy “quanto” option<sup>1</sup>, extensively discussed in Caporin et al. (2012), Benth et al. (2015) and Brik and Roncoroni (2016). These are offered as bespoke weather derivative products by the insurance industry (eg Munich Re<sup>2</sup> and Endurance Re<sup>3</sup>. To understand the payoffs from such options, their prices and the optimal design of strikes, a joint stochastic model for the power price and production (Wind or PV) is required. Typically solved by Monte-Carlo methods, not only are stochastic models for wind and prices needed, but also their correlation. In Benth and Ibrahim (2017) a simple AR(3) model with constant Gaussian noise is assumed for the hourly prices. Other derivative products, specific for particular hours, designed to help with the short term uncertainties for renewable energy producers include the “cap/floor futures” which have been introduced in Germany<sup>4</sup> and Australia<sup>5</sup>. These effectively manage the risk, on an hourly basis, of high and low prices, above and below specified thresholds. Pricing these derivatives evidently requires accurate estimation, particularly regarding the tails, of the density functions involved.
- *Demand-side Engagement:* Operational interest in day-ahead price extremes is also reflected on the demand-side and can be expected to increase with more consumer em-

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<sup>1</sup>A long term version of this is sometimes called a *Proxy Revenue Swap*, eg for Capital Power’s Bloom Wind Farm (see <https://www.environmental-finance.com/content/sections/weather-risk-hub/weather-is-the-new-fuel-risk.html>).

<sup>2</sup><https://www.munichre.com/weatherandcommodity/en/group/index.html>

<sup>3</sup>[https://platts.com/IM.Platts.Content/ProductsServices/ConferenceAndEvents/emea/EU-Power/presentations/Ralph\\_Renner.pdf](https://platts.com/IM.Platts.Content/ProductsServices/ConferenceAndEvents/emea/EU-Power/presentations/Ralph_Renner.pdf)

<sup>4</sup><https://www.eex.com/en/products/energiewende-products/german-intraday-cap-futures>

<sup>5</sup>[https://www.asxenergy.com.au/products/overview\\_of\\_the\\_australian\\_el](https://www.asxenergy.com.au/products/overview_of_the_australian_el)

powerment and distributed resources. Exposure to price extremes and their operational remedies can often be quite specific and detailed. For example, in Britain, drawing upon the theory of peak load pricing, the TSO recovers transmission charges from the demand side based upon their consumption in the highest three, non-consecutive trading periods in the winter (the so-called “triads”, National Grid, 2015). There is a large incentive to reduce demand in these periods but they are only known ex post, and commercial forecasting services have emerged to provide forecasts<sup>6</sup>. Generally, small distribution-connected turbines are started and run to reduce the net demand of retailers during these periods. But, it has been estimated (Frontier, 2017) that the search cost for these extremes involves targeting over 100 trading periods to ensure coverage of the maximum 3. This is one specific example but, evidently, improved modelling of the extreme price risks has benefits beyond this “triad chasing” to the extent that suppliers can influence demand-side engagement in a more timely and economic manner.

Regarding the need for more accurate price formation models in the above, and other, operational contexts, although there is a large amount of published work on modelling the fundamental drivers of power prices and a growing body of work on the disruptive effects of renewable generation, there is relatively little on the specification of electricity density forecasts. Most of the research on price formation has been in terms of relating their expected values to exogenous factors, such as fuel prices, demand, reserve margin as well as lagged effects, and the model formulations have often justified nonlinear, regime-switching and time-varying specifications (eg Huisman (2008); Karakatsani and Bunn (2008); Chen and Bunn (2010), amongst many). In parallel, stochastic models, often motivated by the need to support derivative pricing, have become increasingly elaborated to take account of non-normality, jumps and mixed processes (eg Benth et al. (2007); Panagiotelis and Smith (2008); Frestad et al. (2010)).

Regarding the particular changes in price formation induced by wind, Gelabert et al. (2011), looking at Spain, demonstrated the negative effects of renewables on price levels. In Texas, similar evidence of negative effects is presented by Baldick (2012), and also by Woo et al. (2011), the latter observing that an increase in wind generation reduces electricity prices but increases the variance and this happens to varying extents throughout the day. The price-wind-demand interrelationship is discussed in the Australian context by Cutler et al. (2011), in which they observe a general lack of correlation between wind and demand, emphasise that demand is the more important driver, but also note periods of low (high) market prices associated with high (low) wind generation at all hours of the day. The additional effects of regional imports and exports, induced by wind variations, have also been investigated by Mulder and Scholtens (2013) in The Netherlands, and by Mauritzen (2013) who identified Nordic hydropower as a natural complement to Danish intermittent wind generation.

From a forecasting perspective, Cruz et al. (2011) compare the predictive accuracy of several univariate, multivariate, linear and nonlinear models for Spanish day-ahead prices, including hourly load and wind generation forecasts as explanatory variables, with results

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<sup>6</sup>Npower Triad Warning Service <https://www.npower.com/business-solutions/buying-energy/demand-management/triadwarningservice/> and Flexitricity Triad Management <https://www.flexitricity.com/en-gb/solutions/triad/>

justifying the multivariate specifications. Similarly, Kristiansen (2012) developed a forecasting model for hourly day-ahead prices in Nord Pool based on an autoregressive model with exogenous variables, with the extended specification adding value to the previous work of Weron and Misiorek (2008).

With respect to the evolutionary nature of the model specifications, Paraschiv et al. (2014) considered the effects of both wind and solar generation on the day-ahead price formation in Germany, showing that there has been a continuous electricity price adaptation process to market fundamentals, and that price drivers differ across hours with solar and wind generally reducing wholesale electricity prices. They argue that wind effects determine downspikes and even negative prices, whereas solar output balances the high demand during peak hours. Ketterer (2014) also studied the effect of wind in Germany looking at volatility dynamics as well as price levels. She showed that wind power reduces electricity price level but increases its volatility and, through rolling regressions over 3 years, found that the wind effect on mean prices was becoming less negative over time.

Finally, closer to the objectives of this paper, Serinaldi (2011) considered the short-term forecasting of Californian and Italian electricity price densities using the Johnson's  $S_U$  distribution, with time varying means and variances, but constant skewness and kurtosis, whilst Panagiotelis and Smith (2008) applied the skew- $t$  distribution in a daily vector autoregressive formulation. Otherwise, rather more researchers have approached the distributional specification through interval forecasts using semiparametric quantile regressions (eg Jónsson et al., 2014; Bunn et al., 2016), also demonstrating the time varying effects of wind, solar and other exogenous variables on particular quantile estimates. The formulation we describe below is an extension of these themes, with a time-varying specification of all four-moments from a parametric density representation of prices, with exogenous drivers and autoregressive latent variable persistence, benchmarked against forecasts from quantile regression and other models, including the simpler specification of Serinaldi (2011).

### 3. Evolution and Fundamentals of German Prices

In a relatively short period of time, since the turn of this century, the German electricity market has been characterized by a series of radical structural changes: liberalisation, emission trading, a nuclear power phase-out and, most recently, the growth in renewable generation. One consequence of the rapid penetration of wind in particular has been the need to allow negative prices to emerge in the German and coupled spot markets<sup>7</sup>. Negative prices may occur when demand falls and/or wind production is high and they signal an urgent need for generators to reduce output or for consumers to increase demand. However, producers of inflexible plants may prefer to pay for continuing to produce, as this may cost less, or be more practical, than stopping and restarting their plants over a short period of time. Less extreme than negative prices, is negative skewness, and for similar reasons, this is expected to be induced by low demand and/or high wind. Solar could have a similar effect, although being a midday producer, it does not generally coincide with low demand, and so its effect may be more manifest in reducing the otherwise positive skewness in those periods.

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<sup>7</sup>Negative pricing has been introduced on the German/Austrian day-ahead market in 2008.



Germany is therefore an appropriate case study to develop and test a stochastic price formulation model in which there is explicit dependence of the shape of the densities on wind, solar and other short-term fundamental drivers. To this aim, we model the individual hourly electricity prices produced by the coupled German/Austrian day-ahead auction market, from January 2006 to December 2016. These 24 hour price vectors are recorded on a 7-day basis, thereby providing 24 hourly time series each containing 4018 observations<sup>8</sup>. In addition and on the same daily horizon, we have considered actual load, forecasted wind and solar PV generation, coal, gas,  $CO_2$  prices all quoted or converted in €/MWh. This data set has been carefully compiled from different sources, namely the EPEXSpot<sup>9</sup> (for hourly day-ahead prices), the four German TSOs websites (for actual and forecasted wind and solar generation aggregated on hourly level), ENTSO-e (for hourly actual loads), and Datastream<sup>10</sup> (for coal ICE API2 CIF ARA, TTF natural gas, and  $CO_2$  daily prices).

Figure 2 shows the evolution of average hourly curves for load, solar and wind production, computed yearly over 2006-2016 together with the ‘net load’ faced by conventional thermal generators after the feed-in of wind and solar production. The intra-daily load profiles show a slow decline in levels, whereas those for wind and solar show remarkable increases in output over this period. It should be mentioned that the full time series exhibit the usual annual time-varying patterns following calendar seasons, with higher solar PV generation during summer.

Descriptive statistics of price levels are reported in Table 2 in the supplementary Appendix 6.2 for all individual hours, showing the evolution of empirical sample moments across years. Thus, it can be observed that negative skewness, on average, characterized prices densities at times of steep increase and decline in load, ie mid morning and late evening at hours 6, 7, 8,

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<sup>8</sup>Regarding the clock changes in spring and autumn, we have excluded from the analysis hour 25, observable at the autumn clock change, and for the spring clock change when the price for hour 3 was missing, we averaged the prices of the previous and following days. Indeed, when the clock is advanced to summer time the data reporting system automatically deletes the values/slots for hour 3 (i.e. from 2.00 am to 3.00 am). Furthermore, in our hour-by-hour approach, the leap year is not awkward as it is simply an extra day influencing the weekly seasonality that we already included in our modelling.

<sup>9</sup>The day-ahead auction DE/AT (Phelix) hourly prices are the reference prices for delivery of electricity on the following day in 24 hour intervals on the German/Austrian TSO zones. The physical deliveries are made within any of the 4 German TSOs zones as well as in the Austrian Power grid. However, EEX is planning to split it into two different zones, and, given our focus on the German market, we limit our analysis on the German TSOs hence considering only actual and forecasted variables (as wind and solar PV) registered in this market by Tennet, 50Herz, Transnet and Amprion. Thus, load and renewable data for Austria are not included.

<sup>10</sup>We have also interpolated Datastream quotations over missing weekends and holidays. The tickers of used series are, respectively: LMCYSPT for the settlement prices of coal Intercontinental Exchange API2 cost, insurance and freight Amsterdam, Rotterdam and Antwerp converted in €/MWh using the USEURSP rates from US\$ to Euro (WMR&DS); TRNLTTD for the 1st Future Day settlement prices for the natural gas TTF NL quoted in €/MWh; and finally, EEXEUAS for the EEX-EU  $CO_2$  Emissions E/EUA in €. The four German TSOs used to retrieve wind and solar data are: Tennet ([www.tennetso.de](http://www.tennetso.de)), Amprion ([www.amprion.net](http://www.amprion.net)), Transnet BW ([www.transnetbw.com](http://www.transnetbw.com)) and 50Hertz ([www.50hertz.com](http://www.50hertz.com)). Lagged actual load has been used as a proxy for the public unavailability of forecasted load, hence the load observed yesterday is considered the best forecast for today. Through the modelling, we have been attentive to the data that would be available to the market at the time when participants make their bids and offers to the day ahead auction.

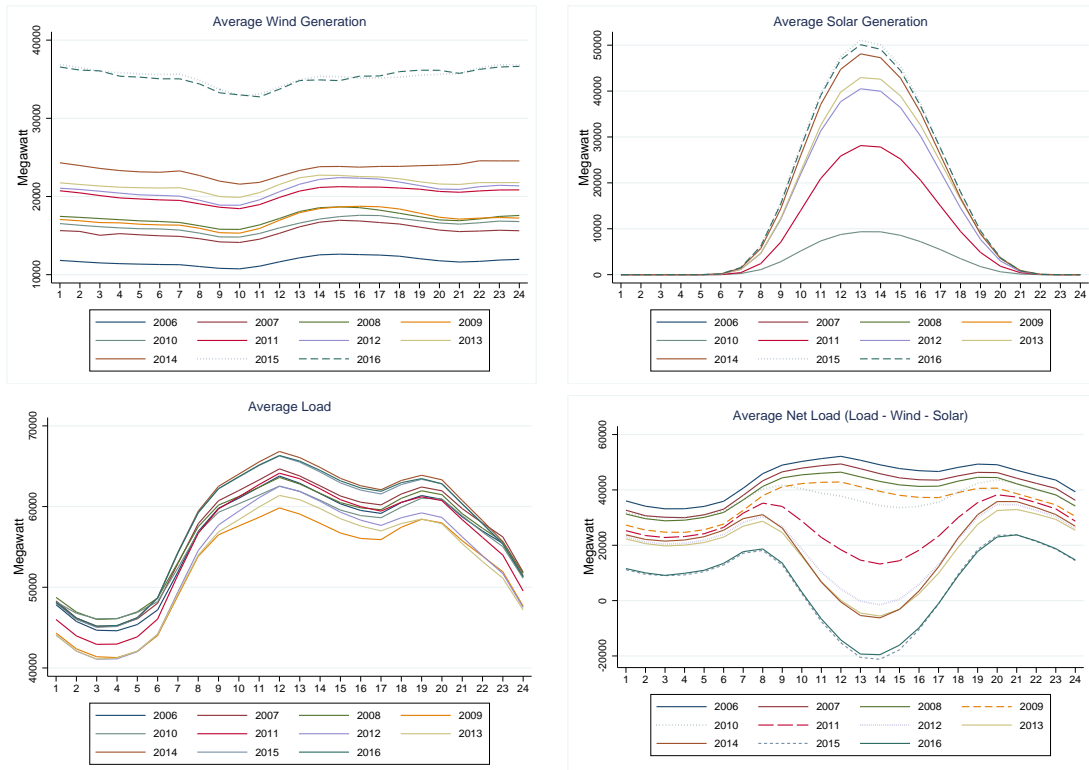


Figure 2: Average Intra-Daily Profiles for Load, Net Load, Wind and Solar Generation. Data sources: Tennet ([www.tennetso.de](http://www.tennetso.de)), Amprion ([www.amprion.net](http://www.amprion.net)), Transnet BW ([www.transnetbw.com](http://www.transnetbw.com)) and 50Hertz ([www.50hertz.com](http://www.50hertz.com)) for actual wind and solar generation; and ENTSO-E ([www.entsoe.eu](http://www.entsoe.eu)) for actual load.

23 and 24, at the beginning of our sample, but after 2010, negative skewness started to occur across the daytime hours as well, when solar generation created a new cycling requirement on the thermal generators. These observations motivated our modelling choice of selecting non-censored distributions with both positive and negative mean and skewness. Thus, to fit the deseasonalised densities of hourly prices, adjusted for holidays, we have considered 3 different classes of distributions with these features and also the capabilities to work within the multivariate formulations we require for estimation in the next section. The first one is a class of 4-parameter distributions, the *Johnson's  $S_U$*  (in its original parametrization as in Johnson, 1949 and in its alternative parametrization as in Johnson, 1954; see respectively *JSUo* and *JSU*), the *sinh-arcsinh* (as in Jones and Pewsey, 2009; see SHASHo and SHASHo2), the *skew exponential power* (as in Fernandez et al., 1995; see SEP1 and SEP2), the *skew- $t$*  (as in Azzalini, 1986, in Azzalini and Capitanio, 2003 and in Jones and Faddy, 2003; respectively ST1, ST2 and ST5). The second one is a 3-parameter family represented by the *skew-normal* distributions, specifically the skew normal ‘type 1’ which is a special case of the skew exponential power with  $\tau = 2$  (SN1). Thirdly, we selected as a baseline, the 2-parameter *normal* distribution (NO) as this is often used for simplicity in operational models (see previous section).

To identify the best fitting density functions, yearly values of three measures of the goodness-of-fit (the Kolmogorov-Smirnov *KS*, the Cramer-von Mises *CVM*, and the Anderson-Darling *AD*) are reported in Tables 3-10 in Appendix 6.3. According to these measures of

fit and accounting for the absolute maximum, the squared and the weighted squared differences (to give more attention on the tails), as well as the AIC criterion to discourage over-parameterisation, we observed the general superiority of the skew student-t distributions (specifically ST1 and ST2). Also recorded in these tables are details of the computational estimation times (for a PC with Intel Core Duo i7-3520M CPU 2.9 GHz and 8GB RAM) which reveal some of the computational difficulties, particularly with the two JSUs. It is also interesting to observe that SN1 and NO emerged to perform well during midday hours which is when, as we observed earlier, the historic positive skewness had been tempered to become more symmetrical through the impact of solar. When we further repeated the analysis on just the deseasonalized prices over the shorter sample 2010-2016 which we use in the multivariate modelling in the next section (shorter because forecast solar data was only available from 2010), we observed that ST2 and JSU were the two best fitting distributions (the former on hours 1-8 & 24, whereas the latter over the hours 9-23; see Table 11 in Appendix 6.3).

On balance, however, we considered the Skewed-t to be most appropriate on the basis of its general fitting and analytical properties. We note that the skewed-t had previously been used for hourly Australian prices in Panagiotelis and Smith (2008) whilst Serinaldi (2011) used the the Johnson's  $S_U$  distribution for Californian and Italian electricity price densities. The flexibility of the skew-t distribution to the range of shapes is shown in Figures 3-5, where two forms of the *skew-t* distribution were compared with the JSU, SN1 and NO, for the same motivating sample of hours and years that we displayed in Figure 1. Regarding the skew-t variants, comparing their performances, we decided to focus upon the second skew-t, in which the pdf of the skew-t type 2 distribution, denoted  $ST2(\mu, \sigma, \nu, \tau)$ , is defined by

$$f_Y(y|\mu, \sigma, \nu, \tau) = \frac{2}{\sigma} f_{Z_1}(z) F_{Z_2}(\omega) \quad (1)$$

for  $-\infty < y < +\infty$ , where  $-\infty < \mu < +\infty$ ,  $\sigma > 0$ ,  $-\infty < \nu < +\infty$  and  $\tau > 0$ , and where  $z = (y - \mu)/\sigma$ ,  $\omega = \nu\lambda^{1/2}z$ ,  $\lambda = (\tau + 1)/(\tau + z^2)$  and  $f_{Z_1}$  is the pdf of  $Z_1 \sim TF(0, 1, \tau)$  (a t-distribution with  $\tau > 0$  degrees of freedom treated as continuous parameter) and  $F_{Z_2}$  is the cdf of  $Z_2 \sim TF(0, 1, \tau + 1)$ . The mean and the variance of  $Y$  are given by  $E(Y) = \mu + \sigma E(Z)$  and  $Var(Y) = \sigma^2 Var(Z)$ , where  $E(Z) = \nu\tau^{1/2}\Gamma(\frac{\tau-1}{2}) / [\pi^{1/2}(1 + \nu^2)^{1/2}\Gamma(\frac{\tau}{2})]$  for  $\tau > 1$  and  $E(Z^2) = \tau/(\tau - 2)$  for  $\tau > 2$ . This distribution is the univariate case of the multivariate skew-t distribution introduced by Azzalini and Capitanio (2003).

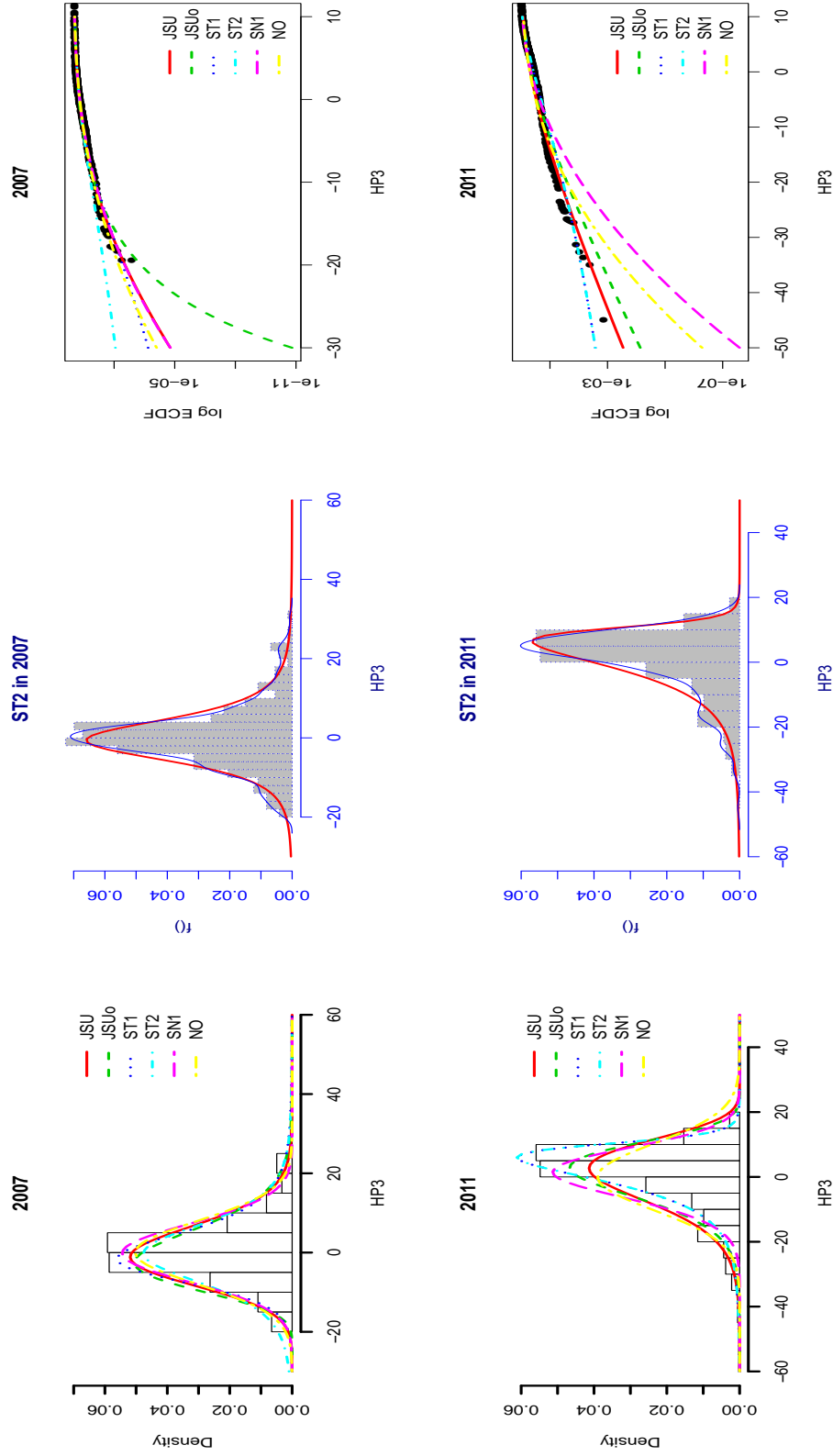


Figure 3: Comparisons of Density Fits (on the first column), the skewed-t fit vs a kernel density (in the middle) and the ECDF with Density in logarithmic scale for hour 3 in 2007 and 2011 (in rows). Descriptive statistics of deseasonalized prices:  $\mu = 0.000$ ,  $\sigma = 7.939$ ,  $\nu = 0.546$  and  $\tau = 4.487$  in 2007; and  $\mu = 0.000$ ,  $\sigma = 10.234$ ,  $\nu = -1.320$  and  $\tau = 4.610$  in 2011.

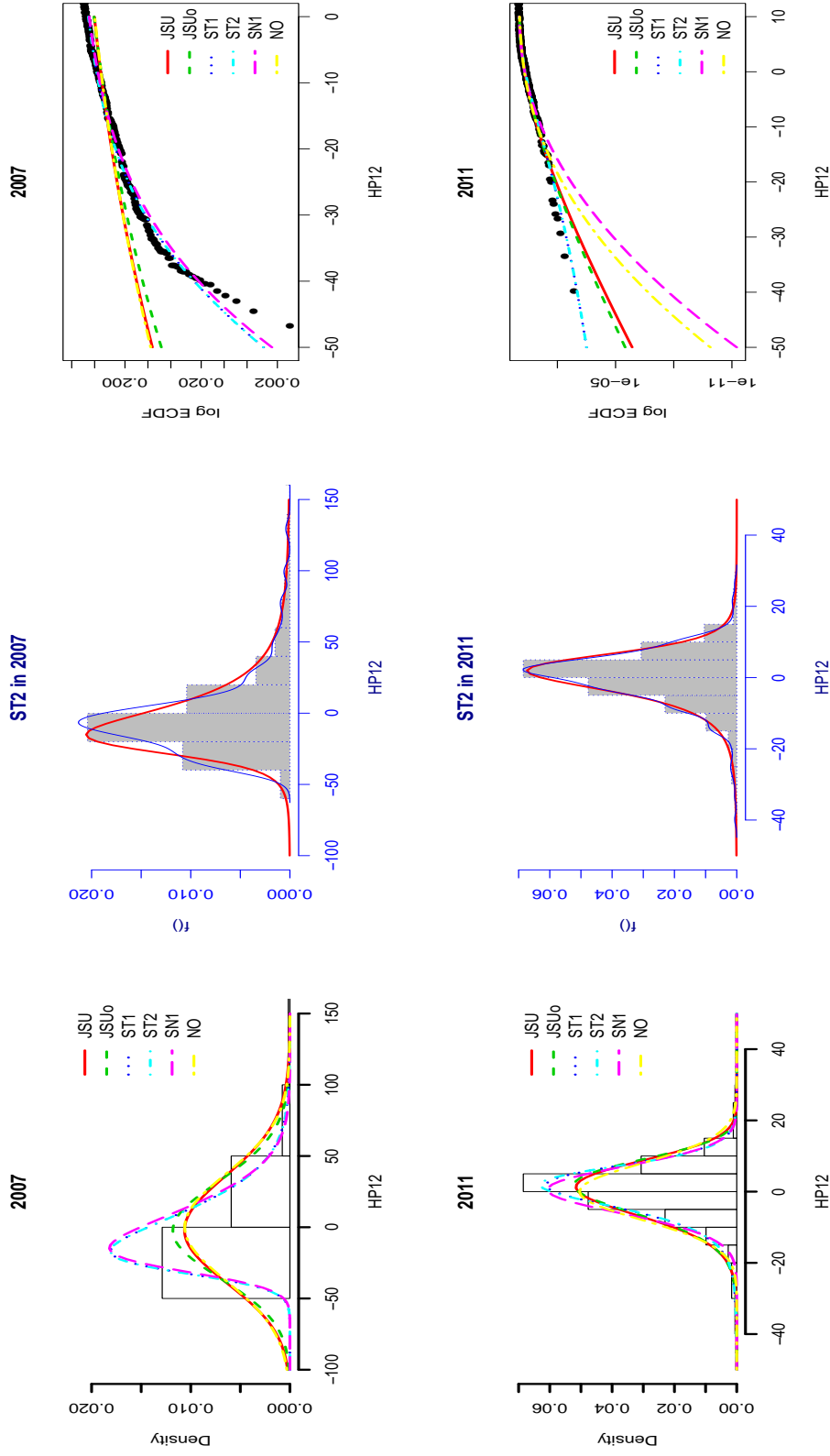


Figure 4: Comparisons of Density Fits (on the first column), the skewed-t fit vs a kernel density (in the middle) and the ECDF with Density in logarithmic scale for hour 12 in 2007 and 2011 (in rows). Descriptive statistics of deseasonalized prices:  $\mu = 0.000$ ,  $\sigma = 37.618$ ,  $\nu = 3.642$  and  $\tau = 23.575$  in 2007; and  $\mu = 0.000$ ,  $\sigma = 7.908$ ,  $\nu = -0.948$  and  $\tau = 6.362$  in 2011.

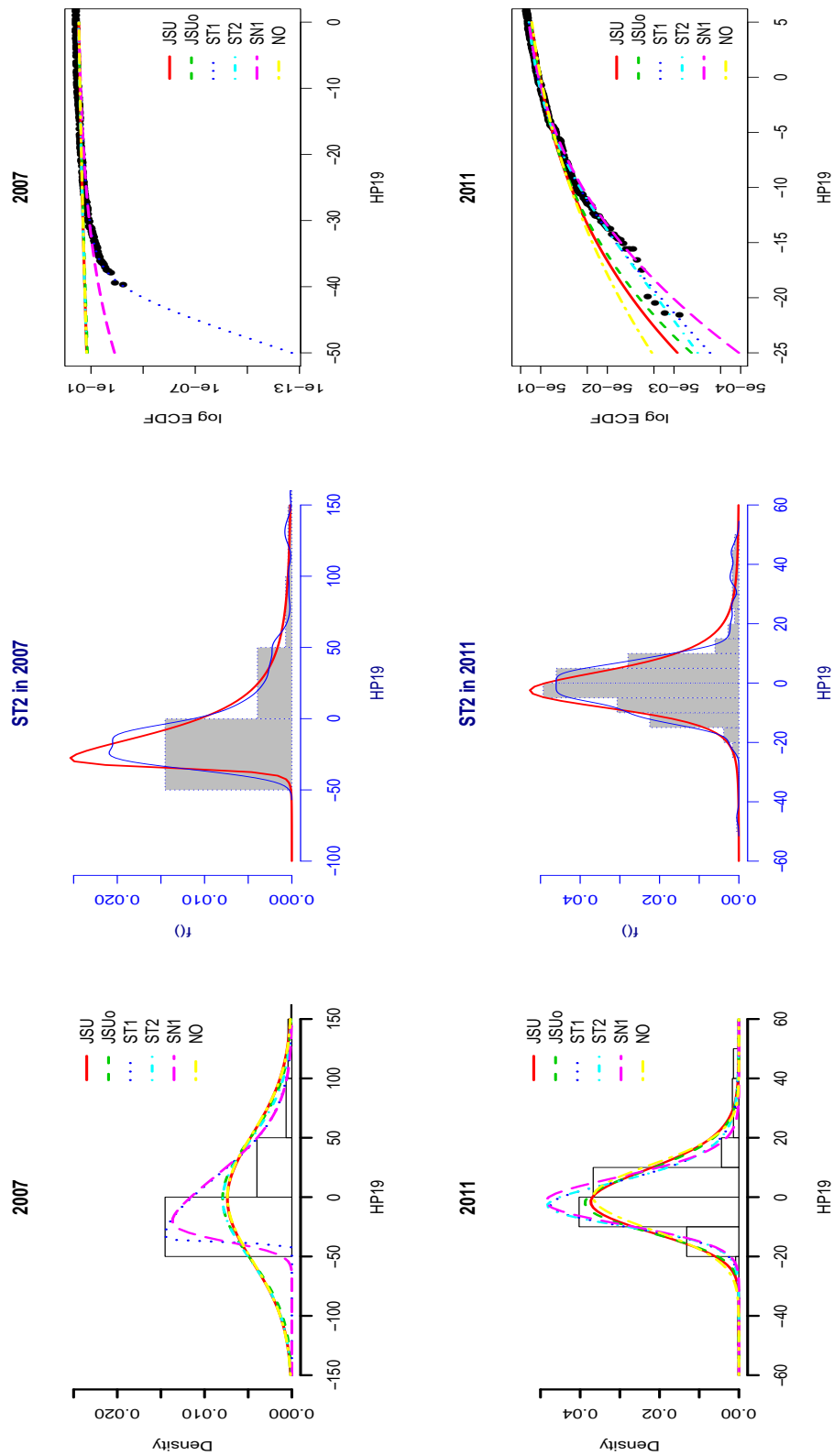


Figure 5: Comparisons of Density Fits (on the first column), the skewed-t fit vs a kernel density (in the middle) and the ECDF with Density in logarithmic scale for hour 19 in 2007 and 2011 (in rows). Descriptive statistics of deseasonalized prices:  $\mu = 0.000$ ,  $\sigma = 54.069$ ,  $\nu = 6.172$  and  $\tau = 60.714$  in 2007; and  $\mu = 0.000$ ,  $\sigma = 10.870$ ,  $\nu = 1.357$  and  $\tau = 7.921$  in 2011.

#### 4. Linear Multifactor Dynamic Estimation of the Density Moments

With the attractive flexibility of the four parameter skew-t densities for fitting the various hourly prices, the consequent research question is whether the specification of the first four moments of the skew-t can be well represented in terms of the dynamics of fundamental short term drivers of price formation. To this end, we considered whether these exogenous variables could be formulated and estimated within a generalized model for the first four moments (representing the level  $\mu$ , the volatility  $\sigma$ , skewness,  $\nu$ . and kurtosis,  $\tau$ ), resulting from an extension of the Generalized Linear Models in Nelder and Wedderburn (1972); Generalized Additive Models in Hastie and Tibshirani (1986) and Hastie and Tibshirani (1990); and the Generalized Additive Models for Location, Scale and Shape, `gamlss`, as in Rigby and Stasinopoulos (2005) and Stasinopoulos and Rigby (2007). In so doing, we seek to substantially extend the scope of applications undertaken with similar methodology by Serinaldi (2011), Matsumoto et al. (2012) and Scandroglio et al. (2013). Within this framework we formulate the hourly electricity price as a response variable whose distribution function varies according to multiple exogenous factors. From the previous section we choose to represent the response variable (the deseasonalised hourly electricity price) as a the skew-t density with the mean,  $\mu$ , standard deviation,  $\sigma$ , skewness,  $\nu$ , and kurtosis,  $\tau$  modelled as multifactor linear functions as follows.

Let  $Y$  be the response variable, it is assumed that independent observations  $y_i$  for  $i = 1, \dots, n$  have distribution function  $F_Y(y_i; \theta^i)$

with  $\theta^i = (\theta_1^i, \dots, \theta_p^i)$  a vector of  $p$  distribution parameters accounting for position, scale and shape. Generally,  $p$  is less than or equal to four, since the 4-parameter families provide enough flexibility.

Given an  $n$  length vector of the response variable  $\mathbf{y}^T = (y_1, \dots, y_n)$ , let  $g_k(\cdot)$  for  $k = 1, \dots, p$  be monotonic link functions relating the distribution parameters to explanatory variables and random stochastic effects to account for extra not explained variability through an additive model given by

$$g_k(\theta_k) = \eta_k = \mathbf{X}_k \beta_k + \sum_{j=1}^{J_k} \mathbf{Z}_{jk} \gamma_{jk} \quad (2)$$

where  $\theta_k$  and  $\eta_k$  are vectors of length  $n$ , e.g.  $\theta_k^T = \{\theta_k^1, \dots, \theta_k^n\}$ ,  $\beta_k^T = \{\beta_{1k}, \dots, \beta_{J_k k}\}$  is a parameter vector of length  $J_k$ ,  $\mathbf{X}_k$  is a known design matrix of order  $n \times J_k$ ,  $\mathbf{Z}_{jk}$  is a fixed known  $n \times q_{jk}$  design matrix and  $\gamma_{jk}$  is a  $q_{jk}$ -dimensional random variable.

The linear predictors  $\eta_k$ , for  $k = 1, \dots, p$  comprise a parametric component  $\mathbf{X}_k \beta_k$  and additive components  $\mathbf{Z}_{jk} \gamma_{jk}$ ; the first term represents a linear function of explanatory variables and the second one represents random effects. For sake of parsimony, we used only linear components in link functions. We assumed identity link functions,  $g_1(\cdot)$  and  $g_3(\cdot)$ , for the expected hourly prices and their skewness; whereas logarithmic link functions were used for  $g_2(\cdot)$  and  $g_4(\cdot)$  to ensure positivity for standard deviation and kurtosis, obtained by taking the exponential of the filtered log series.

Based upon the conventional considerations of market fundamentals and with regard to the information that would generally be available to market participants by the time they make offers and bids into the day ahead auction, we have expressed the expected hourly

price in reduced form as a function of its value observed on the day before ( $y_{t-1}$ ), as well as on electricity load observed on the day before ( $load_{t-1}$ , in thousands of MW), forecasts for wind and solar PV generation ( $fwind_t$ , and  $fsolar_t$ , also in thousands of MW) available to the market prior to the auction, lagged prices of coal, gas and  $CO_2$  allowances (respectively  $coal_{t-1}$ ,  $gas_{t-1}$ ,  $co2_{t-1}$ ), together with calendar holidays and weekends in a dummy variable,  $hol_t$ , which takes value 1 for weekends and German holidays<sup>11</sup>.

Formally, in its basic formulation, this dynamic multi-factor skew t “MFST” model has  $g_1(\theta_1) = \eta_1 = E(y_t) = \mu_t$ , with a time-varying latent mean

$$\mu_t = \alpha_1 + \gamma_1 y_{t-1} + \beta_{11} hol_t + \beta_{12} load_{t-1} + \beta_{13} fwind_t + \beta_{14} fsolar_t \quad (3)$$

$$+ \beta_{15} coal_{t-1} + \beta_{16} gas_{t-1} + \beta_{17} co2_{t-1}. \quad (4)$$

We assumed that the dispersion, estimated dynamically as a time varying latent volatility (standard deviation) state variable, is a function of fundamental drivers through  $g_2(\theta_2) = \eta_2 = \log(\sqrt{Var(y_t)}) = \log(\sigma_t)$ , with

$$\log(\sigma_t) = \alpha_2 + \beta_{21} hol_t + \beta_{22} load_{t-1} + \beta_{23} fwind_t + \beta_{24} fsolar_t + \beta_{25} coal_{t-1} + \beta_{26} gas_{t-1} + \beta_{27} co2_{t-1}. \quad (5)$$

Distinct from previous formulations (eg Serinaldi, 2011), we extend the scope of dynamic multifactors to the third and fourth moments through the time varying latent parameters,  $g_3(\theta_3) = \eta_3 = \nu_t$  and  $g_4(\theta_4) = \eta_4 = \log(\tau_t)$  as follows

$$\nu_t = \alpha_3 + \gamma_3 hol_t + \beta_{31} load_{t-1} + \beta_{32} fwind_t + \beta_{33} fsolar_t + \beta_{34} coal_{t-1} + \beta_{35} co2_{t-1} + \beta_{36} gas_{t-1} \quad (6)$$

$$\log(\tau_t) = \alpha_4 + \gamma_4 hol_t + \beta_{41} load_{t-1} + \beta_{42} fwind_t + \beta_{43} fsolar_t + \beta_{44} coal_{t-1} + \beta_{45} co2_{t-1} + \beta_{46} gas_{t-1}. \quad (7)$$

In order to investigate possible persistence in the latent moments, we also considered a new expanded formulation to include the autoregressive dynamics of the latent moments into the above mean, variance, skewness and kurtosis equations, thus defining an autoregressive multifactor skew-t model, “AR-MFST”. In the “AR-MFST” models, the 1-lag autoregressive variables  $\mu_{t-1}$ ,  $\sigma_{t-1}$ ,  $\nu_{t-1}$  and  $\tau_{t-1}$  are included in each of the corresponding equations 4-7 above. Furthermore, extending this concept to include possible implicit effects between these latent moments, we also considered a vector autoregression version in which the first lags of all four of the latent moments are included in each latent moment equation, 4-7, to give the “VAR-MFST” formulation<sup>12</sup>.

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<sup>11</sup>To avoid over-parametrization, we have included weekly seasonality together with holidays in one single dummy variable, equal to one over weekends and holidays such as: New Year, Good Friday, Easter Monday, Labour Day, Ascension Day, Whit Monday, German unit day, Christmas Eve, Christmas Day, Boxing day and New Years Eve. Given our focus on the German TSOs market, we have not considered Austrian public holidays nor regional holidays, such as Pentecost, Corpus Christi Assumption of Mary, Reformation day, All Saints day and Repentance Day.

<sup>12</sup>In the former case,  $\mu_{t-1}$  is replacing lagged prices. And autoregressive terms have been extracted after the estimation of the basic MFST model presented in eqs. 4-7.



All parameters are estimated by maximizing the likelihood function<sup>13</sup>, through an adaptation of Cole and Green (1992) algorithm, which uses the first, second and cross derivatives of the likelihood function with respect to the distribution parameters,  $\theta(\mu, \sigma, \nu, \tau)$ . As the computation of cross derivatives proved to be intractable, we adopted a generalization of the algorithm developed in Rigby and Stasinopoulos (1996a), and Rigby and Stasinopoulos (1996b) for fitting the mean and dispersion additive models which does not require the cross derivatives. Initial values for autoregressive sample parameters have been obtained by fitting the model to the entire sample, then lagged series have been included (and later in the forecasting performance, updated through the rolling iterations).

Optimisation in ML estimations such as this are often sensitive to starting values, leading to local optima, or even singularities with small samples, but with the length of time series in our study, neither of these were problems<sup>14</sup>. Overfitting, on the other hand, was a serious consideration and for that reason we restricted our factor specifications to plausible drivers on the basis of what is known about electricity price formation and we undertook extensive out-of-sample testing in a forecasting context with some challenging benchmark testing.

Whilst it should be recalled that the main objective of this modelling is to elucidate a general-purpose price formation model, flexible enough to accommodate the range of shapes that hourly power prices may take, in a way that relates these shape changes parametrically to fundamental exogenous drivers, the estimation process also derives the time-varying latent estimates of the moments. For several financial engineering applications in particular, such latent estimates of the instantaneous volatility and skewness states are attractive alternatives to historic estimates based upon lagged finite rolling windows. For example, Figure 6 shows the time series of the latent moments for hour 12, whereas similar series are shown for hour 19 in Figure 10 in Appendix 6.1.

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<sup>13</sup>The estimation has been carried out using the statistical software R and some of the "gamlss" library models (<http://www.gamlss.org/>).

<sup>14</sup>There are two algorithms to maximize the likelihood function: the first is the CG algorithm, a generalization of the Cole and Green (2002) algorithm which uses first, (expected or approximated) second and cross derivatives of the likelihood function with respect to the distribution parameters; the second one is the RS algorithm, a generalization of the algorithm used by Rigby and Stasinopoulos (1996a) and Rigby and Stasinopoulos (1996b) for fitting the mean and the dispersion of additive models and it does not use cross derivatives. Singularities in the likelihood function similar can potentially occur, especially when the sample size is small as in our yearly analysis. The RS algorithm has an outer cycle which maximizes the penalized likelihood with respect to  $\beta_k$  and  $\gamma_{jk}$  for  $j = 1, \dots, J_k$  in the model successively for each  $\theta_k$  in turn, for  $k = 1, \dots, p$ ; and at each calculation in the algorithm, the current updated values of all quantities are used. Roughly, the RS algorithm starts initializing the fitted values  $\theta_k$  and random effects  $\gamma_{jk}$  in the first outer and inner cycle iterations by regressing partial residuals against a 'weighted' design matrix to obtain updated parameter estimates. Then, the linear predictors  $\eta_k$  are evaluated and updated, and the cycle is repeated until the change in the penalized likelihood is sufficiently small. At this point, convergence is obtained and results produced. On the contrary, in the CG algorithm all weight matrices are evaluated and updated after fitting of all  $\theta_k$ . Further details on the functioning of algorithms and the maximization of the likelihood can be found in Rigby and Stasinopoulos (2005) and in Stasinopoulos et al. (2008). In all our estimation, we used the RS algorithm and control parameters set to: 0.5 as for the the convergence criterion for the algorithm (*c.crit* and *cc*), and the tolerance level for the backfitting algorithm (*bf.tol*); 1000 for *n.cyc*, for *cyc*, as the number of cycles of the algorithm, and for the number of cycles of the backfitting algorithm (*bf.cyc*). Finally, *Inf* was used for the global deviance tolerance level (*gd.tol*), to allow the algorithm to converge even if the global deviance changes dramatically during the iterations.

Residual analysis for enlarged models is presented in Appendix B.5, Figures 11 and 12, which contain the ACF and PACF of residuals from the main models under consideration; in addition, ACF and PACF for level, squared and cubic residuals are shown in Figures 13 and 14. The PACFs indicated some residual correlations which was expected. We did not include any nonlinear specification in the models, particular with respect to load. Supply functions are known to be nonlinear at low and high levels and whilst we chose a simple linear response as a robust assumption, it will presumably be underspecified. There are also interaction effects. In some of the subsequent modelling we have therefore included AR(7) to capture serial effects of up to a week. For additional insight, Table 17 in Appendix 6.4.3 presents the descriptive statistics of normalized (quantile) residuals for a sample of hours. The *normalized quantile* residuals are given by  $\hat{r}_i = \Phi^{-1}(u_i)$  where  $\Phi^{-1}$  is the inverse cumulative distribution function of a standard normal variate,  $u_i = F(y_i|\hat{\theta}^i)$  and  $F(y|\theta)$  is the cumulative distribution function with  $\theta = (\mu, \sigma, \nu, \tau)$ . If the “MFST” models are correctly specified, then the normalized quantile residuals should behave as standard normal ones, see Dunn and Smyth (1996). In our results, these residuals generally exhibit zero mean, unit variance, zero asymmetry and kurtosis equal to three (except for the simpler SN1 and NO distributions) thus indicating model adequacy (the results for other hours are similar and available on request).

#### 4.1. Dependence of Higher Moments on Exogenous Fundamental Drivers

In order to avoid over-elaboration and to justify the multifactor, time-varying representation of the moments, we developed a series of progressively more complex specifications. According to the multifactor formulations of eqs. 4-7, four models were successively estimated:

- M1: time-varying mean, but all other moments constant;
- M2: time-varying mean and standard deviation, with constant skewness and kurtosis;
- M3: time-varying mean, variance and skewness, constant kurtosis;
- M4: all four moments time varying.

In all cases, we also specified the models with and without each of the renewable energy drivers (wind and solar) and the results confirmed their incremental impacts (these have not been reported for lack of space, but they are available on request).

Expectations for these factor effects follow from previous work, but as such only inform price levels and variance (eg from Karakatsani and Bunn (2010), Ketterer (2014), Paraschiv et al. (2014), Cló et al. (2015) and Bunn et al, 2016, among others) as this research is the first to consider the higher skewness and kurtosis drivers. Thus, previous research would imply:

1. positive autoregression at lag one in price levels and the higher moments, reflecting some *adaptive behavior and persistence*;
2. positive effect of load (i.e. demand) on the mean power price because of the increasing fundamental marginal cost supply function, and on volatility, reflecting the conventional “inverse leverage” observation that at times of high demand and prices, volatility also increases (in contrast to the usual leverage in equity markets with higher volatility at lower prices);

	Hour 3				Hour 12				Hour 19			
	$\mu$	$\log(\sigma)$	$\nu$	$\log(\tau)$	$\mu$	$\log(\sigma)$	$\nu$	$\log(\tau)$	$\mu$	$\log(\sigma)$	$\nu$	$\log(\tau)$
$hol_t$	-	+	-	+	-	+	-	-	-	$\pm$	-	+
$y_{t-1}$	+				+				+			
$\mu_{t-1}$	+	+	-	+	-	-		-	$\pm$	-	-	-
$\log(\sigma_{t-1})$	+	+			-	+		-	+	+	-	-
$\nu_{t-1}$		-	+		+	+	-		-	-	-	+
$\log(\tau_{t-1})$				-		+			+	+		+
$load_{t-1}$	+	-	+	-	+	-	-	+	+	$\pm$	$\pm$	-
$fwind_t$	-	+	-	+	-	+	-	-	-	-	-	+
$fsolar_t$					-	-	-		-	-	-	+
$gas_{t-1}$	+	+	-	+	+	+	+	-	+	+	+	-
$coal_{t-1}$	+	$\pm$	-	-	+	$\pm$	-	$\pm$	+	-	-	-
$co2_{t-1}$	+	+	-	-	+	+			+	+	+	-

Table 1: High level summary of significant signs for the full model M4 and its AR and VAR variations.

3. fuel prices and  $CO_2$  generally increasing the mean power price because of their input cost;
4. wind (and solar) reducing electricity prices (especially for peak hours as consequence of balancing excess demand), but increasing the volatility.

A high level summary of the significant signs of the full model specifications for the MFST, AR-MFST and VARM-MFST models is shown in Table 1, whereas the full results for estimated coefficients and t-values are in Tables 12-14 in Appendix 6.4.1 for a sample of hours. The entries in Table 1 are for the significant (5%) coefficients and their signs. Where plus and minus signs are overlaid, the indications from all three MFST variations differ. The R-squares (the generalised R-squared in Nagelkerke (1991)), the Global Deviance (defined as a function of the log-likelihood, formally  $GD = -2\log\mathcal{L}$ ), and information criteria about the progressive modelling are reported in Tables 15 and 16 in Appendix 6.4.2. These results present a generally coherent interpretation, mostly consistent with expectations but with some new insights. The most important observations are the shape-shifts induced by wind and solar. Both wind and solar production do indeed reduce the skewness of hourly electricity prices and this is more evident at hour 12 when solar is at its maximum level. In addition, both increase the kurtosis of these prices at peak hour 19. The consistency of the results across all of the modelling progressions, with the various inclusions of wind and solar, adds considerably to the robustness of the fundamental specification. The key factor influences are:

- 1'** Lagged price is positive for all four MFST models on price level, indicating adaptive behaviour consistent with expectations. However, for the latent moment autoregressions the results are mixed. Holidays, as expected, reduce business activities and therefore price levels. Latent volatility was positively persistent on itself, as expected and had a positive effect on price levels in periods 3 and 19, but negative in period 12. For the higher moments, some mixed results might suggest over-fitting with the AR MFST and particularly VAR MFST.
- 2'** Load (i.e. demand) has a positive coefficient on the price levels, consistent with conventional expectations and previous research, but negative on price variance for hours 3 and 12. Hour 3 is when more negative price spikes are observed compared to hours 12 and 19 and low load levels over night will therefore manifest higher volatility.

- 3' Among fuel prices, we find that *natural gas* increases mean and volatility. During the day it increases skewness, whereas it reduces the kurtosis. At night it reduces skewness and increases kurtosis. These effects seem plausible as peaking generation during the day may be associated with positive spikes, whereas its use at night might be counteracting negative price tendencies. *coal* increases mean but it reduces skewness. We also confirm that  $CO_2$  affects price levels and volatility.
- 4' Wind lowers prices and lowers skewness. Hence the appearance of negative skewness, as noted earlier, can be confirmed as a wind-induced factor. Solar has effects during the day, with negative effects on price levels, volatility and skewness. The wind and solar effects are consistent across all modelling specifications.

It is questionable whether the gains of expanding the dynamic specifications in the model from 3 to 4 parameters, and in extending the specifications to AR and VAR latent moments is worthwhile. In one respect, whilst the interpretations of the kurtosis factor coefficients are generally significant, intuitions regarding their sign are equivocal, and the gains in fit from  $M3$  to  $M4$  are small. The dynamic three parameter improvement over a two parameter model is substantial, and the skewness story is persuasive; but less so for the kurtosis in going to four parameters. Likewise, the AR and VAR inclusions of the latent estimates produced equivocal estimations and this suggests specification or overfitting problems, despite their conceptual appeal. Thus, in the next section we report results on out-of-sample forecast testing performed on rolling windows of 365 days<sup>15</sup>. The motivation is not primarily to suggest a forecasting method, but to test the robustness of the specifications.

#### 4.2. Forecasting Performance

For robustness and as a check against over-fitting, we test the performance of the MFST, AR-MFST and VAR-MFST models through one period ahead, out-of-sample forecasting, using rolling window estimations and also considering all one-, two-, three- and four-moment specifications. We compare against two benchmarking techniques, one being the well-established semi parametric quantile regression method to derive empirical interval limits and the other being a conventional approach for estimating the conditional means and variances of electricity prices using ARMA-GARCH type models.

Benchmarking against quantile regressions is a challenging test insofar as these estimates of particular points on the density function (eg 5%, 95% intervals) make no distributional assumptions and are purely empirical. The MFST approach will only be as accurate as quantile regression at specific quantiles if its parametric specification is appropriate. More precisely, we compare M1- AR1- and VARM1-MFST versus Quantile Regressions, including an AR(7) structure together with drivers, holidays and seasonality. When the first two moments are considered, an ARX-EGARCHX(1,1), specified with a student-t and a skewed-student-t for the innovations, will estimate volatility persistence and its formulation clearly recalls the  $\log(\sigma_t)$  in the M2-MFST versions, which will only capture this to the extent that the drivers of heteroscedasticity are in the exogenous multifactor dynamics. But, in the

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<sup>15</sup>Not reported here were results based on rolling windows of 730 days and an expanding window of 365 days. These confirmed those found in the rolling approach presented here.

ARMA-GARCH framework, the innovations cannot change density shape as effectively as in the MFST, and then the AR- and VAR-MFST should capture some of the persistence effect through the inclusion of lagged latent moments. In addition, we compare the (AR)M2-MFST (that is specified with two moment equations) with the model formulated in Serinaldi (2011) based on the Johnsons'  $S_U$  with daily and hourly dummies, quadratic and cubic loads, and price functionals.

Quantile methods, following Koenker and Bassett (1978), are extensively applied as regression models for expressing specific percentiles of a response variable as a function of exogenous factors. Their main attractive features are firstly their semiparametric formulation of interval estimates of the predictive distribution; and secondly, the fact that they distinguish the impact of explanatory variables to different intervals of the distribution. Thus, in the conventional way, we let  $q \in [0, 1]$  be a quantile of interest,  $Y_t$  be the dependent variable (that is the hourly electricity price levels) and  $X_t$  a  $d$ -dimensional vector of explanatory variables (e.g. load, forecasted wind and solar generation; gas, coal, and  $CO_2$ ) with a constant included. The linear conditional quantile function is given by  $Q_q(Y_t|X_t) = X_t\beta_q$  and we have used the fundamental drivers as in eq.(4) to forecast and compare selected quantiles:

$$Q_q(y_t) = \alpha^q + \sum_{i=1}^7 \gamma_i^q y_{t-i} + \beta_1^q hol_t + \beta_2^q load_{t-1} + \beta_3^q fwind_t + \beta_4^q fsolar_t + \beta_5^q coal_{t-1} + \beta_6^q gas_{t-1} + \beta_7^q co2_{t-1} \quad (8)$$

As observed by Chernozhukov and Umantsev (2001), data scarcity may be a problem in estimating the extreme tails of the distribution.

Benchmarking with the ARX-EGARCHX(1,1) model we test both student-t and skew student-t error distributions. Again, we have specified an AR(7) structure with the same factors as eq.8, and in this case with the conditional variance following an EGARCH(1,1) process also driven by the load, wind, solar and lagged fuel drivers. Formally, the conditional mean being as follows

$$y_t = c + \sum_{i=1}^7 \phi_i y_{t-i} + \lambda_1 hol_t + \lambda_2 load_{t-1} + \lambda_3 fwind_t + \lambda_4 kf solar_t + \lambda_5 coal_{t-1} + \lambda_6 gas_{t-1} + \lambda_7 co2_{t-1} + \theta \varepsilon_t \quad (9)$$

and the conditional variance as follows

$$\begin{aligned} \log(\sigma_t^2) &= \omega + \alpha \log(\sigma_{t-1}^2) + \beta g(\varepsilon_{t-1}) + \varphi_1 hol_t + \varphi_2 load_{t-1} + \varphi_3 fwind_{t-1} + \varphi_4 fsolar_{t-1} \\ &\quad + \varphi_5 coal_{t-1} + \varphi_6 gas_{t-1} + \varphi_7 co2_{t-1} \end{aligned} \quad (10)$$

with  $g(\varepsilon_t) = \theta \varepsilon_t + \varrho[|\varepsilon_t| - E(|\varepsilon_t|)]$  with the conditional density set to be a Student-t,  $\varepsilon_t|I_{t-1} \sim t(0, \sigma_t^2)$ , or a skew Student-t,  $\varepsilon_t|I_{t-1} \sim st(0, \sigma_t^2)$ .

We expect that the four parameter, dynamic, multifactor skew-t models ("MFST" and "AR-MFST") to perform better than the ARMAX-GARCHX method, to the extent that the latter is only able to capture mean and variance dynamics. Even if the GARCH element would add the extra responses to conditional volatility and the persistence of shocks, the AR-MFST model is expected to exhibit competitive performance due to the extra flexibility in the density shape and the lagged latent moment persistence.

Having a full dataset of 2557 observations from the beginning of 2010 (because of the solar data not being available before), we perform an in-sample estimation using a rolling

window of 365 days. We then forecast the next observation as an out-of-sample test, and recursively advance the process through the time-series<sup>16</sup>.

We assess the calibration of the forecast densities by simply using conventional tests, such as Kupiec (1995) unconditional (UC), Christoffersen (1998) conditional coverage (CC) and the Engle and Manganelli (2004) dynamic quantile (DC) tests on yearly basis. In the coverage tests, the null hypothesis is that the calibration frequencies at each quantile are correct. Thus, in the results, a p-value greater than 0.01 indicates that we cannot reject the null hypothesis under a significance test at 1% (hence we are looking for high p values for well calibrated coverage). Tables 18-20, 21-23 and 24-26 in Appendix 6.5 summarise the results for hour 3, 12 and 19, for lower, middle and upper quantiles respectively. Results for a sample of other hours are available in Tables 27, 28, and 29. On this basis, we observe that the this forecasting process on a rolling window of 365 observations provides poor results for *quantile regression*, most likely for the sample size reasons indicated in Chernozhukov and Umantsev (2001).

For hour 3, most practical interest would be in the lower quantiles, for the occurrence of downspikes, and here the MFST and the AR-MFST outperform the quantile regression and the GARCH methodology. For hour 12, practical interest would be in both the high and low quantiles, and here again the MFST and AR-MSFT performances in terms of coverage are better than the two benchmarks especially at lower quantiles (even with the shortest rolling window). For hour 19, most practical interest would be in the high quantiles for the risk of high prices, and we see again that the MFST models outperform the benchmarks. In addition, with the lower quantiles, the flexibility and forecasting ability of MFST models continues to be beneficial with the benchmarks being outperformed. Furthermore, we observe that the ARM3-MFST outperforms the ARM4-MFST in the out-of-sample forecasting testing, and this provides empirical evidence, as suspected, that there is little to be gained through modelling with the fourth moment being dynamic, and potential overfitting can be avoided. Likewise, the VAR representation proved to be less robust than the AR for out-of-sample, and together with the mixed interpretation of the coefficients in Table 1, appears to reflect overspecification.

Finally, to summarise the main comparisons, we show in in Figure 7 the theoretical number of hits (exceedances at particular quantiles) versus the empirical frequencies across the quantiles, for three key models. For illustration we plot the graphs for hour 12 in 2011 and 2015 (similar results for other hours are available on request, showing the same indications). This clearly displays the superiority of the proposed ARM3-MFST, being closest to the theoretical curve, compared to the JSU density model used by Serinaldi (2011) and the EGARCH with skew student t which would perhaps be the most appropriate of the conditional volatility models typically used for Value-at-Risk analysis.

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<sup>16</sup>Thus, we start by estimating the models using the first 365 observations, and from this forecast the 1%, 2%, 5%, 25%, 50%, 75%, 95%, 98% and 99% quantiles of the 366<sup>th</sup> observation. Thereafter, we estimate the models using observation 2 to 366 to forecast quantiles of observation 367, and so on. The recursive (V)AR-MFST models have been initialized by using the lagged filtered moments obtained from the MSFT estimation on the whole sample; then, the autoregressive terms have been recursively updated by rolling estimations and used into the forecasting procedures.

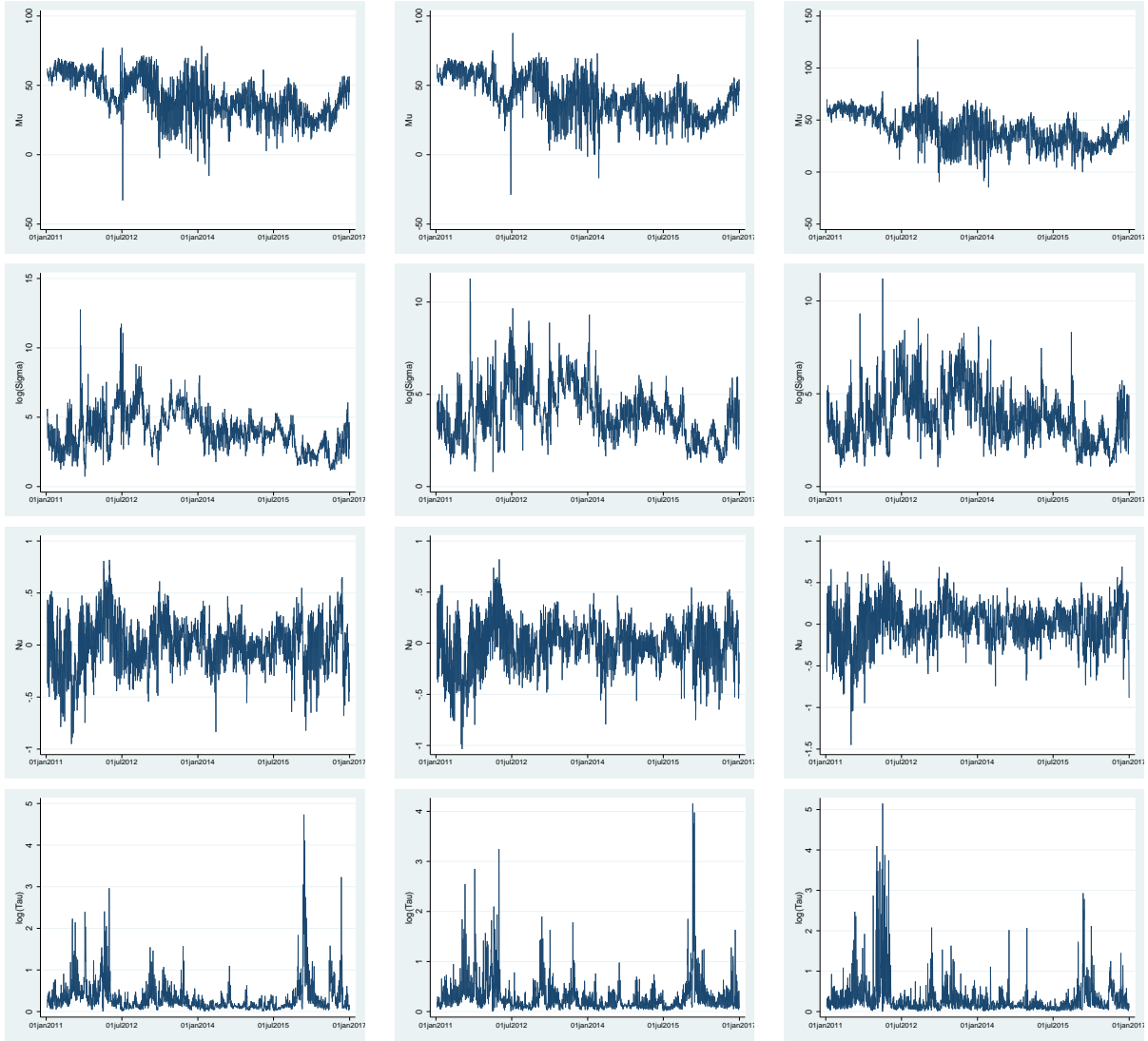


Figure 6: Filtered time series of mean ( $\hat{\mu}_t$ ) on the first rows, volatility ( $\log(\hat{\sigma}_t)$ ) on the second rows, skewness ( $\hat{\nu}_t$ ) on the third rows and kurtosis ( $\log(\hat{\tau}_t)$ ) on the last rows, from a skew-t representation of prices at hour 12 based on the MFST (first column), AR-MFST (second) and VAR-MFST models (third column) estimated on a rolling window of 365 days and continuously updated from 2010 towards the end of our sample. Static filtered moments can also be extracted once the model is estimated on the full sample.

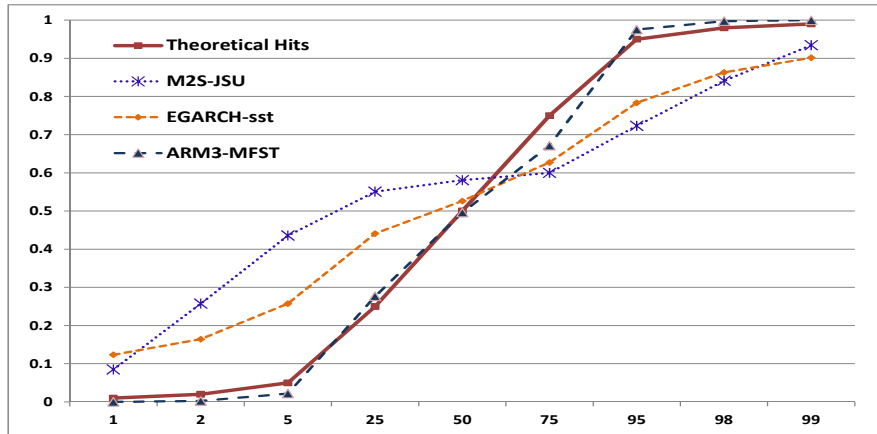
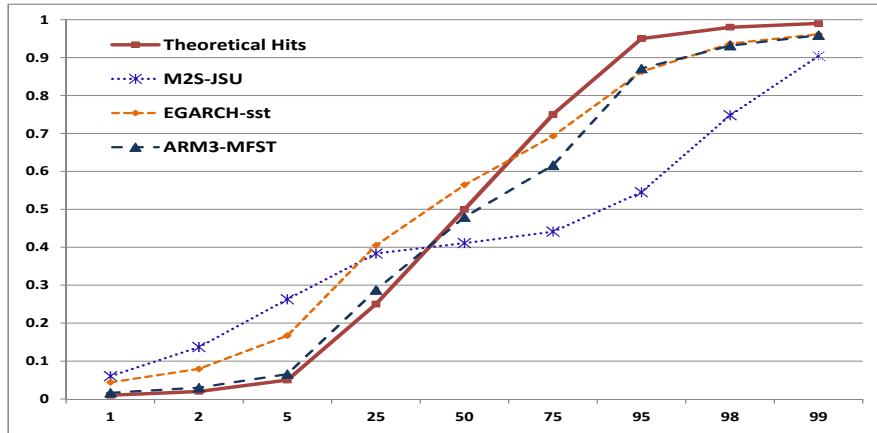


Figure 7: Theoretical versus Empirical Hits of Selected Models across Quantiles for hour 12 in 2011 (first row) and in 2015 (second row). Theoretical Hits are simply 1%, 2%, 5%, 25%, 50%, 75%, 95%, 98%, 99%; M2S-JSU is the model proposed by Serinaldi (2011); EGARCH-sst is the AR(7)X-EGARCH(1,1)-X with a skew student-t distribution as formulated in eqs. 9-10; ARM3-MFST is the ‘MFST’ model with three moment equations and autoregressive terms included (as formulated in Section 4).



## 5. Final Comments and Conclusion

The development of an accurate, flexible and analytically tractable representation for electricity price processes has considerable practical value for operations control, risk management and financial products, and the increasing penetration of renewable energy, through solar and wind, is not only adding to the complexity of price formation, but also the greater need for short-term hedging products. Closed form solutions are desirable for hedging, but the choice of an appropriate density function is awkward in power markets because of the rapid shape changes that may occur over time due to intermittent wind and solar output as well as the usual demand and fuel price shocks. The increasing interest in battery storage operations and EV charging logistics is also motivating the use of analytics that require accurate short-term models of the hourly prices. Furthermore, whilst generators have always needed to plan unit commitment several days in advance, retailers are now looking to anticipate demand-side engagement at the day ahead stage, and both generators and retailers are carefully considering their offer quantities to the day ahead auctions in the light of reserving capacities for the profitable intra day and balancing markets.

With this context and methodological need in mind, we have examined the applicability of a stochastic price formation model based upon dynamic latent moments estimated within a skewed- $t$  density to accommodate the range of shapes that hourly power prices exhibit, and furthermore related these shape changes dynamically to a set of exogenous drivers. This is conveniently and transparently achieved through linear multifactor representations of the first four moments of this density, estimated as dynamic latent variables. Benchmarked against quantile regression and ARMAX-GARCHX, the method performed well. In particular, the ability to capture the swings between positive and negative skewness by time of day and according to the amount of renewable energy generation is an appealing feature and could provide a useful ingredient into the daily optimisation of trading positions and operational scheduling. Furthermore, since the evolution of market structure is represented through the exogenous variables, the frequent re-specification that a more empirical approach would require is avoided. The MFST approach therefore offers shape flexibility and stability of specification. Furthermore, introducing lagged latent moments into the model, as AR-MFST, is attractive for interpreting persistence in skewness and volatility, as well as adaptive evolution in the mean, and this was robust to out-of-sample testing.

The approach was not outperformed by the nonparametric quantile regression benchmark, which does not offer analytical solutions, but would have been expected to estimate the percentiles more precisely. In fact our proposed approach was clearly better in terms of out-of-sample performance. This is reassuring for the general functional form of the skew- $t$  and its multifactor drivers. Regarding its comparison to an ARX-EGARCHX, also in this case, the (V)AR-MFST models outperformed, showing that extreme quantiles were better calibrated by the multifactor skew- $t$  models compared to the GARCH model. We observe that the inclusion of conditional volatility and lagged higher moments made the specification more dynamic and superior to the GARCH approach.

It is an open question if the dynamic specification of the fourth moment adds value, with the three moment version performing better out of sample, but for situations where this may be useful, eg portfolio optimisation models that explicitly use the first four moments (Giesecke et al. (2014)), the formulation appears sufficiently robust. As regards, the choice

of further exogenous variables, the reserve margin and the flow of imports/exports in the German context would be potentially valuable and may improve accuracy. There is certainly scope for a more comprehensive multifactor modelling of the price formation process, but the main methodological objectives of this research have nevertheless been well supported by the specification, as applied.

Beyond the electricity case which motivated this study, this general approach should have quite wide appeal in capturing the shape-shifting properties in the market price densities not only of a wide range of commodities but also for prices in any market where the key ingredient is a role for significant and time-varying exogenous drivers in determining dynamic shifts in the density shapes.

## 6. APPENDICES

### 6.1. Reference Figures

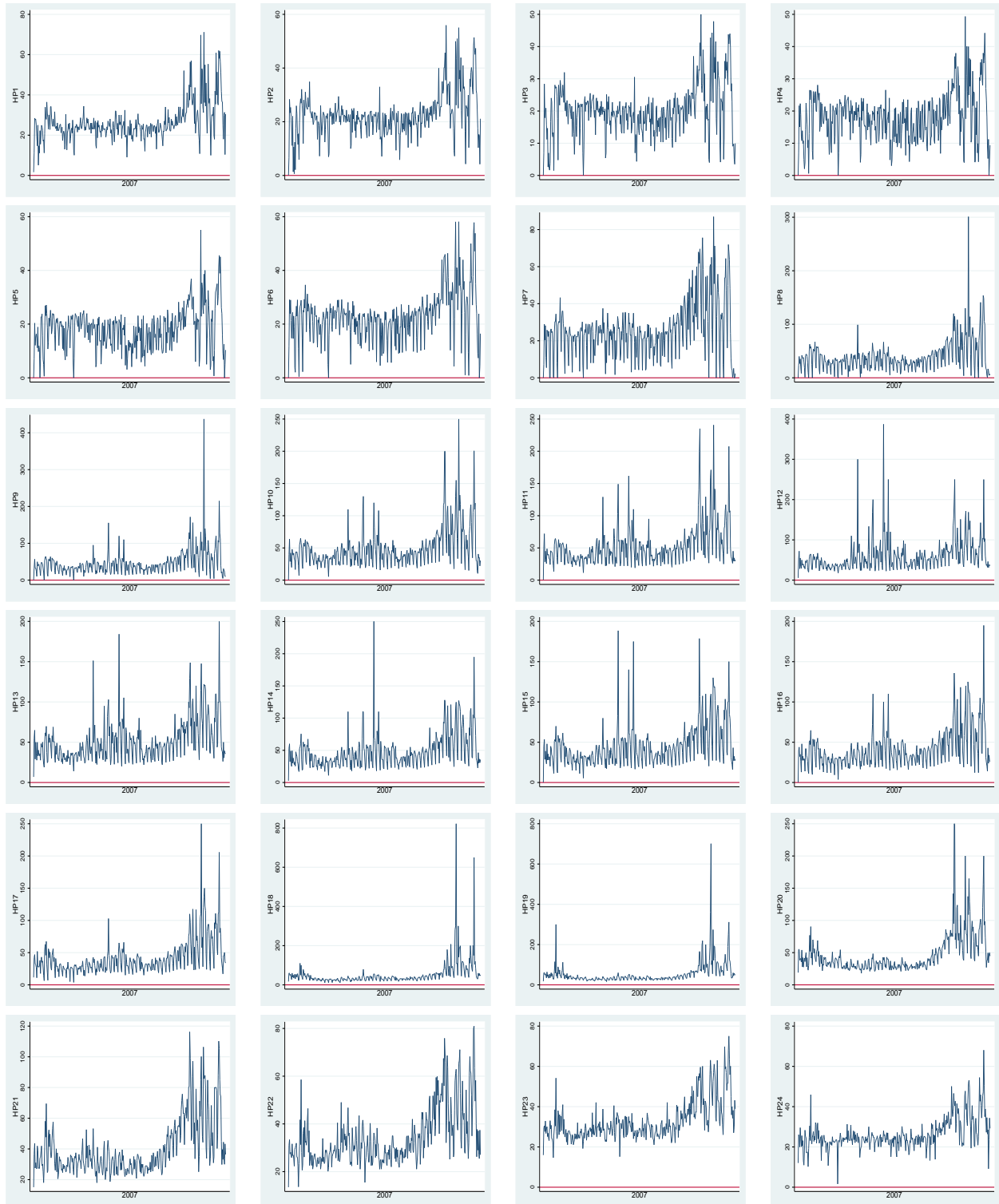


Figure 8: 24 daily time series in 2007, one for each of the separately determined hourly prices.



Figure 9: 24 daily time series in 2011, one for each of the separately determined hourly prices.

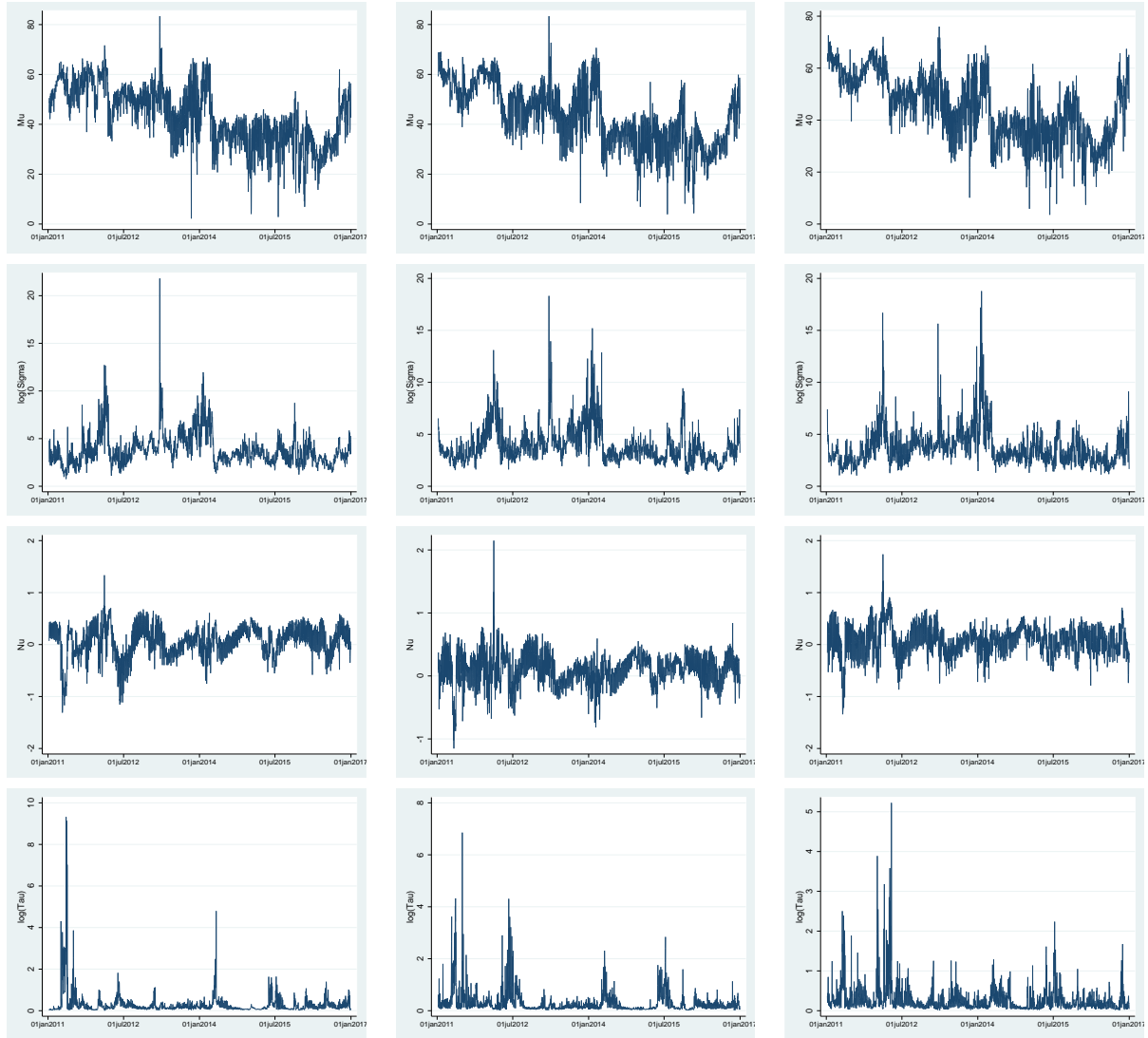


Figure 10: Filtered time series of mean ( $\hat{\mu}_t$ ) on the first rows, volatility ( $\log(\hat{\sigma}_t)$ ) on the second rows, skewness ( $\hat{\nu}_t$ ) on the third rows and kurtosis ( $\log(\hat{\tau}_t)$ ) on the last rows, from a skew-t representation of prices at hour 19 based on the M4-MFST (first column), ARM4-MFST (second) and VARM4-MFST models (third column) estimated on a rolling window of 365 days and continuously updated from 2010 towards the end of our sample. Static filtered moments can also be extracted once the model is estimated on the full sample.

## 6.2. Yearly Descriptive Statistics across 24 Hours

Hours	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
<b>Mean</b>											
1	36.09	26.42	50.23	30.30	37.46	43.28	34.31	28.99	26.10	25.17	23.96
2	31.46	22.59	43.52	25.05	33.77	39.87	30.69	26.25	23.92	23.27	22.30
3	28.07	20.19	38.93	20.85	30.56	36.91	28.38	24.15	22.43	21.90	21.26
4	25.03	18.12	35.41	19.02	27.63	34.85	26.21	23.29	21.14	21.29	20.58
5	25.65	18.13	36.31	19.66	28.01	35.44	26.61	23.74	21.69	21.69	21.00
6	30.90	22.88	43.08	24.45	32.00	39.16	29.74	26.15	23.89	23.81	22.41
7	36.18	25.69	50.70	30.57	38.29	45.49	36.90	34.18	30.55	30.08	27.03
8	52.41	39.21	70.19	41.52	46.19	54.31	46.96	43.60	37.53	36.86	32.95
9	58.50	45.91	75.64	45.00	50.07	57.44	51.38	46.71	39.65	38.85	34.94
10	64.99	49.11	81.77	47.97	52.23	58.32	51.04	45.75	38.53	36.99	34.09
11	69.35	52.44	86.11	50.45	53.28	58.72	49.77	43.84	36.87	34.93	32.28
12	80.78	59.83	93.43	53.56	54.86	59.48	49.50	43.39	36.57	34.21	31.74
13	68.40	50.89	84.96	50.25	52.84	57.92	46.65	40.36	34.19	31.58	29.51
14	64.74	48.06	79.73	46.78	49.94	55.18	44.02	38.10	32.37	30.10	27.96
15	60.94	44.70	75.70	43.25	47.57	52.83	42.05	36.41	31.51	29.42	27.15
16	57.13	41.37	71.04	40.28	45.76	51.29	42.04	36.88	32.08	30.52	28.21
17	54.41	41.38	69.62	40.05	46.00	51.78	43.26	38.50	33.61	32.23	29.74
18	58.27	51.53	76.14	45.53	50.82	57.52	49.87	45.41	38.66	37.78	34.50
19	69.39	53.33	80.78	49.90	54.54	62.55	56.12	50.95	43.37	41.61	36.83
20	58.78	46.39	78.22	48.88	53.52	62.37	56.39	51.29	44.20	42.53	37.19
21	55.07	40.15	74.32	44.98	49.42	58.93	50.98	46.29	39.76	38.70	34.01
22	48.30	34.26	65.82	40.36	45.81	53.63	46.35	41.46	35.61	34.91	30.84
23	46.53	32.90	63.61	40.08	46.23	52.85	45.10	39.14	33.78	33.24	29.36
24	37.57	26.20	52.93	33.78	40.85	46.85	37.97	31.86	28.33	27.35	25.66
<b>Standard Deviation</b>											
1	10.76	9.23	12.87	11.95	7.28	8.70	14.58	8.20	7.13	9.13	7.74
2	11.20	8.13	14.15	16.98	8.83	9.68	18.63	9.43	7.88	9.33	8.52
3	11.26	7.97	15.24	30.92	10.28	10.34	19.79	11.01	8.24	9.96	9.24
4	11.52	7.70	15.11	17.63	10.60	10.71	20.99	10.78	9.00	9.21	9.14
5	11.02	7.87	14.93	14.86	10.07	10.54	19.04	10.56	8.36	9.18	8.76
6	11.52	9.25	15.17	12.76	10.32	10.11	18.65	9.99	8.29	8.32	8.84
7	16.52	15.03	23.68	20.55	13.40	13.40	22.40	14.09	11.11	11.46	11.11
8	25.05	28.81	30.52	23.94	15.84	15.51	22.01	18.17	14.45	14.20	13.44
9	28.89	34.81	28.59	19.00	14.66	13.83	19.35	18.14	13.81	13.88	13.42
10	40.30	30.07	28.68	16.35	12.28	11.62	16.21	16.30	12.61	12.37	12.20
11	59.40	31.40	29.73	15.43	11.33	10.31	15.19	15.51	11.92	11.84	12.02
12	128.53	41.02	35.17	16.00	11.05	9.99	14.22	15.89	11.77	11.57	11.96
13	49.95	25.73	25.70	13.70	9.97	9.64	13.62	14.80	11.65	11.10	12.82
14	46.54	27.11	25.26	14.25	11.11	10.64	14.04	15.53	13.43	12.33	14.47
15	47.91	25.96	26.43	13.76	11.51	11.09	13.95	17.19	13.74	12.92	15.80
16	42.89	23.66	24.34	12.94	11.74	10.87	13.49	16.69	13.44	12.70	14.44
17	28.21	27.12	22.19	13.41	12.39	10.28	13.57	15.34	12.31	11.82	14.89
18	26.61	64.62	31.94	17.64	15.50	10.73	16.60	17.97	12.61	12.41	15.42
19	131.19	55.41	26.75	19.39	13.40	11.83	20.13	18.06	12.70	12.06	12.08
20	21.96	30.50	23.56	16.72	10.78	9.79	15.85	15.67	11.56	11.39	10.54
21	17.46	18.01	19.63	11.69	7.49	8.42	11.49	12.07	8.30	9.02	8.31
22	13.69	11.72	14.54	7.07	5.39	7.33	9.44	10.28	6.98	8.28	7.11
23	12.53	9.76	11.60	7.10	4.98	6.30	8.30	8.45	6.23	7.99	6.37
24	9.82	7.61	11.28	8.24	5.72	7.70	10.69	7.94	6.86	7.96	7.12
<b>Skewness</b>											
1	0.56	1.77	-0.88	-5.48	-0.66	-1.84	-7.75	-1.18	-1.86	-1.79	-1.49
2	0.30	0.90	-0.97	-6.09	-1.07	-1.71	-9.04	-1.51	-2.13	-1.94	-1.97
3	0.15	0.50	-2.48	-13.48	-1.07	-1.42	-8.86	-2.53	-2.07	-2.24	-2.66
4	0.14	0.42	-2.33	-4.85	-0.77	-1.10	-8.11	-2.03	-3.09	-1.82	-2.38
5	0.08	0.52	-2.46	-4.13	-0.69	-1.14	-8.17	-1.64	-2.56	-2.21	-2.00
6	-0.29	0.55	-0.89	-4.29	-1.16	-1.67	-8.64	-1.24	-2.87	-1.42	-2.25
7	-0.21	0.93	-0.84	-5.00	-1.27	-1.85	-6.76	-1.11	-1.24	-1.11	-2.32
8	-0.07	3.00	-0.33	-2.66	-0.68	-1.50	-1.71	-0.29	-0.66	-0.68	-1.05
9	1.93	4.88	0.19	-1.22	-0.50	-1.18	1.15	-0.10	-0.35	-0.43	-0.54
10	5.13	2.55	0.64	0.68	-0.23	-1.21	0.61	-0.11	-0.12	-0.24	0.40
11	11.07	2.58	0.81	1.19	-0.04	-1.15	0.61	-0.12	-0.05	-0.15	0.46
12	12.24	3.35	1.55	1.42	0.06	-1.01	0.52	0.30	0.09	-0.03	0.49
13	8.07	1.97	0.83	1.25	0.01	-1.27	0.35	-0.07	-0.31	-0.14	-1.15
14	8.76	2.44	0.47	1.01	-0.35	-1.08	0.19	-0.36	-1.57	-1.32	-1.87
15	10.64	2.16	0.49	0.71	-0.30	-1.03	0.05	-1.81	-1.71	-1.88	-2.82
16	9.64	2.00	0.28	0.57	-0.33	-1.05	-0.05	-1.65	-1.85	-1.34	-0.84
17	3.69	2.91	0.27	0.75	0.10	-0.79	0.43	-0.45	-0.74	-0.30	-0.47
18	2.06	7.55	6.58	1.44	1.48	0.41	1.54	0.75	0.44	0.37	1.38
19	16.47	6.11	2.84	1.73	1.19	1.23	2.90	0.79	0.64	0.41	0.92
20	0.90	3.16	3.02	2.14	0.92	0.20	1.87	0.85	0.67	0.44	0.68
21	0.61	1.67	1.27	1.31	0.77	-0.68	1.01	0.29	-0.03	-0.25	0.00
22	0.68	1.44	0.50	1.12	0.33	-0.39	-0.31	0.14	-0.41	-0.42	-0.91
23	0.85	1.57	0.17	1.32	0.22	-0.85	-0.74	-0.19	-0.89	-0.27	-0.60
24	0.66	1.42	-0.13	-1.95	-0.63	-4.46	-5.38	-1.91	-2.28	-1.08	-1.70
<b>Kurtosis</b>											
1	3.61	8.22	4.84	71.08	3.32	7.03	89.13	4.67	7.17	8.46	9.36
2	3.44	5.94	5.22	57.11	4.66	6.22	105.79	6.60	9.54	8.03	12.53
3	2.74	4.48	21.84	223.38	4.63	4.79	102.88	15.72	9.82	10.35	18.26
4	2.44	3.90	20.44	41.09	3.47	3.47	86.69	13.98	23.16	7.73	17.27
5	2.49	4.67	21.82	35.88	2.95	3.63	89.33	10.07	18.23	12.46	15.70
6	3.05	5.20	3.78	47.10	3.87	5.65	99.38	6.07	20.83	5.71	18.00
7	2.64	4.59	3.70	50.96	4.19	8.29	66.90	6.20	5.61	5.06	18.50
8	2.51	22.35	2.95	30.85	3.66	6.56	27.15	2.81	3.76	3.42	11.49
9	15.69	47.70	3.43	18.27	3.83	5.10	10.20	3.02	2.82	3.05	8.93
10	46.66	13.01	4.43	6.40	3.96	5.92	7.10	2.95	3.15	3.30	4.83
11	166.68	12.63	4.39	5.34	4.29	5.87	6.61	2.90	3.36	3.32	4.54
12	167.81	20.11	7.27	5.63	3.74	6.36	5.92	5.02	3.28	3.13	4.37
13	88.86	8.92	4.83	5.09	3.82	6.46	4.95	3.40	5.46	3.65	15.65
14	109.26	13.64	3.19	4.93	4.24	5.11	4.36	3.67	13.76	12.44	20.53
15	158.61	9.78	3.14	4.99	4.09	5.17	4.24	14.34	14.04	17.31	30.61
16	136.73	9.38	2.77	5.58	4.59	5.65	4.36	14.38	14.72	11.72	12.65
17	29.62	16.78	2.80	5.77	5.16	6.18	6.00	4.95	7.96	4.06	10.88
18	13.01	78.17	82.38	5.86	7.69	7.21	9.72	4.43	4.11	4.42	6.21
19	293.55	58.69	17.11	7.26	5.90	7.98	18.27	3.82	3.27	3.70	4.89
20	3.45	17.01	24.23	13.67	4.15	6.20	12.79	4.45	3.73	4.40	5.02
21	2.56	5.64	6.73	6.19	3.97	4.52	12.48	2.93	3.42	3.48	5.36
22	2.86	4.95	3.48	6.50	4.27	4.91	6.36	3.36	3.95	3.94	6.05
23	3.19	5.52	2.49	7.66	4.23	7.30	5.86	3.86	5.14	4.10	4.61
24	3.12	7.13	2.55	20.81	4.30	42.67	60.59	11.06	11.52	5.87	10.10

Table 2: Descriptive Statistics for German hourly electricity prices from 01/01/2006 to 31/12/2016.

### 6.3. Yearly Goodness-of-fit Statistics and Computational Times

	SEP1	SEP2	SHASHo	SHASHo2	JSU	JSUo	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 1														
2010	sec	1.95	0.88	0.84	0.45	2.94	0.62	0.97	1.22	0.53	0.76	0.08	0.08	0.10
	KS	0.1043	0.1311	0.1019	0.0989	0.0345	0.0401	0.0261	0.2004	0.0795	0.0797	0.1533	0.0765	0.1662
	CVM	1.3808	2.1892	1.1370	1.0399	0.0872	0.0964	0.0299	0.0297	0.5773	0.1932	3.1913	0.6422	3.1808
	AD	9.6540	12.9543	6.3452	5.2505	0.4870	0.5755	<b>0.3833</b>	<b>0.3927</b>	30.8319	3.3187	3.3320	20.3288	4.0299
	AIC	2560	2571	2518	2503	<b>2462</b>	2466	2472	2474	2773	2488	2486	2625	2483
2011	sec	1.90	0.63	0.79	0.39	> 100	0.39	1.16	0.97	0.43	0.69	0.08	0.06	0.06
	KS	0.5537	0.3347	0.3385	0.1570	0.1279	0.0550	<b>0.0549</b>	0.3067	0.0774	0.1696	0.2198	0.1967	0.3663
	CVM	50.9773	17.7589	13.7136	2.5864	1.6536	0.2247	<b>0.2226</b>	11.7844	0.6778	3.1368	6.4255	4.2294	16.7820
	AD		105.9948	60.6156	13.7888	10.1099	2.374	<b>2.3246</b>	63.9873	9.2319	17.8803	35.1438	20.3593	77.4224
	AIC		11508	3423	2697	2548	<b>2461</b>	<b>2461</b>	3046	2580	2616	2742	2541	2994
2012	sec	16.62	51.18	0.81	0.55	17.63	0.48	0.99	1.01	0.60	1.76	0.08	0.06	er
	KS		0.6393	0.5794	0.2199	0.2114	<b>0.1392</b>	0.1394	0.4675	0.0463	0.2209	0.2530	0.2940	0.9816
	CVM		38.5683	42.4846	5.6398	5.0497	<b>1.6275</b>	1.6311	26.7599	0.1571	5.6783	10.7433	9.0326	119.2940
	AD			193.3144	30.5878	27.3843	<b>8.6018</b>	8.6160	126.4099	1.8496	30.7987	56.9362	44.4275	> 1900
	AIC			3678	2969	2742	<b>2742</b>	<b>2742</b>	4455	2465	2995	3068	2836	7588
2013	sec	er	er	0.80	0.68	94.60	0.65	1.22	0.58	0.88	0.08	0.07	0.08	0.08
	KS	0.2128	0.2762	0.1899	0.2105	0.0814	0.0662	<b>0.0295</b>	0.0304	0.2564	0.1044	0.1127	0.1906	0.1297
	CVM	7.9361	12.6973	3.7454	4.8465	0.6839	0.4256	0.0429	<b>0.0416</b>	7.6231	1.2110	1.4358	4.3985	1.7883
	AD			17.7897	22.2952	3.6564	2.6397	0.4862	<b>0.4810</b>	45.1560	7.6349	8.3450	25.8997	9.3280
	AIC	3175	3223	2597	2605	2512	2510	<b>2489</b>	<b>2489</b>	2916	2567	2566	2700	2531
2014	sec	23.79	er	0.81	0.54	er	0.43	1.13	1.44	0.61	0.98	0.08	0.08	0.08
	KS	0.6325	0.3497	0.3474	0.1613	0.1470	0.0704	0.0707	0.3267	0.0977	0.1739	0.2495	0.2785	0.3985
	CVM	60.6188	19.5052	14.2807	3.0959	2.2901	<b>0.4359</b>	0.4391	11.9734	1.0063	3.6671	6.4328	4.9500	19.2615
	AD			63.8955	15.9956	13.2023	<b>3.7782</b>	3.7818	64.5449	12.1341	19.9817	34.9132	21.9710	88.2576
	AIC			8851	2513	2352	<b>2352</b>	<b>2352</b>	2846	2373	2417	2525	2343	2855
2015	sec	4.35	er	0.93	0.38	0.58	0.35	0.94	1.01	0.38	0.61	0.06	0.07	0.10
	KS			0.2890	0.3161	0.1425	0.1232	<b>0.0683</b>	0.0692	0.3132	0.1069	0.1555	0.2033	0.1730
	CVM			10.4052	11.8170	2.0225	1.4370	0.4010	<b>0.3982</b>	12.9457	1.0474	2.4432	6.0687	3.1722
	AD			89.7501	53.9219	10.5565	7.8600	2.6301	<b>2.5690</b>	69.1543	7.3633	13.1756	33.9590	16.0647
	AIC			6579	2804	2595	2590	2534	<b>2532</b>	3151	2634	2645	2769	2599
2016	sec	2.61	3.96	0.87	0.46	1.09	0.42	0.83	0.86	0.47	0.95	0.06	0.08	0.12
	KS			0.3542	0.3176	0.1086	0.0927	0.0723	<b>0.0696</b>	0.3153	0.0910	0.1187	0.1866	0.1490
	CVM			20.3441	10.4512	1.0312	0.7630	0.4876	<b>0.4574</b>	12.9752	0.5995	1.1565	5.0358	2.0256
	AD				48.5671	5.5252	4.1592	2.6349	<b>2.4987</b>	69.4496	3.8469	6.4984	28.9854	11.0424
	AIC			5892	2502	2502	2500	2471	<b>2470</b>	3115	2535	2537	2622	3108
HP 2														
2010	sec	1.46	2.47	0.62	0.44	er	0.57	0.67	0.75	0.49	0.70	0.06	0.08	0.09
	KS	0.1967	0.2493	0.1563	0.1731	0.0640	0.0555	<b>0.0429</b>	0.0457	0.2463	0.0977	0.0985	0.1672	0.0970
	CVM	6.0047	9.7827	2.8068	3.5846	0.2902	0.2028	<b>0.1073</b>	0.1229	6.9717	0.8188	8.8548	3.6102	1.1048
	AD	44.8287	13.5729	17.1401	1.4014	1.4047	<b>0.7084</b>	0.8007	42.3148	4.5120	4.7178	22.6634	6.2499	29.2194
	AIC	3274	3316	2644	2659	2574	<b>2573</b>	<b>2572</b>	2574	2992	2622	2621	2756	2594
2011	sec	1.63	1.26	0.62	0.45	er	0.39	1.81	2.12	0.53	0.75	0.06	0.08	0.09
	KS	0.5076	0.3641	0.3177	0.1688	0.1430	<b>0.0665</b>	0.0666	0.2965	0.0989	0.1845	0.2187	0.2029	0.3559
	CVM	39.7275	17.3078	11.9079	2.5446	1.7575	0.2871	<b>0.2844</b>	10.6147	0.9205	3.2174	6.0129	3.9994	14.5305
	AD			78.8731	52.6372	12.9447	10.1919	2.6181	<b>2.6078</b>	58.7266	11.8056	17.6847	33.1361	19.0758
	AIC			6232	2740	2620	2609	<b>2541</b>	<b>2541</b>	3081	2640	2601	2821	3034
2012	sec	9.60	er	0.77	0.19	er	0.46	0.69	0.83	0.47	0.88	0.08	0.07	0.08
	KS			0.7787	0.9945	0.2168	0.2117	<b>0.1605</b>	<b>0.1605</b>	0.4745	0.0463	0.2182	0.2948	0.3057
	CVM			59.5991	120.0109	7.2292	6.3019	<b>2.6126</b>	2.6134	27.4254	0.1587	7.2688	12.5223	11.5668
	AD				39.6691	34.6152	<b>13.0893</b>	13.0913	129.0777	1.8496	39.8791	65.4567	57.0516	> 1900
	AIC			>>	>>	3144	3142	<b>2831</b>	2832	4703	2465	3170	3232	2984
2013	sec	1.67	0.71	0.81	> 150	0.47	0.72	0.80	0.64	0.71	0.08	0.07	0.06	0.09
	KS	0.4962	0.4013	0.2482	0.1049	0.0964	<b>0.0855</b>	0.0859	0.2939	0.1133	0.1215	0.2067	0.1264	0.3058
	CVM	41.4389	24.0605	8.8667	1.1364	0.9043	<b>0.3702</b>	0.3723	9.9905	1.4381	1.6227	4.2936	2.0785	12.9561
	AD			41.8339	5.9565	4.9003	<b>3.1641</b>	3.1871	56.3943	9.1054	8.9442	26.2086	11.0885	61.2545
	AIC			>>	2752	2604	<b>2564</b>	<b>2564</b>	3129	2658	2660	2792	2608	3056
2014	sec	er	er	1.23	0.47	er	0.5	0.93	0.91	0.72	0.72	0.09	0.1	0.08
	KS			0.7671	0.8333	0.3566	0.1603	<b>0.0653</b>	<b>0.0653</b>	0.3467	0.0847	0.1702	0.2451	0.1987
	CVM			78.8824	91.8229	16.6291	2.7307	0.2149	<b>0.2141</b>	13.6960	0.6803	3.1409	6.1295	25.3378
	AD				76.3807	14.5059	11.9148	2.8460	<b>2.8443</b>	72.2225	9.1220	17.1070	34.1889	21.1688
	AIC			>>	2638	2422	2412	<b>2305</b>	<b>2305</b>	3017	2423	2480	2601	2398
2015	sec	1.01	0.54	0.72	0.42	0.86	0.44	0.84	0.82	0.41	0.78	0.08	0.07	0.08
	KS	0.6497	0.6847	0.3330	0.1457	0.1228	<b>0.0438</b>	0.0445	0.3245	0.0811	0.1567	0.2169	0.1855	0.3954
	CVM	65.4341	65.9317	14.1985	2.2203	1.5379	<b>0.2041</b>	0.2078	12.8114	0.7799	2.6480	6.0242	3.7042	19.8659
	AD			64.2224	11.8988	8.7393	1.9964	<b>1.9951</b>	68.6445	7.6692	14.8774	33.6903	18.3982	92.5434
	AIC			>>	2740	2594	<b>2511</b>	<b>2511</b>	3266	2625	2625	2778	2818	3126
2016	sec	31.18	2.28	0.97	0.47	5.90	0.51	0.78	0.83	0.51	1.10	0.08	0.08	0.12
	KS			0.9587	0.3712	0.1322	0.1143	<b>0.0774</b>	0.0781	0.3438	0.0981	0.1389	0.1966	0.1719
	CVM			> 110	15.4599	1.5066	1.0976	0.6328	<b>0.6098</b>	15.4381	0.7325	1.6343	5.6916	2.6364
	AD				69.9090	8.0036	5.8978	3.4560	<b>3.3517</b>	80.0143	4.6192	8.9379	32.1092	13.9219
	AIC			>>	2867	2565	2562	2520	<b>2519</b>	3276	2596	2603	2723	2567
HP 3														
2010		64.76	11.20	0.66	0.50	1.06	0.35	1.89	2.13	0.65	0.75	0.06	0.06	0.08
	1	0.1952	0.2497	0.1444	0.1669	0.0732	0.0639	<b>0.0524</b>	0.0574	0.2436	0.1085	0.1096	0.1803	0.1043
	2	5.5759	8.9326	2.4148	3.4800	0.2943	0.2243	<b>0.1462</b>	0.1706	6.7414	0.8837	0.8990	3.5237	1.0820
	3	39.3994	3320	11.6616	16.4643									



		SEP1	SEP2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 4															
2010	sec	9.74	er	0.93	0.88	6.77	0.61	0.87	1.17	0.58	0.76	0.08	0.06	0.07	0.1
	KS	0.1207	0.1509	0.0856	0.1114	<b>0.0333</b>	0.0344	0.0341	0.0474	0.2193	0.0866	0.0866	0.1670	0.0719	0.1761
	CVM	1.9020	2.9639	0.7369	1.3779	0.0637	<b>0.0632</b>	0.1015	4.9719	0.6317	0.6320	3.0000	6.6382	3.7895	
	AD	12.5125	17.0817	3.9722	6.5940	0.4469	<b>0.4321</b>	0.8183	1.1257	32.5812	3.6354	3.6362	19.8885	4.0828	18.6208
	AIC	2867	2881	2756	2761	<b>2721</b>	<b>2721</b>	2735	2738	3070	2756	2754	2893	2741	2923
2011	sec	1.59	0.87	0.72	0.59	74.45	0.5	1.05	1.15	1	0.59	0.09	0.08	0.08	0.08
	KS	0.2045	0.2274	0.1734	0.2071	0.1113	0.1004	<b>0.0598</b>	0.0601	0.2433	0.1477	0.1441	0.2093	0.1479	0.2390
	CVM	4.9371	6.5266	2.9125	4.4781	1.0009	0.8106	<b>0.1849</b>	0.1856	5.6471	2.1763	2.1438	4.1293	3.1761	5.9168
	AD	26.4488	33.4352	12.7205	19.7660	5.0023	4.8065	<b>1.6121</b>	1.6406	35.5928	12.4633	12.0514	24.9330	11.1234	29.3874
	AIC	2789	2810	2690	2716	2681	<b>2682</b>	<b>2666</b>	<b>2666</b>	3030	2763	2761	2900	2717	2924
2012	sec	er	er	30.22	0.61	> 30	0.72	1.47	0.96	0.57	2.3	0.09	0.08	0.13	er
	KS	0.8000	0.6756	0.2046	0.2046	0.1923	0.1256	0.1256	0.1256	0.4689	<b>0.0463</b>	0.2055	0.3075	0.2954	0.9743
	CVM	64.3944	58.5051	7.0742	6.2841	2.0964	2.0964	2.0964	2.0964	26.9361	<b>0.1587</b>	7.1161	12.6411	11.5732	118.1021
	AD	>>	283.5335	40.4860	36.5685	12.0376	12.0502	12.0502	12.0502	<b>1.8496</b>	40.7246	66.2035	57.5411	> 700	
	AIC	>>	3997	3228	2914	2914	2914	2914	2914	<b>2465</b>	3257	3322	3322	3073	7376
2013	sec	er	0.62	0.89	0.55	> 200	0.57	0.57	0.62	1.54	0.72	0.09	0.08	0.06	0.08
	KS	1.1780	0.8870	0.4113	0.3202	0.0855	0.0904	0.0769	<b>0.0736</b>	0.3603	0.1063	0.0930	0.1814	0.0901	0.5797
	CVM	> 100	19.7004	15.7141	0.5893	0.5324	<b>0.5045</b>	0.5271	14.9981	0.7890	0.7671	3.6982	1.2739	57.6342	
	AD	>>	74.2578	3.5322	<b>2.9158</b>	3.3162	3.5938	3.5938	78.3246	4.3443	4.5371	24.2414	7.9567	> 300	
	AIC	>>	3057	2716	2712	<b>2687</b>	2688	3543	2747	2750	2877	2704	4008		
2014	sec	er	>>	0.9	1.03	er	0.7	0.49	0.56	0.7	0.92	0.08	0.06	0.07	er
	KS	0.7923	0.4263	0.1378	0.1356	<b>0.0888</b>	0.1356	<b>0.0888</b>	0.4096	0.0909	0.1435	0.2413	0.1653	0.7805	
	CVM	62.7834	24.2725	1.9257	1.6512	<b>0.4388</b>	0.4390	0.4390	19.3243	0.7114	2.0834	5.5590	3.4282	88.0624	
	AD	>>	111.9962	11.1687	9.3618	<b>4.3842</b>	4.3847	95.8934	6.8059	12.0344	32.6887	18.3608	624.5921		
	AIC	>>	2978	2539	2535	<b>2431</b>	<b>2431</b>	3523	2526	2575	2687	2488	4490		
2015	sec	0.98	0.67	0.95	0.52	27.81	0.81	er	0.75	0.58	0.59	0.06	0.08	0.08	0.11
	KS	0.6582	0.6307	0.3021	0.3021	0.1321	0.1213	<b>0.0652</b>	0.0653	0.3262	0.0789	0.1442	0.2242	0.1560	0.3750
	CVM	69.0908	50.3467	13.6487	1.8487	1.3801	0.2247	<b>0.2242</b>	12.3242	0.8497	2.2599	5.3449	3.1991	21.2121	
	AD	>>	62.7400	10.1942	7.9779	2.5013	<b>2.5003</b>	66.6485	9.2079	13.0111	30.9241	16.3746	99.7264		
	AIC	>>	2784	2589	2581	<b>2507</b>	<b>2507</b>	3167	2621	2648	2775	2577	3177		
2016	sec	1.64	0.65	1.49	0.59	2.66	0.71	0.96	1.13	0.6	1.02	0.08	0.07	0.08	0.11
	KS	0.8017	0.4045	0.1507	0.1397	0.1397	<b>0.1001</b>	0.1010	0.3808	0.1238	0.1575	0.1871	0.1778	0.7141	
	CVM	65.6259	21.0197	1.9191	1.5136	0.8754	<b>0.8563</b>	18.2593	0.9933	2.0247	6.0170	3.7624	76.6072		
	AD	>>	94.6277	9.6661	7.5677	4.5088	<b>4.4793</b>	91.8512	5.8836	10.3508	33.5933	15.7247	> 400		
	AIC	>>	3022	2619	2616	<b>2565</b>	<b>2565</b>	3479	2642	2653	2770	2606	4219		
HP 5															
2010	sec	er	er	1.43	er	> 100	0.56	0.73	0.7	2.95	0.67	0.11	0.07	0.07	0.08
	KS	0.0944	0.1146	0.0961	0.0764	0.0370	<b>0.0279</b>	0.0379	0.0419	0.1989	0.0755	0.0755	0.1701	0.0592	0.1475
	CVM	1.1780	1.6612	0.7643	0.6348	0.4828	<b>0.4828</b>	4.9528	0.4828	24.9638	0.5355	2.8956	2.6604	2.6604	
	AD	7.4178	9.4164	4.8496	3.4398	0.5738	<b>0.4049</b>	0.8594	1.1115	28.5020	3.2294	3.2311	19.3156	3.5624	14.1081
	AIC	2736	2744	2723	2704	2679	<b>2682</b>	2695	2698	2983	2704	2702	2842	2698	2822
2011	sec	1.78	0.72	0.96	0.46	> 200	0.53	0.68	0.72	1.05	0.69	0.06	0.08	0.07	0.08
	KS	0.2008	0.2320	0.1616	0.1933	0.1012	0.0883	<b>0.0558</b>	0.0562	0.2402	0.1408	0.1392	0.1984	0.1372	0.2287
	CVM	5.0548	6.9943	2.7795	4.2929	0.8396	0.6466	<b>0.1266</b>	0.1301	5.8866	1.9412	1.9388	4.1271	2.0270	6.0205
	AD	27.6920	36.2844	12.1794	18.8648	4.1508	3.7962	<b>1.1785</b>	1.2106	36.7400	11.1488	10.8856	24.8255	10.2691	29.6591
	AIC	2801	2825	2691	2709	2667	<b>2666</b>	<b>2644</b>	2655	2742	2740	2828	2698	2910	
2012	sec	31.2	74.84	1.01	1.19	er	0.85	0.67	0.72	1.25	1.86	0.1	0.07	0.08	er
	KS	0.7432	0.6797	0.1868	0.1732	0.1022	<b>0.1021</b>	0.4682	0.4682	0.0463	0.1876	0.2926	0.2814	0.9778	
	CVM	53.4748	63.6934	5.9456	5.1884	1.2801	<b>1.2782</b>	26.9331	0.1587	5.9829	11.6338	10.1940	118.2875		
	AD	>>	322.0774	34.9762	31.0550	7.7130	<b>7.7049</b>	127.1051	1.8496	35.2018	62.0799	51.6763	> 300		
	AIC	>>	4347	3153	3150	<b>2860</b>	2860	4684	2465	3182	3247	7378			
2013	sec	1.47	0.83	1.46	0.74	er	0.8	0.76	0.93	0.79	0.66	0.08	0.08	0.11	0.11
	KS	0.7298	0.8525	0.2747	0.0953	0.0945	0.0735	<b>0.0684</b>	0.3259	0.1140	0.1080	0.1776	0.0973	0.4415	
	CVM	84.7781	105.2470	11.1016	0.5250	0.4685	<b>0.4290</b>	0.4550	12.2342	0.7995	0.7761	3.4898	1.0956	32.5742	
	AD	>>	53.7360	2.9419	<b>2.5454</b>	2.9308	3.2438	66.4745	4.4272	4.3997	22.9379	6.7880	> 160		
	AIC	>>	2950	2691	<b>2688</b>	<b>2675</b>	2677	3374	2727	2727	2858	2692	3562		
2014	sec	er	er	1.04	er	0.97	er	0.8	0.64	0.55	0.78	0.92	0.06	0.08	er
	KS	0.7773	0.5817	0.1322	0.1322	0.0828	<b>0.0828</b>	0.0829	0.3906	0.0843	0.1392	0.2262	0.1524	0.7046	
	CVM	60.2882	21.3293	1.7193	1.5044	0.4637	<b>0.4633</b>	17.6099	0.8749	1.9229	5.0631	2.9084	77.4100		
	AD	>>	99.0188	9.5598	8.1941	<b>4.8234</b>	4.8253	88.8364	7.9863	10.6761	30.0715	15.4657	> 500		
	AIC	>>	2874	2475	2471	<b>2393</b>	<b>2393</b>	2933	2484	2512	2630	2438	4167		
2015	sec	er	> 170	1	0.39	er	0.58	0.95	0.96	0.61	0.82	0.07	0.07	0.07	0.09
	KS	0.3617	0.1196	0.1196	0.1196	0.1196	<b>0.0677</b>	0.0678	0.3703	0.0724	0.1282	0.2189	0.1495	0.6061	
	CVM	34.6601	19.2105	1.7322	1.4146	<b>0.2740</b>	<b>0.2740</b>	16.0455	0.7163	1.9349	5.2639	3.0257	58.8175		
	AD	>>	88.9700	9.7655	8.0192	<b>3.4736</b>	3.4765	82.8491	7.4749	11.3890	30.8338	15.7673	> 300		
	AIC	>>	2937	2596	2590	<b>2513</b>	<b>2513</b>	3379	2611	2639	2762	2565	3896		
2016	sec	22.86	9.37	1.66	0.59	4.29	0.71	1.17	0.89	0.59	1.09	0.1	0.06	0.09	0.12
	KS	0.6960	0.3935	0.1383	0.1289	0.1005	0.1016	0.3710	0.1233	0.1460	0.1894	0.1606	0.7136		
	CVM	48.3794	19.0627	1.7331	1.4365	1.0039	<b>0.9737</b>	17.6625	1.1272	1.8013	5.6729	2.7295	77.0855		
	AD	>>	86.2933	8.5103	7.0486	5.0997	<b>4.9628</b>	89.3696	5.9599	8.9804	31.6439	14.1862	> 460		
	AIC	>>	2991	2589	2587	<b>2550</b>	<b>2549</b>	3425	2614	2738	2596	4212			
HP 6															
2010	sec	er	0.67	0.99	er	er	0.42	er	er	0.52	er	0.06	0.08	0.06	0.08
	KS														

	SEP1	SEP2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 7														
2010	sec	er	er	2.61	0.56	er	0.68	0.62	0.71	0.63	0.63	0.06	0.07	0.07
	KS	0.0752	0.0912	0.1924	0.1632	<b>0.0610</b>	0.1282	0.0724	0.0698	0.2022	0.0698	0.0698	0.1574	0.1194
	CVM	0.5737	0.7299	3.8903	2.8400	<b>0.4199</b>	1.6399	0.5261	0.4391	6.1206	0.4902	0.4903	3.7541	1.5716
	AD	12.5869		18.8995	14.1395	<b>2.3583</b>	9.4350	3.3794	2.8187	37.6391	2.8151	2.8151	22.2702	8.6786
	AIC	2978	2980	2727	2707	<b>2607</b>	2684	2615	2612	2930	2614	2612	2748	2665
2011	sec	2.25	0.72	2.11	0.54	2.4	0.66	0.92	1.15	0.53	0.91	0.08	0.08	0.08
	KS	0.7288	0.8001	0.3168	0.1688	0.0851	0.0678	0.0334	<b>0.0329</b>	0.3197	0.0705	0.0958	0.1723	0.1331
	CVM	83.1678	95.2119	11.5326	0.6412	0.3403	0.0781	<b>0.0753</b>	12.4506	12.4506	0.8548	4.5012	1.6179	28.0037
	AD	>>	>>	53.1121	3.8073	2.2633	0.7338	<b>0.7281</b>	67.2618	2.8777	5.3406	26.8478	9.0252	130.9830
	AIC	>>	>>	2929	2685	2681	<b>2654</b>	2655	3321	2722	2851	2689	2689	3410
2012	sec	25.06	18.09	0.62	0.44	11.23	0.39	0.91	1.14	0.72	1.36	0.06	0.08	er
	KS	0.7681	0.6574	0.2375	0.2238	0.1487	0.1488	0.4688	<b>0.0463</b>	0.2384	0.2937	0.3282	0.3282	0.9777
	CVM	60.3252	49.8804	6.2658	5.4580	1.7007	1.7022	26.8757	<b>0.1587</b>	6.3057	12.0031	10.3090	117.7743	
	AD	> 20	> 20	36.3452	32.2419	10.6528	10.6596	126.8747	<b>1.8496</b>	36.5996	63.6392	51.3834	> 300	> 300
	AIC	>>	>>	3879	3185	3182	2930	4694	<b>2465</b>	3214	3278	3038	2726	723
2013	sec	er	er	0.77	1.68	er	1.03	1.05	0.81	0.99	1.36	0.09	0.08	0.11
	KS	0.4651	0.5836	0.4780	0.2744	0.0558	0.0966	0.0507	0.0484	0.3098	<b>0.0427</b>	0.0530	0.1658	0.1139
	CVM	66.5509	40.5945	7.0983	0.2320	0.7238	0.2587	0.2422	10.9645	<b>0.1192</b>	0.1234	3.0961	0.7421	22.5975
	AD	>>	>>	36.3694	1.6609	6.2181	1.7268	1.6661	> 60	<b>1.0314</b>	1.2406	21.1882	5.6781	> 108
	AIC	>>	>>	2919	2687	2785	2680	2682	3334	<b>2707</b>	2707	2837	2713	3368
2014	sec	27.06	2.75	2.01	0.23	> 100	0.69	0.74	0.59	0.77	0.06	0.06	0.06	0.06
	KS	0.5365	0.1318	0.2989	0.0854	0.1359	<b>0.0559</b>	0.0577	0.3135	0.0577	0.0870	0.1441	0.1441	0.3506
	CVM	56.1613	1.9358	8.7181	0.4091	1.7066	<b>0.2598</b>	0.2681	11.843	0.1977	0.4819	4.1285	1.2977	17.1937
	AD	>>	>>	19.9211	41.3323	3.2375	11.9159	<b>1.7304</b>	1.7744	61.5034	2.4080	4.2174	25.5815	8.2111
	AIC	>>	>>	3920	2645	2440	2560	<b>2417</b>	2419	3038	2476	2601	2452	2963
2015	sec	er	15.89	0.92	0.95	er	1.58	1.14	0.96	0.83	0.07	0.08	0.06	0.1
	KS	0.2752	0.2932	0.1793	0.1993	<b>0.0662</b>	0.0586	0.0587	0.0703	0.2702	0.0769	0.0668	0.1724	0.0950
	CVM	12.1973	18.2420	3.4826	4.6419	0.1908	<b>0.1649</b>	0.3144	0.4347	7.6377	0.4407	0.4549	3.2894	0.8635
	AD	> 160	> 160	17.7708	22.9289	1.2946	<b>1.0443</b>	1.7031	2.3209	45.7958	3.0922	3.2932	21.7750	6.9613
	AIC	4900	4971	2648	2667	2553	<b>2551</b>	2554	2558	3042	2599	2597	2732	2907
2016	sec	32.62	1.26	2.21	0.64	46.35	0.86	1.03	1.1	0.72	0.83	0.07	0.1	0.12
	KS	0.7732	0.4460	0.1102	0.1368	0.0872	0.0872	<b>0.0845</b>	0.3965	0.0854	0.1148	0.1982	0.1544	0.8195
	CVM	61.3611	22.2828	1.4433	2.1732	0.8066	<b>0.7672</b>	19.6343	<b>0.7643</b>	1.4376	5.6762	2.6115	95.2370	
	AD	>>	>>	99.5174	8.0098	12.3993	4.5409	<b>4.802</b>	97.5620	4.6339	8.2723	32.4566	14.8361	> 600
	AIC	>>	>>	3123	2659	2737	2612	<b>2611</b>	3648	2680	2686	2800	2667	4723
HP 8														
2010	sec	2.26	1.28	0.95	0.95	er	1.06	1.06	1.37	0.64	1.02	0.06	0.06	0.08
	KS	0.0664	0.0855	0.1979	0.1606	0.0455	0.0801	0.0423	<b>0.0394</b>	0.1954	0.0588	0.0587	0.1641	0.1276
	CVM	0.1691	0.7973	3.3874	11.5070	1.0418	3.2946	1.0645	<b>0.8776</b>	32.7814	1.8214	1.8211	20.0594	10.6722
	AD	5.7753	2894	2839	2810	2715	2750	2724	<b>2722</b>	3031	2722	2859	2824	2765
	AIC	2891	2894	2839	2810	2715	2750	2724	<b>2722</b>	3031	2722	2859	2824	2765
2011	sec	3.83	1.22	0.63	2.51	25.12	0.98	0.8	1.17	0.45	0.73	0.08	0.06	0.07
	KS	0.7405	0.3138	0.0976	0.0943	0.0526	<b>0.0502</b>	0.0526	0.1081	0.1101	0.1855	0.1184	0.4660	
	CVM	86.5030	12.7256	0.8444	0.5743	<b>0.1559</b>	0.1561	12.8831	0.7243	1.1353	4.4290	1.7502	33.6274	
	AD	>>	>>	59.1597	4.7174	3.2577	<b>1.34874</b>	1.3824	69.1771	4.6302	6.5632	26.6984	9.6352	> 160
	AIC	>>	>>	2956	2695	2691	<b>2659</b>	2659	3353	2734	2834	2737	2834	3539
2012	sec	er	er	0.44	0.37	0.7	0.43	1	1.61	0.39	1.5	0.07	0.07	0.11
	KS	0.9973	0.4679	0.1479	0.1505	0.1155	0.1101	0.4379	<b>0.0463</b>	0.1493	0.2433	0.6423	0.9584	
	CVM	> 120	22.8226	3.3136	3.4879	1.9205	1.6004	24.6120	<b>0.1587</b>	3.3049	8.8558	58.0876	> 110	> 110
	AD	> 100	> 100	20.2012	21.1687	12.4271	10.6276	> 110	<b>1.8496</b>	20.1758	48.2391	19.1789	64.129	> 120
	AIC	>>	>>	3751	3095	3128	3013	2996	<b>2465</b>	3344	3193	4199	1629	> 100
2013	sec	er	er	0.47	0.4	0.45	0.25	0.72	0.78	0.78	0.06	0.08	0.08	0.07
	KS	0.0778	0.0799	0.1285	0.0918	0.0807	0.0979	<b>0.0678</b>	0.0886	0.2022	0.0684	0.0685	0.1602	0.0996
	CVM	0.6309	0.6153	2.3371	1.0441	0.6979	0.8599	<b>0.5155</b>	0.6014	4.3108	0.5276	2.6632	0.9936	0.8628
	AD	>>	>>	13.5252	6.5539	3.7773	7.3672	3.8294	4.0120	29.4136	3.0859	<b>3.0857</b>	18.9109	7.7148
	AIC	2897	2897	2893	2858	2812	2900	2840	2839	3136	2812	<b>2810</b>	2950	2916
2014	sec	1.62	0.94	2.37	1.51	er	1.36	0.94	1.07	0.78	0.78	0.06	0.08	0.06
	KS	0.1691	0.1949	0.3047	0.1645	0.0513	0.1006	0.0562	0.0523	0.2502	<b>0.0612</b>	0.0612	0.1638	0.1049
	CVM	3.8198	7.6138	9.7525	2.3710	0.1224	1.0482	0.1706	0.1743	7.5051	<b>0.1161</b>	0.1164	3.1463	4.9332
	AD	>>	>>	50.6024	14.8664	1.0810	7.8303	1.3845	1.3462	44.8921	1.1781	<b>1.1801</b>	20.7476	5.4684
	AIC	6215	6257	2900	2717	2576	2672	<b>2573</b>	3027	2588	2812	2810	2622	2845
2015	sec	57.6	er	0.49	0.34	er	0.9	1.37	0.92	0.48	0.61	0.06	0.08	0.08
	KS	0.0893	0.1275	0.0879	0.1049	<b>0.0254</b>	0.0278	0.0353	0.0448	0.2153	0.0585	0.0584	0.1614	0.0784
	CVM	1.1654	2.2407	1.0259	1.1053	<b>0.0340</b>	0.0350	0.0683	0.09340	5.4766	0.2148	2.9534	0.4469	3.0405
	AD	11.6563	16.5843	6.6147	6.7323	<b>0.2536</b>	0.2550	0.5981	0.7187	35.1751	1.3207	1.3196	19.6718	3.5445
	AIC	2962	2976	2703	<b>2637</b>	2641	2646	2644	3004	2656	2641	2792	2660	2823
2016	sec	76.41	83.93	0.81	0.41	> 100	0.54	0.79	0.94	0.45	0.98	0.08	0.06	0.1
	KS	0.1691	0.1949	0.3047	0.1645	0.0513	0.1006	0.0562	0.0523	0.2502	<b>0.0612</b>	0.0612	0.1638	0.1049
	CVM	3.8198	7.6138	9.7525	2.3710	0.1224	1.0482	0.1706	0.1743	7.5051	<b>0.1161</b>	0.1164	3.1463	4.9332
	AD	> 100	> 100	14.0426	1.2409	1.6410	<b>0.6014</b>	0.9002	17.2711	1.0052	1.1597	5.0421	3.4564	77.3720
	AIC	>>	>>	66.7838	7.0025	9.7371	<b>3.2896</b>	5.1441	87.7998	5.6934	6.6224	29.4270	18.5967	> 100
HP 9														
2010	sec	21.81	24.44	1.7	1.02	34.38	0.92	1.12	1.42	0.95	0.84	0.06	0.08	0.06
	KS	0.0444	0.0628	0.2039	0.1784	0.0365	0.0793	0.0390	<b>0.0352</b>	0.2090	0.0403	0.0402	0.1471	0.1283
	CVM	0.2346	0.4484											

	SEP1	SEP2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 10														
2010	sec	72.65	1.2	1.45	0.28	> 200	0.83	0.97	1.04	0.84	0.7	0.06	0.07	0.08
	KS	0.0503	0.0624	0.1972	0.1573	<b>0.0276</b>	0.0595	0.0444	0.0397	0.2170	0.0337	0.0337	0.1144	0.1233
	CVM	0.2593	0.5877	4.3911	2.8226	<b>0.0471</b>	0.4333	0.1050	0.0961	5.9571	0.0850	0.0849	3.1086	2.1320
	AD			23.4270	16.0225	<b>0.4089</b>	2.9392	0.9735	0.8397	37.4577	0.7282	0.7279	20.1967	5.3250
	AIC	3211	3214	2803	2776	<b>2635</b>	2671	2640	2639	3004	2642	2640	2777	2779
2011	sec	69.39	er	5.24	1.64	3.27	0.42	1.5	1.64	0.52	0.94	0.1	0.08	0.08
	KS		0.4043	0.1124		0.0522	0.0440	<b>0.0201</b>	0.0204	0.2755	0.0716	0.0765	0.1750	0.0968
	CVM		31.5557	1.7880		0.2612	0.1387	<b>0.0172</b>	0.0217	9.4574	1.4059	0.5691	3.8703	1.0218
	AD					1.5750	0.8963	<b>0.1391</b>	0.1688	53.9736	2.5255	3.4554	23.9321	6.3186
	AIC		>>	4662		2565	2564	<b>2548</b>	2549	3080	2601	2600	2731	2585
2012	sec	19.29	er	0.89	0.4	7.26	0.92	0.68	1.21	0.46	1.06	0.06	er	0.08
	KS			0.8253	0.3315	0.1032	0.0879	0.0592	0.0630	0.3324	<b>0.0463</b>	0.1069	0.1921	0.4425
	CVM			102.1823	11.4260	0.9149	0.6272	0.2528	0.4634	14.3101	<b>0.1587</b>	1.0182	5.2631	27.0913
	AD				54.1023	5.8183	4.1656	<b>1.7414</b>	3.4890	75.2884	1.8496	6.6542	30.6382	11.6370
	AIC		>>		3130	2853	2857	<b>2809</b>	2833	3535	<b>2465</b>	2855	3006	3531
2013	sec	er	0.69	0.75	0.49	er	1.07	0.8	0.84	0.73	0.61	0.06	0.08	0.08
	KS	0.0694	0.0695	0.1314	0.0936	0.0681	0.0784	0.0851	0.0785	0.1802	<b>0.0574</b>	0.0575	0.1410	0.0783
	CVM	0.2513	0.2500	2.0387	0.7047	0.3248	0.6720	0.2684	0.2479	3.0853	<b>0.1752</b>	<b>0.1752</b>	2.3456	0.5864
	AD	2.1025	2.0998	10.0898	3.3673	1.9644	5.2252	3.0222	2.7309	22.7405	<b>1.1668</b>	1.1670	17.0352	4.7692
	AIC	2865	2865	2900	2866	2863	2932	2905	2908	3127	2856	<b>2854</b>	2996	2925
2014	sec	er	18.91	er	1.04	er	0.73	0.8	0.8	1.04	0.67	0.08	0.08	0.08
	KS	0.0450	0.0448	0.2035	0.1582	0.0343	0.0638	0.0624	0.0559	0.1987	<b>0.0321</b>	<b>0.0321</b>	0.1464	0.0911
	CVM	0.1297	0.1362	4.5719	2.7480	0.1094	0.4892	0.2474	0.2396	6.3495	0.0597	<b>0.0596</b>	2.4997	0.7502
	AD	2.4311	2.4801	22.4636	13.9794	0.7751	3.2891	2.3508	2.2261	25.6064	0.6342	<b>0.6337</b>	17.4354	5.7328
	AIC	2678	2678	2740	2704	2632	2676	2660	2665	2914	2631	<b>2629</b>	2767	2696
2015	sec	er	26.88	er	0.77	> 140	1.31	0.8	0.84	0.43	0.69	0.06	0.08	0.06
	KS	0.0485	0.0486	0.1986	0.1642	<b>0.0275</b>	0.0824	0.0507	0.0471	0.2003	<b>0.2017</b>	0.0387	0.1389	0.1002
	CVM	0.1563	0.1684	4.1766	2.5294	<b>0.0336</b>	0.6233	0.1552	0.1262	4.2876	0.0543	0.0542	2.7466	0.9546
	AD	3.2949	3.3616	20.2099	12.2884	<b>0.3132</b>	4.0804	1.6463	1.4172	28.9195	0.4415	0.4414	18.4196	6.1122
	AIC	2777	2777	2788	2756	<b>2678</b>	2739	2701	2702	2978	2679	2677	2817	2741
2016	sec	21.41	14.03	5.21	er	93.51	1.26	0.76	0.83	0.54	0.89	0.08	0.08	0.12
	KS	0.2056	0.2695	0.1228	0.1585	0.0846	0.0748	0.0562	<b>0.0552</b>	0.2436	0.1141	0.1137	0.1715	0.2371
	CVM	5.6213	10.1727	1.7080	3.4811	0.5761	0.4886	0.2078	<b>0.1857</b>	9.9960	1.0322	4.1668	6.5916	1.3198
	AD			9.6122	17.7386	2.9205	2.5730	1.0314	<b>0.9016</b>	46.9116	5.2446	5.4066	24.6907	7.4699
	AIC	4117	4161	2929	2849	2732	2733	2714	<b>2712</b>	3141	2763	2761	2895	2993
HP 11														
2010	sec	47.18	70.18	0.47	0.32	1.06	1.28	0.95	1.17	0.95	0.71	0.06	0.06	0.08
	KS	0.0894	0.1093	0.3459	0.1564	0.0556	0.1190	0.0545	<b>0.0499</b>	0.2348	0.0631	0.0632	0.1561	0.1697
	CVM	0.7792	1.8038	13.6504	3.2676	0.1747	1.2615	0.2249	<b>0.2082</b>	6.9006	<b>0.2017</b>	0.0387	3.1667	3.1287
	AD			65.2800	18.7759	1.1430	8.2509	<b>1.4677</b>	1.3490	41.9763	1.4909	1.4918	21.5030	6.2869
	AIC	3866	3877	2950	2775	2609	2696	2607	<b>2606</b>	3007	2619	2617	2752	2789
2011	sec	> 100	er	0.58	0.38	8.89	0.48	2.34	2.56	0.36	0.86	0.07	0.06	0.08
	KS		0.3214	0.1144	0.1895	0.0555	0.0454	0.0249	<b>0.0219</b>	0.2691	0.0790	0.1045	0.0944	0.2563
	CVM		19.9330	1.8311	4.5118	0.3062	0.2003	0.0304	<b>0.0255</b>	8.7766	0.5351	0.6834	3.9525	1.0858
	AD			11.0628	22.7053	1.7412	1.1878	0.4856	<b>0.1857</b>	50.7722	3.1869	4.0666	24.1639	6.5356
	AIC		7004	2688	2659	2512	<b>2495</b>	2495	<b>2495</b>	2985	2549	2547	2679	2535
2012	sec	7.03	56.19	7.05	0.52	0.78	0.84	0.79	1.15	0.52	1.05	0.06	0.08	er
	KS			0.8211	0.2955	0.0741	0.1257	0.0382	<b>0.0369</b>	0.3149	0.0463	0.0806	0.1674	0.4146
	CVM			106.2392	9.5626	0.4177	1.6358	0.1578	<b>0.1451</b>	12.3665	0.1587	0.4822	4.2711	24.8778
	AD					2.8854	10.8206	1.0590	<b>1.0027</b>	66.9752	1.8496	3.5701	26.1186	8.1018
	AIC		>>		3085	2837	2947	2811	<b>2811</b>	3478	<b>2485</b>	2867	2964	3508
2013	sec	54.18	94.15	0.53	0.42	> 120	0.93	1.34	1.89	0.61	0.86	0.06	0.06	0.07
	KS	0.0498	0.0498	0.1316	0.0746	0.0658	0.0834	0.0730	0.0924	1.1702	<b>0.0445</b>	<b>0.0445</b>	0.1402	0.0881
	CVM	0.2400	0.2396	2.2357	0.6379	0.4323	0.6550	0.4405	0.3663	2.4872	0.1999	<b>0.1998</b>	2.1463	0.4465
	AD	1.6247	1.6236	11.2423	2.9485	2.5933	4.8432	4.0809	3.5991	19.4797	1.2646	<b>1.2644</b>	16.2537	3.9384
	AIC	2857	2857	2910	2862	2876	2928	2923	2934	3115	2862	<b>2860</b>	3004	2916
2014	sec	er	0.605	0.0615	0.2095	1.36	er	1.12	0.87	1.47	0.67	0.07	0.06	0.08
	KS	0.1937	0.2011	4.8993	3.0166	0.1615	0.4814	0.3034	0.3060	3.7196	0.0962	<b>0.0961</b>	2.4935	0.7861
	CVM	0.1937	0.2011	4.8993	3.0166	0.1615	0.4814	0.3034	0.3060	3.7196	0.0962	<b>0.0961</b>	2.4935	0.7861
	AD	2.5966	2.6573	24.2718	15.3131	1.0415	3.1903	2.5853	2.5653	26.0167	0.8269	<b>0.8264</b>	17.4978	5.8157
	AIC	2688	2688	2758	2718	2635	2680	2663	2635	2924	2635	<b>2633</b>	2771	2704
2015	sec	er	0.8	0.64	0.36	er	0.73	1.09	1.07	0.97	0.7	0.08	0.08	0.08
	KS	0.0543	0.0609	0.1755	0.1448	<b>0.0379</b>	0.0727	0.0498	0.0454	0.1960	0.0519	0.0518	0.1447	0.1033
	CVM	0.2200	0.2575	3.9107	0.1056	<b>0.1056</b>	0.4056	0.1507	0.1408	3.7921	0.1107	0.1107	2.5471	0.4590
	AD	2.5256	2.6901	18.9831	10.7169	<b>0.7231</b>	3.0729	1.7377	1.6771	26.4623	0.7400	0.7396	17.7372	5.8200
	AIC	2701	2730	2774	2739	2680	2738	2706	2709	2970	2679	<b>2678</b>	2818	2738
2016	sec	> 100	71.61	1.09	0.97	23.82	1.25	1.09	1.3	0.7	0.9	0.07	0.08	0.12
	KS	0.1638	0.2209	0.1329	0.1484	0.0707	0.0695	0.0441	<b>0.0402</b>	0.2424	0.1030	0.1030	0.1753	0.2182
	CVM	3.5903	6.6320	2.3704	2.6339	0.3718	0.3054	0.0879	<b>0.0743</b>	6.9919	0.8783	0.8786	3.8793	5.3784
	AD			13.0624	13.7835	2.0329	1.8169	0.5479	<b>0.4707</b>	42.1953	4.7944	4.7956	23.4516	25.9748
	AIC	3382	3413	2845	2842	2747	2749	2735	<b>2733</b>	3128	2778	2776	2911	2974
HP 12														
2010	sec	7.06	29.8	0.61	0.42	> 300	0.86	1.19	1.28	0.83	0.71	0.06	0.08	0.08
	KS	0.0670	0.0692	0.1451	0.1159	0.0532	0.1110	0.0563	0.0612	0.2046	<b>0.0488</b>	<b>0.0488</b>	0.1475	0.1342
	CVM	0.3258	0.4597	2.8225	1.7496	<b>0.1344</b>	1.1306	0.2723	0.1531	5.2886	0.1429	0.1428	3.0524	1.7698
	AD			15.0941	9.8419	<b>0.7262</b>	7.2733	1.9895	1.5929	33.9847	0.9044	0.8999	19.7703	9.9772
	AIC	2892	2894	2733	2741	<b>2623</b>	2709	2637	2642	2958	2629	2627	2765	2748
2011	sec	> 100	75.94	0.5	0.45	28.16	0.58	0.8	0.81	0.51	0.72	0.06	0.08	0.09
	KS		0.3147	0.3451	0.1987	0.0651	0.0619	0.0375	<b>0.0367</b>	0.2761	0.0756	0.0825	0.1692	0.1022
	CVM		18.8497	14.3808	4.5295	0.5151	0.4365	0.1012	<b>0.0780</b>	9.6160	0.6346	0.7836	4.3122	1.2447
	AD			68.3512	24.3070	3.0084	2.6374	0.5842	<b>0.4422</b>	54.5331	3.7518	4.5758	25.6308	7.7005
	AIC		>>	2869	2703	2524	2527	2498	<b>2492</b>	3002	2549	2547	2678	2564
2012	sec	er	56.41	1.33	er	1.33	er	1.08	0.8	0.69	0.8	0.07	0.08	0.08
	KS	0.5098	0.3871	0.2507	0.0558	0.1122	0.0519	0.0363	0.2957	0.0620	0.0620	0.		

	SE1	SE2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 13														
2010	sec	6.83	88.29	0.84	0.54	40.02	1.82	1.53	0.88	0.5	0.61	0.07	0.07	0.07
	KS	0.0476	0.0529	0.1691	0.1393	<b>0.0406</b>	0.0978	0.0668	0.0520	0.2054	0.0450	0.0450	0.1564	0.173
	CVM	0.1977	0.2704	3.6881	2.4433	0.1258	0.9880	0.2815	<b>0.1176</b>	5.5504	0.1352	0.1352	3.1596	0.9760
	AD			19.4998	13.4850	<b>0.8423</b>	6.8207	2.1527	1.2938	35.3496	1.0417	1.0416	20.3154	9.6731
	AIC	2907	2908	2696	2671	<b>2562</b>	2638	2575	2572	2905	2568	2566	2703	2678
2011	sec	26.29	0.67	0.42	0.34	24.44	0.78	0.89	0.95	0.42	1.04	0.08	0.08	0.28
	KS		0.3637	0.1109	0.2019	0.0740	0.0681	<b>0.0468</b>	0.0517	0.2681	0.0999	0.0985	0.1687	0.0998
	CVM		23.2394	1.7751	5.1405	0.3558	0.2308	<b>0.1344</b>	0.1446	8.8388	0.6169	0.7356	3.8633	1.1413
	AD			11.2706	25.4102	2.0057	1.2905	<b>0.7077</b>	0.7943	51.1465	3.5847	4.3753	24.0429	6.8241
	AIC			6989	2650	2630	2490	<b>2475</b>	2475	2979	2532	2531	2663	2508
2012	sec	er	er	6.15	0.7	> 120	0.94	0.67	0.92	1.61	1.04	0.08	0.08	0.11
	KS	0.2558	0.2929	0.2085	0.1928	0.0729	0.1064	0.0728	<b>0.0475</b>	0.2684	0.0483	0.0485	0.1526	0.2367
	CVM	11.3868	18.4062	4.1662	3.4001	0.3421	1.1210	0.3927	<b>0.1758</b>	8.3866	0.2141	0.2139	3.1945	7.8670
	AD			22.2215	19.1702	2.0987	8.5340	2.4539	<b>1.6086</b>	49.2535	1.8019	1.8005	21.3379	5.7866
	AIC	>>	>>	2934	2939	2793	2903	<b>2791</b>	2799	2811	2809	2811	3155	2821
2013	sec	er	er	8.99	1.17	0.49	er	0.46	0.47	1.04	0.64	0.06	0.06	0.11
	KS	0.0791	0.0797	0.0953	<b>0.0514</b>	0.0692	0.0717	0.0796	0.0739	0.1925	0.0573	0.0573	0.1411	0.0799
	CVM	0.4537	0.4543	1.1431	0.3268	0.4594	0.5052	0.4448	0.4396	3.4207	<b>0.2872</b>	0.2873	2.1734	0.8587
	AD			6.5695	2.3493	2.9543	3.8621	3.7299	24.9515	<b>1.9632</b>	1.9634	16.8207	1.8236	3.8236
	AIC	2884	2884	2889	2871	2864	2942	2901	2911	3170	2859	2857	2999	2884
2014	sec	er	er	7.1	0.67	1	5.76	1.51	0.86	0.64	0.81	0.06	0.06	0.1
	KS	0.1140	0.1275	0.2818	0.1351	0.0504	0.0962	<b>0.0466</b>	0.0472	0.2599	0.0486	0.0485	0.1594	0.2077
	CVM	1.1636	2.7071	7.4497	2.1421	0.1529	0.8163	<b>0.1328</b>	0.1965	7.0104	0.1577	0.1571	2.8760	1.1280
	AD			38.0211	13.9006	1.2298	6.8236	<b>1.0033</b>	1.2506	42.6400	1.3162	1.3145	19.9111	7.4999
	AIC	5718	5740	2859	2788	2648	2738	2645	<b>2642</b>	3088	2654	2652	2786	2718
2015	sec	35.32	73.49	0.59	0.36	71.64	0.68	1.19	1.57	0.56	0.7	0.06	0.06	0.07
	KS	0.0640	0.0684	0.1535	0.1168	0.0625	0.0823	0.0530	<b>0.0485</b>	0.1936	0.0614	0.0614	0.1591	0.0983
	CVM	0.3164	0.3631	3.0635	1.7063	0.2423	0.5344	<b>0.2064</b>	0.2536	4.0011	0.2493	0.2493	2.6486	0.9956
	AD	3.5021	3.6988	14.8345	8.5011	<b>1.5576</b>	4.6962	1.9334	1.9543	27.6365	1.6322	1.6322	18.3446	6.4368
	AIC	2731	2731	2738	2714	2671	2741	2692	2692	2969	2670	<b>2668</b>	2809	2720
2016	sec	er	er	62.73	1.36	> 130	0.76	0.76	1.59	0.81	1.11	0.06	0.21	0.11
	KS			0.9320	0.3914	0.1009	0.1276	<b>0.0706</b>	0.0925	0.3598	0.0998	0.0999	0.2128	0.1590
	CVM			> 100	1.1446	1.2878	1.5703	<b>0.5653</b>	0.9776	16.9905	1.1696	1.1696	4.8637	3.2644
	AD				66.4082	7.4275	9.6116	<b>3.3455</b>	5.8965	86.6441	6.832	6.8322	28.6817	17.8404
	AIC			>>	3237	2837	2893	<b>2800</b>	2803	3674	2848	2846	2968	2928
HP 14														
2010	sec	11.48	er	2.04	0.92	er	0.67	1.17	1.01	0.94	er	0.07	0.07	0.08
	KS	0.0469	0.0468	0.3801	0.1736	<b>0.0322</b>	0.0654	0.0567	0.0637	0.2290	0.0333	0.0333	0.1501	0.0916
	CVM	0.1199	0.1199	15.7608	3.3779	<b>0.0520</b>	0.1701	0.1470	0.1370	39.0968	0.6773	0.6773	20.2556	7.6918
	AD			78.1265	18.7133	<b>0.5045</b>	4.2966	1.3726	3.1374	39.0968	0.6773	0.6773	20.2556	7.6918
	AIC	3454	3454	3165	2733	<b>2585</b>	2633	2593	2604	2970	2592	2590	2726	2677
2011	sec	4.73	58.67	0.43	0.88	> 100	0.73	0.91	0.96	0.47	0.7	0.06	0.08	0.14
	KS	0.2049	0.2558	0.1652	0.1713	0.0440	<b>0.0362</b>	0.0470	0.0541	0.0714	0.0758	0.1762	0.0963	0.2174
	CVM	7.3313	12.0170	3.4298	3.6409	0.1472	<b>0.0870</b>	0.1050	0.1427	7.3115	0.4936	0.5382	3.4803	6.2168
	AD			17.0496	18.1984	0.9203	<b>0.5755</b>	0.6029	0.8323	44.0862	3.1063	3.1063	22.3179	30.6597
	AIC	3686	3737	3574	2586	2487	<b>2485</b>	2487	2487	2932	2530	2529	2663	2506
2012	sec	er	er	1.25	2.89	er	0.74	1.08	1.48	2.2	0.98	0.06	0.06	0.13
	KS	0.2539	0.2638	0.3886	0.1916	0.0636	0.1062	0.0695	0.0691	0.2735	<b>0.0498</b>	0.0498	0.1591	0.2212
	CVM	9.6495	15.8761	17.2357	2.9699	0.3559	1.0810	0.4524	0.4440	8.0048	<b>0.2253</b>	0.2254	3.0412	7.3351
	AD			> 200	79.3107	17.5300	2.3165	8.5423	2.9240	29.182	2.0137	<b>2.0128</b>	20.8042	5.5563
	AIC	8692	8765	3066	2913	<b>2770</b>	2882	2771	2776	3267	2788	2785	2921	3124
2013	sec	er	er	11.4	> 110	0.37	0.68	0.78	0.87	0.8	0.08	0.08	0.09	0.07
	KS	0.0693	0.0686	0.1388	0.0813	0.0785	0.0918	0.0800	0.0915	0.1974	<b>0.0658</b>	<b>0.0658</b>	0.1537	0.1011
	CVM	0.6348	0.6338	2.7305	0.8834	0.6922	0.5688	0.5931	0.7064	3.4743	<b>0.4939</b>	<b>0.4939</b>	2.2371	0.5434
	AD	3.9993	3.9959	> 16	5.5782	4.1048	4.0564	4.5536	4.9931	> 25	3.0343	<b>3.0342</b>	> 17	4.5066
	AIC	2886	2886	2968	2908	2870	2941	2907	2915	3180	2864	<b>2862</b>	3004	2899
2014	sec	er	er	2.13	0.94	er	1.12	1.39	1.23	0.64	1.01	0.06	0.06	0.06
	KS	0.0659	0.0659	0.9059	0.3955	0.0880	0.1159	0.0701	0.0700	0.3652	<b>0.0624</b>	0.0624	0.1957	0.1442
	CVM			> 90	15.1828	0.4071	0.8924	0.3037	0.2940	16.1546	<b>0.2182</b>	0.2182	4.0365	1.2405
	AD			>>	70.6951	3.3690	7.2238	2.1097	2.0460	82.8453	<b>1.8748</b>	3.2967	25.8534	8.9085
	AIC			>>	3088	<b>2721</b>	2800	2688	2688	3619	2743	2744	2862	2747
2015	sec	11.87	21.8	0.78	0.43	64.52	0.94	1.27	1.07	0.66	0.99	0.08	0.06	0.06
	KS			0.8953	0.3917	0.0824	0.1149	0.0821	0.0807	0.3651	<b>0.0677</b>	0.0677	0.1883	0.1359
	CVM			98.9341	15.2374	0.4288	0.7811	0.4436	0.4336	15.9531	<b>0.2622</b>	0.2622	3.6452	1.1225
	AD			>>	70.9565	2.7799	6.1226	2.4336	2.4336	82.3336	<b>2.0986</b>	2.0986	23.8689	7.7545
	AIC			>>	3102	2717	2797	<b>2696</b>	2696	3612	2739	2738	2864	2740
2016	sec	er	er	5.37	0.97	1.57	0.63	1.29	1.53	0.78	1.09	0.1	0.07	0.1
	KS			0.6742	0.4614	0.1288	0.1557	0.1070	<b>0.1067</b>	0.3856	0.1101	0.1304	0.2347	0.1694
	CVM			45.0243	19.7031	1.6071	2.0497	1.2583	1.1885	19.4454	1.1981	1.1515	5.5892	3.0892
	AD			>>	89.0716	9.3613	12.2560	7.3276	<b>6.9967</b>	96.7877	7.2012	8.9807	32.1070	17.5176
	AIC			>>	3372	2908	2971	2870	<b>2867</b>	3876	2925	2925	3043	2966
HP 15														
2010	sec	52.89	31.17	1.61	0.76	68.99	0.73	0.89	1.09	0.83	0.72	0.06	0.08	0.06
	KS	0.0564	0.0567	0.2174	0.1939	<b>0.0353</b>	0.0875	0.0615	0.0477	0.2200	0.0386	0.0387	0.1448	0.1132
	CVM	0.1792	0.2538	5.6815	4.4362	<b>0.0859</b>	0.7697	0.4456	0.0925	6.1645	0.1274	0.1276	3.2576	1.6458
	AD			28.4026	22.7725	<b>0.4204</b>	4.8226	3.5816	0.9281	38.3672	0.9895	0.9892	20.7571	

	SEPI	SEP2	SHASHo	SHASHo2	JSU	JSUo	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 16														
2010	sec	26.08	35.24	1.45	0.71	7.05	0.83	1.03	1.12	1.18	0.83	0.07	0.06	0.07
	KS	0.0668	0.0852	0.3390	0.2125	0.0518	0.0902	0.0446	<b>0.0399</b>	0.2298	0.0608	0.0608	0.1451	0.1457
	CVM	0.3359	0.5392	13.1291	5.3241	0.1896	0.7842	0.1660	<b>0.1238</b>	6.6722	0.2548	0.2546	3.5183	2.2249
	AD			64.1514	26.5369	1.1716	4.7793	1.2043	<b>0.9323</b>	40.7208	1.6351	1.6346	21.8255	12.4152
	AIC	3503	3505	3020	2805	2639	2687	2636	<b>2622</b>	3009	2647	2645	2780	2763
2011	sec	> 120	> 260	1.41	0.97	er	0.79	0.9	1.05	0.88	1.06	0.06	0.09	0.06
	KS	0.2037	0.2469	0.1146	0.1905	0.0459	<b>0.0407</b>	0.0409	0.0457	0.2526	0.0460	0.0538	0.1520	0.1054
	CVM	8.0548	13.7828	1.0433	3.4378	0.1075	0.0967	<b>0.0806</b>	0.0941	7.8142	0.1885	0.2437	3.4422	0.7457
	AD			7.0857	17.8594	0.8300	0.7077	<b>0.5163</b>	0.5594	46.4573	1.5668	1.9235	21.9901	5.0965
	AIC	5375	5436	2711	2638	2515	2515	<b>2511</b>	2513	2978	2544	2542	2676	2538
2012	sec	er	er	0.7	1.14	2.87	1.03	0.92	1.06	1.28	0.78	0.08	0.08	0.13
	KS	0.2294	0.2749	0.5711	0.1748	0.0401	0.0956	0.0420	0.0435	0.2709	<b>0.0359</b>	<b>0.0359</b>	0.1485	0.2401
	CVM	10.4634	16.9921	55.3655	3.0380	0.1188	1.1158	0.1551	1.0478	8.3062	<b>0.0970</b>	0.0973	3.1300	8.5582
	AD			17.8697	17.8697	0.8556	7.9771	1.1301	1.0998	48.8683	<b>0.9010</b>	0.9028	20.7621	4.9850
	AIC	>>	>>	3540	2875	2712	2817	<b>2708</b>	2710	3206	2726	2724	2859	3090
2013	sec	3.08	er	0.6	0.52	er	1.13	0.92	1	0.85	1.47	0.06	0.08	0.08
	KS			0.6655	0.4377	0.0705	0.0923	0.0795	0.0793	0.3938	0.0765	<b>0.0678</b>	0.1815	0.1366
	CVM			> 40	19.8103	0.3563	0.5139	0.5957	0.6008	18.1028	0.5040	<b>0.3474</b>	3.3001	0.8419
	AD			> 90	> 90	<b>3.0675</b>	5.2609	3.5571	3.6012	91.3107	3.1781	<b>3.0886</b>	23.2795	7.0456
	AIC	>>	>>	3363	2896	2969	<b>2868</b>	2869	2869	4021	2917	2919	3042	5100
2014	sec	er	1.3	1.24	0.95	> 200	1.22	0.81	0.96	0.82	0.06	0.06	0.06	0.06
	KS			0.7320	0.4106	0.0837	0.1138	<b>0.0469</b>	0.0473	0.3781	0.0506	0.0834	0.1865	0.1423
	CVM			> 50	> 10	4.108	1.0130	0.2446	<b>0.2429</b>	17.1868	0.1635	0.4059	4.2448	1.2977
	AD			> 80	> 80	3.5768	8.0281	1.6875	<b>1.6802</b>	87.1247	1.6080	3.7069	26.9468	9.1147
	AIC	>>	>>	3096	2704	2786	<b>2664</b>	2664	2664	3654	2727	2731	2846	2713
2015	sec	5.18	33.96	1.38	0.92	> 100	0.84	0.95	1.23	0.45	1.33	0.07	0.08	0.08
	KS			0.4079	0.3859	0.0778	0.1100	0.0791	0.0788	0.3627	<b>0.0611</b>	0.0767	0.1840	0.1336
	CVM			16.7883	14.9597	0.3278	0.7756	0.3621	0.3627	15.5394	<b>0.2560</b>	0.3000	3.6228	0.9767
	AD			> 70	> 70	2.4809	6.2930	2.1007	2.1132	80.6172	<b>1.7933</b>	2.4864	23.8810	7.0573
	AIC	>>	>>	3100	2724	2808	<b>2701</b>	2702	2702	3612	2747	2747	2872	2746
2016	sec	> 100	11.1	1.41	0.86	8.63	0.65	1.07	1	0.62	1.55	0.08	0.08	0.11
	KS			0.5527	0.3569	0.1184	0.1473	0.0808	<b>0.0779</b>	0.3470	0.1148	0.1148	0.2211	0.1851
	CVM			51.6103	11.2212	1.9110	2.1750	0.7449	<b>0.6605</b>	15.6688	1.8265	1.8265	5.2714	4.3196
	AD			> 100	> 100	10.5566	12.4839	4.9778	<b>4.6054</b>	81.1302	10.1560	10.1560	30.1652	22.292
	AIC	>>	>>	3264	2914	2969	<b>2868</b>	2868	<b>2849</b>	3630	2921	2919	3044	3012
HP 17														
2010	sec	13.73	7.52	1.59	0.71	1.84	0.81	1.26	1.23	1.25	1.03	0.09	0.08	0.08
	KS	0.1487	0.2127	0.2733	0.1425	0.0800	0.0728	0.0534	<b>0.0500</b>	0.2465	0.0976	0.0975	0.1609	0.2290
	CVM	2.6714	5.9413	10.1330	3.2979	0.4949	0.6013	0.1751	<b>0.1307</b>	7.9830	0.7424	0.7418	4.1570	5.5665
	AD			54.0124	18.3030	2.6921	3.3510	0.9089	<b>0.6989</b>	46.8011	4.1611	4.1599	24.4887	26.5762
	AIC	4534	4561	3133	2875	2722	2736	2703	<b>2699</b>	3122	2741	2739	2872	2946
2011	sec	er	27.99	1.33	0.99	52.31	0.58	1.6	0.85	0.92	1.03	0.19	0.08	0.08
	KS	0.1774	0.2172	0.4432	0.1680	0.0502	0.1067	0.0490	<b>0.0450</b>	0.2622	0.0545	0.0545	0.1606	0.0972
	CVM	5.9888	11.2401	24.9856	3.4952	0.1413	1.1963	0.1042	<b>0.0900</b>	8.7976	0.1645	0.1650	3.5664	1.0741
	AD			113.2372	20.8130	1.2370	8.2458	0.9291	<b>0.7797</b>	51.0977	1.4838	1.4838	22.5877	7.0323
	AIC	>>	>>	2907	2718	2527	2674	2514	<b>2512</b>	3014	2539	2537	2669	2598
2012	sec	er	7.16	0.59	0.61	0.45	1.17	0.85	0.94	0.6	0.86	0.09	0.08	0.11
	KS			0.5393	0.2828	0.0561	0.0420	<b>0.0304</b>	0.0337	0.3078	0.0607	0.0607	0.1554	0.4253
	CVM			55.5371	9.0858	0.1964	0.0887	<b>0.0323</b>	0.0377	11.5214	0.3374	0.3374	3.7053	27.3728
	AD			>>	1.2968	0.6282	<b>0.2198</b>	0.2623	63.3377	2.2653	2.2651	23.3898	5.8831	
	AIC	>>	>>	2989	2745	2744	<b>2729</b>	2730	3388	2777	2775	2905	3490	
2013	sec	34.92	0.9	1	0.45	er	1.82	1.2	1.22	0.7	0.7	0.07	0.08	0.08
	KS	0.1010	0.1436	0.3079	0.1445	0.0555	0.1035	0.0677	0.0734	0.2594	<b>0.0549</b>	<b>0.0549</b>	0.1730	0.1104
	CVM	1.3162	2.6710	11.0200	2.1299	0.2759	0.9063	0.4365	0.4938	6.8500	<b>0.2530</b>	<b>0.2530</b>	2.7397	4.2906
	AD			56.4123	14.4083	1.9581	7.6220	2.8365	3.0893	42.1779	<b>1.8909</b>	1.8910	19.3906	6.4900
	AIC	5753	5772	3207	3011	<b>2861</b>	2959	2866	2868	3320	2867	2865	3002	2932
2014	sec	73.46	er	0.62	0.41	3.74	0.97	1.31	1.32	0.6	1.22	0.06	0.08	0.11
	KS			0.127	0.2656	0.0595	0.068	0.0570	<b>0.0551</b>	0.3022	0.0614	0.0615	0.1897	0.1030
	CVM			0.8486	6.3936	0.3161	0.8685	0.3069	0.2763	11.2629	<b>0.2513</b>	0.2515	3.4009	1.2753
	AD			>>	33.7999	2.1153	6.5403	2.1038	1.9170	61.9381	<b>1.8430</b>	1.8452	22.0156	8.1080
	AIC	>>	>>	3950	2924	2672	2750	2659	2657	2924	<b>2682</b>	<b>2680</b>	2808	2731
2015	sec	er	er	0.57	0.35	> 250	1.09	1.2	1.28	0.4	0.7	0.07	0.06	0.08
	KS	0.0723	0.0747	0.1606	0.1210	0.0683	0.0900	0.0731	0.0592	0.2215	0.0571	<b>0.0570</b>	0.1608	0.0996
	CVM	0.4112	0.4481	3.6488	2.0645	0.2825	0.8188	0.4119	0.3346	5.0950	<b>0.2145</b>	0.2145	2.6950	1.3943
	AD			6.4336	21.0507	12.7069	1.7730	6.7015	2.4938	33.4664	<b>1.5242</b>	1.5243	18.9287	5.0202
	AIC	2995	2995	2848	2812	<b>2695</b>	2785	2715	2716	3060	2699	2699	2836	2749
2016	sec	86.35	er	1.51	1.08	3.37	0.79	1.23	1.46	0.96	1.28	0.09	0.08	0.11
	KS	0.6111	0.9213	0.3128	0.3128	0.1332	0.1516	0.0811	<b>0.0806</b>	0.3420	0.1337	0.1338	0.2329	0.2151
	CVM	69.1100	114.7526	8.3838	2.1091	2.4203	0.5974	<b>0.5852</b>	14.3811	2.1343	2.1360	5.5257	5.5208	
	AD			43.2982	11.7663	13.9224	4.5243	<b>4.3743</b>	75.5322	11.9330	11.9378	31.2674	27.5555	
	AIC	>>	>>	3258	2949	3002	<b>2886</b>	2886	<b>2867</b>	3572	2956	2954	3080	
HP 18														
2010	sec	30.34	82.29	0.93	0.49	3.62	1.48	1.21	1.25	0.89	0.76	0.07	0.08	0.13
	KS	0.6075	0.6785	0.3115	0.1159	0.0971	0.0433	0.0433	0.3087	0.0909	0.1291	0.1943	0.3709	0.1564
	CVM		60.9070	72.7608	11.8176	1.4958	0.9832	0.1354	1.1313	11.9370	0.7604	1.9234	5.2619	18.2202
	AD			>>	53.7287	7.8142	5.4161	1.3861	1.3636	64.8716	6.3395	10.5619	30.1565	13.6732
	AIC	>>	>>	3										

	SE1	SEP2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG			
HP 19																	
2010	sec	er	4.12	3.29	1.38	> 190	1.22	1.89	1.86	2.06	1.69	0.08	0.11	0.1	0.9		
	KS	0.3852	0.4243	0.4364	0.2200	0.0935	0.0913	0.0833	0.0843	0.2798	0.1131	0.1131	0.1890	0.3024	1.0776		
	CVM	24.2719	30.8214	32.9072	6.8064	0.8348	0.7045	0.4372	0.4441	8.8725	1.3449	1.3449	3.8118	12.1343	1.5638		
	AD					4.1951	3.6783	3.2392	3.3112	51.3539	7.2872	7.2873	23.8887		8.5508		
	AIC	7947	8044	4825	2975	2838	2835	2820	2820	3336	2890	2888	3023	3288	2849		
2011	sec	33.75	2.77	0.69	0.45	16.69	0.82	1.11	1.4	0.66	1.51	0.08	0.08	0.17	0.12		
	KS	4.0053	0.2055	0.2599	0.1005	0.0881	0.0472	0.0461	0.3094	0.1104	0.1103	0.1911	0.3206	0.3206	0.1418		
	CVM	AD	4.4876	4.4876	6.9619	0.9103	0.6990	0.1364	0.1315	11.7059	1.1730	1.1732	5.2932	13.5056	1.8172		
	AD					25.7360	36.4192	6.4129	5.0856	1.3596	1.3219	63.9166	8.4989	8.4947	30.6685	64.0059	11.1300
	AIC	3106	2989	3106	2989	2747	2747	2692	2689	3291	2782	2780	2904	3146	2798		
2012	sec	31.08	er	2.29	4.32	0.37	3.29	0.77	0.8	0.59	0.78	0.08	0.07	er	0.27		
	KS	0.8998	0.4726	0.1556	0.1361	0.1556	0.1361	0.0445	0.1229	0.4054	0.1582	0.1583	0.2362	0.7415	0.0220		
	CVM	AD	92.4132	27.8655	3.1640	2.3213	1.1395	2.2142	2.1027	20.0709	3.3302	3.3313	7.9301	77.4136	5.6302		
	AIC	>>	>>	3532	3126	19.0161	14.5728	2.0206	15.0650	99.3397	20.1120	20.1450	43.6178		28.5466		
2013	sec	6.79	1.27	0.56	0.36	er	1.52	0.82	1.03	0.97	0.86	0.06	0.06	0.08	0.06		
	KS	0.1276	0.1580	0.1270	0.1556	0.0422	0.0456	0.0527	0.0689	0.2389	0.0654	0.0653	0.1805	0.1798	0.0993		
	CVM	AD	2.8026	4.5604	1.3930	2.4212	1.0277	1.0254	0.2345	0.3897	5.4239	0.5087	0.5066	3.2350	4.2900		
	AIC	3240	3262	3034	3055	11.8717	1.0095	1.0586	1.5678	2.2566	34.8530	3.9093	3.9017	21.0950	22.2125		
2014	sec	1.92	1.1	0.89	0.58	>	1.13	er	0.86	0.86	0.08	0.08	0.08	0.08	0.06		
	KS	0.1198	0.1339	0.0677	0.1031	0.0403	0.0389	0.0547	0.0614	0.1990	0.0933	0.0931	0.1747	0.1661	0.0795		
	CVM	AD	1.5650	2.0688	0.4708	0.9853	0.1389	0.1180	0.1408	0.1758	4.0186	0.8240	0.8213	2.9260	2.9526		
	AIC	8.8296	10.9298	2.7455	4.6030	0.9065	0.7461	1.1235	1.3155	27.4226	4.5463	4.5379	19.3902	15.5070	4.3699		
2015	sec	er	2775	2731	2729	2716	2716	2734	2737	3016	2752	2750	2888	2871	2736		
	KS	0.0781	0.0986	0.0805	0.0907	0.0246	0.0421	0.0375	0.0319	0.2060	0.0543	0.0542	0.1394	0.1417	0.0857		
	CVM	AD	0.7294	1.2712	0.7042	0.7352	0.0448	0.1037	0.0667	0.0770	4.6561	0.1996	0.1985	2.8368	2.4048		
	AIC	2890	2898	2789	2789	2753	2756	2770	2775	3083	2771	2769	2908	2907	2773		
2016	sec	8.7	0.74	2.03	1.23	2.4	0.83	0.98	1.1	0.74	0.78	0.07	0.06	0.14	0.08		
	KS	0.2441	0.3021	0.1895	0.2103	0.0959	0.0791	0.0420	0.0422	0.2570	0.1248	0.1247	0.1986	0.2589	0.1315		
	CVM	AD	9.5332	14.4336	4.1696	5.3642	0.8863	0.6142	0.1297	0.1268	7.8884	1.6238	1.6239	4.3749	7.8199		
	AIC	3543	3595	2837	2851	2758	2755	2734	2734	3176	2817	2815	2950	3056	2776		
HP 20																	
2010	sec	69.87	1.73	0.96	0.49	93.09	1.11	0.86	0.88	0.98	0.81	0.06	0.08	0.08	0.07		
	KS	0.1828	0.2138	0.1145	0.1461	0.0817	0.0772	0.0856	0.0872	0.2434	0.1199	0.1198	0.1971	0.1977	0.1063		
	CVM	AD	23.3879	5.7762	1.6478	2.4523	0.4478	0.3125	3.1024	3.2309	36.8075	6.9085	6.9029	22.1631	24.3473		
	AIC	2895	2917	2731	2739	2686	2686	2683	2683	3067	2742	2740	2879	2927	2710		
2011	sec	er	3.77	0.47	0.42	2.14	1.01	1.08	1.23	1.31	0.75	0.07	0.06	er	0.06		
	KS	0.1676	0.1931	0.3967	0.1363	0.0404	0.0785	0.0389	0.0385	0.2595	0.0357	0.0358	0.1432	0.1945	0.0812		
	CVM	AD	3.9768	7.6441	17.2557	3.0070	0.0641	0.7484	0.0859	0.1128	7.9465	0.0523	0.0523	6.1166	0.9816		
	AIC	>>	>>	83.3927	19.3682	0.5829	0.8209	0.8209	0.8209	47.2847	0.5626	0.5626	19.8404		6.8485		
2012	sec	er	7.25	0.75	0.35	1.08	1	0.72	1.31	0.56	0.91	0.07	0.07	er	0.06		
	KS	0.9631	0.3844	0.0883	0.0696	0.0425	0.1008	0.3625	0.0677	0.0929	0.2162	0.0677	0.6144	0.1426			
	CVM	AD	114.9456	19.0074	1.1178	0.7090	0.0964	0.7514	16.4758	0.3841	1.2849	5.3030	57.8714	2.3829			
	AIC	>>	>>	3297	7.4443	4.7617	1.0483	5.7795	84.5122	8.3364	31.3748	31.3748		13.5765			
2013	sec	er	0.72	0.38	>230	1.31	1.51	1.47	1.46	0.99	1.46	0.09	0.12	0.12			
	KS	0.1729	0.2133	0.1378	0.1668	0.0375	0.0281	0.0405	0.0484	0.2523	0.0530	0.0531	0.1661	0.2009			
	CVM	AD	5.2932	9.1589	1.6840	2.8958	0.0465	0.0403	0.1061	0.1617	6.7756	0.2765	0.2769	3.1420	5.4750		
	AIC	3957	4000	2988	3003	2911	2911	2918	2923	3352	2950	2948	3084	3195			
2014	sec	er	2.84	1.06	1.06	1.8	1.22	1.33	0.96	1.22	0.09	0.12	0.13	0.13			
	KS	0.1149	0.1424	0.1058	0.0936	0.0453	0.0408	0.0337	0.0410	0.2110	0.0835	0.0834	0.1600	0.0712			
	CVM	AD	1.4037	2.3466	1.1505	1.0860	0.0925	0.0807	0.0595	0.0728	4.9523	0.5062	0.5046	3.0883	3.0954		
	AIC	2801	2814	2616	2703	0.4874	0.5280	0.4689	0.5465	32.1657	2.8543	2.8494	19.9418	16.2640			
2015	sec	er	1.25	1.37	0.9	14.56	1.48	1.33	2.14	0.77	0.06	0.19	0.20	0.07			
	KS	0.1171	0.1693	0.2106	0.1144	0.0407	0.0384	0.0301	0.0368	0.2282	0.0681	0.0682	0.1535	0.1017			
	CVM	AD	2.0319	4.0674	7.0519	1.7217	0.0767	0.0815	0.0530	6.4055	0.2875	0.2883	3.0446	4.8772			
	AIC	3581	3603	3015	3023	2705	2710	2705	2710	3215	2722	2720	2857	2958			
2016	sec	> 240	54.74	0.85	0.53	1.23	1.47	1.06	2.53	1.15	0.84	0.06	0.08	0.08			
	KS	0.2052	0.2681	0.2195	0.1738	0.0850	0.1048	0.0389	0.0370	0.2498	0.1151	0.1152	0.1935	0.2479			
	CVM	AD	6.1670	10.5452	6.7896	3.4113	0.5704	0.4381	0.0999	0.0915	7.7567	1.1637	1.1643	6.7753			
	AIC	3791	3834	2948	2798	2679	2680	2657	2655	3086	2715	2713	2848	2944			
HP 21																	
2010	sec	1.69	1.48	2.56	0.94	32.41	1.13	1.27	1.4	0.98	0.68	0.07	0.08	0.08			
	KS	0.1409	0.1761	0.1017	0.1288	0.0513	0.0453	0.0307	0.0348	0.2219	0.0974	0.0973	0.1713	0.1898			
	CVM	AD	2.5694	4.1130	1.3465	1.9030	0.1514	0.1136	0.0393	0.0533	5.4381	0.8428	0.8415	4.2739			
	AIC	17.1928	2613	2486	2480	2427	2428	2428	2429	2769	2468	2466	2604	2624			
2011	sec	er	1.42	0.97	0.66	er	0.84	1.11	1.18	1.08	0.67	0.06	0.07	0.08			
	KS	0.1112	0.1397	0.0935	0.1129	0.0422	0.0411	0.0473	0.0564	0.2259	0.0504	0.0504	0.1511	0.0852			
	CVM	AD	1.7758	3.2149	0.8078	1.2793	0.0777	0.0821	0.1423	0.2005	5.6998	0.1918	0.1921	2.7865			
	AIC	3013	3032	2589	2596	2528	2529	2541	2546	2926	2550	2548	2686	2549			
2012	sec	2.15	4.42	0.75	0.69	0.62	0.62	1.46	0.64	0.66	0.98	0.06	0.06	0.11			
	KS	0.3638	0.4787	0.3638	0.0724	0.1052	0.0445	0.0562	0.0516	0.3515	0.0726	0.0727	0.1789	0.6617			
	CVM	AD	43.0682	14.4854	0.4566	1.2568	0.1313	0.1762	15.9521	0.4859	0.4861	4.4962	65.0816	1.4320			
	AIC	>>	>>	3098	2725	2804	2691	2697	3566	2747	2745	2867	4081	2772			
2013	sec	er	34.32	0.81	0.64	er	0.89	0.88	0.98	0.98	0.77	0.07	0.07	0.06			
	KS	0.0493	0.0496	0.1135	0.0314	0.0371	0.0719</										

		SE1	SEP2	SHASH0	SHASH2	JSU	JSU0	ST1	ST2	ST5	SN1	NO	LO	GU	RG
HP 22															
2010	sec	41.86	19.13	0.86	0.46	> 200	0.64	1.26	1.42	0.63	0.75	0.06	0.08	0.11	0.08
	KS	0.0895	0.1039	0.1228	0.1186	0.0487	0.1217	0.0535	<b>0.0477</b>	0.2123	0.0624	0.0585	0.1492	0.1631	0.0899
	CVM	0.6681	1.3726	2.5141	1.5919	0.1991	1.3547	0.2814	<b>0.1244</b>	6.0187	0.1865	0.1867	3.2528	2.7250	0.9072
	AD			14.1189	9.0448	<b>1.1608</b>	8.8061	1.9714	1.3859	37.5838	1.3050	1.3064	20.6752	14.6565	5.6069
	AIC	2717	2726	2328	2313	<b>2229</b>	2329	2237	2243	2589	2239	2237	2374	2398	2265
2011	sec	52.01	15.58	1.08	0.63	11.51	0.67	1.24	1.26	0.56	0.71	0.06	0.06	0.08	0.07
	KS	0.0838	0.1081	0.1267	0.1225	0.0561	0.1036	0.0590	<b>0.0454</b>	0.2263	0.0466	0.0464	0.1468	0.0837	0.1692
	CVM	0.8363	1.9940	2.0909	1.8636	0.1655	1.2333	0.2616	<b>0.0933</b>	6.7247	0.1497	0.1497	3.1424	0.9517	3.2942
	AD			12.5190	11.2326	0.9689	7.6385	1.9257	<b>0.8151</b>	41.2219	0.9483	0.9500	20.4056	6.3103	16.8321
	AIC	3729	3744	2573	2571	<b>2462</b>	2558	2470	2465	2866	2470	2468	2604	2542	2676
2012	sec	er	er	1.03	0.67	er	0.49	1.11	1.36	1.06	0.98	0.07	0.08	0.08	0.08
	KS	0.0803	0.1309	0.2288	0.2101	0.0483	0.0907	0.0431	<b>0.0389</b>	0.2624	0.0528	0.0527	0.1568	0.1992	0.1530
	CVM	0.6605	2.2344	6.0640	5.1345	0.2387	1.0141	0.1377	<b>0.1018</b>	9.0976	0.2736	0.2735	3.7929	4.5710	2.7857
	AD			32.5091	27.9379	1.6748	6.3693	0.9741	<b>0.7495</b>	52.3133	1.9642	1.9635	23.3896	15.5156	27.432
	AIC	>>	>>	2819	2808	<b>2588</b>	2648	2574	<b>2565</b>	3064	2597	2595	2727	2840	2739
2013	sec	er	er	0.53	0.34	> 200	0.53	0.8	0.97	1.56	0.65	0.06	0.08	0.08	0.06
	KS	0.0464	0.0464	0.2051	0.1801	0.0323	0.0752	0.0599	0.0600	0.1916	<b>0.0321</b>	<b>0.0321</b>	0.1332	0.0830	0.0835
	CVM	0.1322	0.1322	5.4370	3.4538	0.0378	0.6418	0.3171	0.3171	4.3632	<b>0.0314</b>	<b>0.0314</b>	2.6660	0.7894	0.7740
	AD			27.8823	17.6619	0.2660	4.2548	3.3569	3.3569	29.4440	<b>0.2359</b>	<b>0.2359</b>	18.2219	5.1283	5.0260
	AIC	2758	2758	2812	2764	<b>2639</b>	2699	2679	2679	2951	2640	<b>2638</b>	2778	2712	2708
2014	sec	er	er	0.75	0.38	er	0.45	0.7	0.9	0.8	0.7	0.06	0.06	0.08	0.07
	KS	0.0824	0.1144	0.1090	0.0978	<b>0.0269</b>	0.0391	0.0353	0.0341	0.2107	0.0518	0.0513	0.1450	0.0833	0.1547
	CVM	0.9348	1.9032	1.2057	1.1242	<b>0.0302</b>	0.1070	0.0483	0.0551	5.3619	0.1774	0.1866	2.9997	0.5045	2.8042
	AD	10.9022	7.4035	6.8405	6.8405	<b>0.2524</b>	0.8000	0.5166	0.5060	34.3166	1.1735	1.2352	19.5918	3.7535	14.9063
	AIC	2585	2597	2356	2352	<b>2288</b>	2294	2295	2297	2636	2305	2303	2437	2312	2456
2015	sec	er	er	0.89	0.5	er	0.66	1.27	1.2	0.48	0.93	0.07	0.06	0.11	0.06
	KS	0.0642	0.0902	0.1597	0.1243	<b>0.0322</b>	0.0584	0.0393	0.0353	0.2079	0.0503	0.0504	0.1490	0.0745	0.1433
	CVM	0.4459	0.9634	2.8241	1.7470	0.0632	0.3581	0.0784	<b>0.0572</b>	5.4298	0.1824	0.1829	3.2113	0.6587	2.3084
	AD	7.7992	10.0479	15.4738	10.1008	<b>0.4350</b>	2.2794	0.7558	0.5734	34.6471	1.2217	1.2238	20.3835	4.5647	12.6472
	AIC	2780	2786	2624	2600	<b>2505</b>	2529	2510	2510	2839	2515	2513	2651	2548	2638
2016	sec	er	er	1.32	0.5	> 200	0.74	0.91	1.51	0.65	0.72	0.08	0.06	0.08	0.14
	KS	0.1349	0.2049	0.3879	0.1421	0.0415	0.0517	0.0379	<b>0.0345</b>	0.2431	0.0538	0.0564	0.1618	0.0937	0.2067
	CVM	3.7492	7.7812	16.7939	2.7201	0.1608	0.8316	0.0490	<b>0.0306</b>	6.78577	0.2600	0.2600	3.6182	0.8384	5.3872
	AD			78.1542	15.8524	1.2447	1.0877	0.5471	<b>0.3541</b>	46.5602	1.6555	1.9790	22.6790	6.0779	26.3184
	AIC	5080	5120	2820	2562	<b>2428</b>	2436	2417	<b>2415</b>	2863	2444	2442	2576	2468	2685
HP 23															
2010	sec	er	er	0.49	0.26	er	0.6	1.28	1.01	0.41	0.62	0.07	0.06	0.08	0.06
	KS	0.0717	0.0829	0.1717	0.1378	0.0735	0.1298	0.0942	<b>0.0452</b>	0.2170	0.0787	0.0787	0.1841	0.1535	0.1170
	CVM	0.4030	0.6529	3.4625	3.3016	0.2716	1.3021	0.3954	<b>0.1348</b>	6.2837	0.2961	0.2961	3.5252	2.2925	1.3512
	AD			17.5490	12.9825	1.7332	8.3031	2.8787	1.9746	38.7775	1.9746	1.9753	21.6879	12.8608	7.9489
	AIC	2752	2755	2320	2306	<b>2202</b>	2284	2211	<b>2203</b>	2555	2210	2208	2344	2344	2259
2011	sec	er	er	0.76	0.53	> 100	0.42	0.96	1.39	0.5	0.97	0.06	0.07	0.07	0.08
	KS	0.3436	0.3982	0.0873	0.2151	0.0506	0.1003	0.0426	<b>0.0375</b>	0.2733	0.0436	0.0502	0.1550	0.0968	0.2836
	CVM	23.6223	32.3389	0.3284	4.8234	0.2646	1.3031	1.1415	<b>0.1061</b>	10.0699	0.1912	0.2676	3.7548	1.1192	11.6500
	AD			25.8722	1.7193	8.4103	1.0400	<b>0.8038</b>	<b>0.8038</b>	56.7560	1.3155	1.7745	23.3260	7.2841	54.3948
	AIC	>>	>>	8167	2554	<b>2363</b>	2458	2348	<b>2347</b>	2897	2329	2328	2538	2405	2795
2012	sec	er	er	0.84	0.39	> 100	0.58	1.27	1.33	0.73	0.84	0.06	0.08	0.06	0.06
	KS	0.1047	0.1543	0.3743	0.2608	0.0463	0.0709	<b>0.0345</b>	0.0359	0.2453	0.0557	0.0557	0.1632	0.0937	0.1775
	CVM	1.6273	4.0354	16.5040	8.6630	0.2139	0.4273	0.0549	<b>0.0446</b>	7.7297	0.3755	0.3754	3.6958	0.9510	4.3198
	AD			78.7269	41.3853	1.4296	2.8547	0.4128	<b>0.3200</b>	45.9347	2.4818	2.4829	22.9550	22.1810	22.1810
	AIC	4779	4800	2997	2756	<b>2534</b>	2560	2518	<b>2516</b>	2957	2551	2549	2683	2607	2743
2013	sec	er	er	0.48	0.45	er	0.42	0.46	1.46	0.98	0.68	0.07	0.08	0.08	0.06
	KS	0.0748	0.0744	0.1544	0.1228	0.0455	0.0956	0.0654	0.0621	0.2052	<b>0.0430</b>	<b>0.0430</b>	0.1499	0.0917	0.1242
	CVM	0.2653	0.3626	2.2901	1.5358	<b>0.1422</b>	1.1430	0.3012	0.2404	5.2990	0.1480	0.1481	3.1487	0.9911	1.7299
	AD	8.3111	8.6993	11.5351	8.3462	<b>1.0371</b>	7.7056	2.5539	2.1312	33.9628	1.1658	1.1663	20.0905	6.2098	10.3404
	AIC	2788	2790	2610	2602	<b>2536</b>	2623	2553	<b>2553</b>	2863	2542	2540	2678	2578	2661
2014	sec	er	er	0.84	0.52	er	0.98	1.3	1.66	0.57	0.55	0.06	0.07	0.07	0.06
	KS	0.1428	0.2118	0.1651	0.1753	0.0573	0.0516	0.0386	<b>0.0354</b>	0.2488	0.0699	0.0756	0.1609	0.1105	0.2122
	CVM	3.8279	7.7029	2.6683	2.8894	0.2422	0.2343	0.0951	<b>0.0830</b>	7.2268	0.4040	0.4863	3.7961	1.0074	5.4583
	AD			14.4674	14.9949	1.5365	1.4652	0.5910	<b>0.5170</b>	43.1742	2.9494	3.3516	23.0000	6.0309	27.1655
	AIC	3312	3349	2359	2360	<b>2256</b>	2257	<b>2246</b>	<b>2246</b>	2652	2284	2282	2413	2280	2492
2015	sec	er	er	0.46	0.32	er	0.43	0.92	1.25	0.69	0.61	0.07	0.06	0.08	0.08
	KS	0.0558	0.0705	0.2381	0.2159	<b>0.0428</b>	0.0842	0.0470	0.0413	0.2086	0.0535	0.0535	0.1489	0.0954	0.1317
	CVM	0.3201	0.5682	6.3442	5.0422	0.1408	0.7178	0.1597	<b>0.1135</b>	5.7256	0.2330	0.2329	3.4066	1.0204	2.0404
	AD			29.9111	23.9733	<b>0.8959</b>	4.2166	1.2471	0.932	35.9844	1.5830	1.5830	21.0404	6.1835	11.6694
	AIC	2857	2860	2654	2651	<b>2520</b>	2563	2524	<b>2522</b>	2851	2522	2525	2623	2630	2630
2016	sec	er	er	1.28	1.36	er	1.03	0.78	0.83	0.87	0.7	0.07	0.08	0.06	0.11
	KS	0.0874	0.1291	0.1851	0.1487	0.0502	0.0787	0.0353	<b>0.0314</b>	0.2210	0.0643	0.0643	0.1540	0.0912	0.1720
	CVM	0.8192	2.0286	3.3427	2.3763	0.1948	0.4491	0.0976	<b>0.0638</b>	6.5602	0.3464	0.3466	3.5920	0.9031	3.3125
	AD		</												

hours	KS					CVM					AD				
	JSU	JSU <sub>0</sub>	ST1	ST2	ST5	JSU	JSU <sub>0</sub>	ST1	ST2	ST5	JSU	JSU <sub>0</sub>	ST1	ST2	ST5
1	0.0603	0.0822	0.0294	<b>0.0291</b>	0.4210	1.9100	4.3528	0.5453	<b>0.5277</b>	148.5070	12.8945	3.9139	<b>3.8630</b>	727.8232	
2	0.0794	0.0688	0.0260	<b>0.0259</b>	0.4584	4.2045	2.9519	0.3020	<b>0.2985</b>	176.7370	27.9584	3.1511	<b>3.1483</b>	841.7994	
3	0.0885	0.0620	<b>0.0255</b>	<b>0.0255</b>	0.4610	5.7829	2.1785	0.2036	<b>0.2023</b>	179.0372	38.1926	<b>2.8697</b>	<b>2.8709</b>	851.0370	
4	0.0808	0.0735	0.0184	<b>0.0182</b>	0.4619	5.5244	4.2863	0.1258	<b>0.1224</b>	180.2509	37.4213	1.7491	<b>1.7386</b>	855.9105	
5	0.0733	0.0639	0.0194	<b>0.0190</b>	0.4567	3.8933	2.6782	0.1071	<b>0.1021</b>	176.3345	26.8176	1.2072	<b>1.1912</b>	840.1847	
6	0.0645	0.0769	0.0170	<b>0.0167</b>	0.4600	2.7978	4.5500	0.1375	<b>0.1369</b>	178.3401	21.0471	<b>1.3620</b>	<b>1.3644</b>	848.2432	
7	0.0636	0.0775	0.0205	<b>0.0203</b>	0.4549	3.0892	5.1891	0.1415	<b>0.1403</b>	175.8737	24.0319	1.5832	<b>1.5664</b>	838.3356	
8	0.0328	0.0464	0.0264	<b>0.0227</b>	0.3877	0.5175	2.1116	0.1587	<b>0.1478</b>	128.0669	inf	inf	<b>2.0238</b>	644.3292	
9	<b>0.0261</b>	0.0832	0.0293	<b>0.0407</b>	0.2952	<b>0.2976</b>	6.5921	0.6850	0.7924	72.8623	<b>3.0777</b>	inf	<b>2.0238</b>	644.3292	
10	<b>0.0343</b>	0.0648	0.0520	0.0558	0.2121	<b>0.9334</b>	2.7193	1.6108	1.1460	33.5401	<b>6.2472</b>	inf	<b>2.0238</b>	644.3292	
11	<b>0.0467</b>	0.0621	0.0695	0.0641	0.1910	1.7901	2.7249	<b>1.7070</b>	1.8615	25.7141	<b>11.3990</b>	inf	<b>2.0238</b>	644.3292	
12	<b>0.0566</b>	0.0632	0.0742	0.0688	0.1897	2.4602	2.9940	<b>2.2254</b>	2.4308	24.1867	<b>15.5861</b>	inf	<b>2.0238</b>	644.3292	
13	<b>0.0513</b>	0.0642	0.0647	0.0650	0.2146	2.4087	2.8771	2.5482	<b>1.9983</b>	32.0021	<b>15.4343</b>	19.2628	<b>2.0238</b>	644.3292	
14	<b>0.0466</b>	0.1034	0.0537	0.0557	0.2738	<b>1.4318</b>	7.5778	2.1409	2.2748	58.8315	10.4153	15.3257	<b>2.0238</b>	644.3292	
15	<b>0.0426</b>	0.0726	0.0529	0.0540	0.3414	<b>0.8479</b>	3.6727	1.7213	1.8447	96.3967	<b>8.0750</b>	11.0307	<b>2.0238</b>	644.3292	
16	<b>0.0336</b>	0.0756	0.0454	0.0480	0.3075	<b>0.7256</b>	5.0136	1.3505	1.5281	78.6884	<b>5.9686</b>	8.8552	<b>2.0238</b>	644.3292	
17	<b>0.0327</b>	0.0593	0.0478	0.0526	0.2545	<b>0.6182</b>	2.0496	1.4480	1.3419	51.1149	<b>4.4347</b>	inf	<b>2.0238</b>	644.3292	
18	0.0307	<b>0.0245</b>	0.0334	0.0388	0.2623	0.4800	<b>0.4532</b>	0.8896	1.1539	53.7730	3.7851	3.1608	<b>2.0238</b>	644.3292	
19	0.0352	<b>0.0313</b>	0.0376	0.0386	0.3264	0.8963	<b>0.5020</b>	0.9327	1.1456	85.7751	8.0516	4.4464	<b>2.0238</b>	644.3292	
20	<b>0.0170</b>	0.0217	0.0355	0.0425	0.2643	<b>0.1570</b>	0.1950	0.6848	1.0053	55.6637	1.5136	<b>1.5098</b>	<b>2.0238</b>	644.3292	
21	<b>0.0239</b>	0.0337	0.0362	0.0338	0.2122	<b>0.1983</b>	0.6995	0.3370	0.4910	37.0782	<b>1.6723</b>	5.7331	<b>2.0238</b>	644.3292	
22	<b>0.0209</b>	0.0560	0.0509	0.0466	0.1806	<b>0.2626</b>	3.2594	0.8717	0.7708	27.8992	<b>1.4116</b>	22.7194	<b>2.0238</b>	644.3292	
23	<b>0.0472</b>	0.0612	0.0667	0.0606	0.1679	<b>1.4743</b>	4.0055	1.6974	1.6342	22.7213	<b>7.6127</b>	29.9739	<b>2.0238</b>	644.3292	
24	0.0489	0.1069	0.0384	<b>0.0376</b>	0.3323	1.3256	7.6553	1.2046	<b>1.1320</b>	92.5652	8.2081	53.8549	<b>6.5296</b>	495.1395	

Table 11: Comparing JSU, JSU<sub>0</sub>, ST1, ST2 and ST5 over the full sample of deseasonalized electricity prices 2010-2016. KS = Kolmogorov-Smirnov, CVM = Cramer-von Mises, and AD = Anderson-Darling statistics; AIC = Bayesian Information Criterion. “Inf” means ‘infinite number’.



## *6.4. Progressive Modelling*

### *6.4.1. Estimated Coefficients*

Eq.	Hour 3											
	MI	M2	M3	M4	AR-M1	AR-M2	AR-M3	AR-M4	VAR-M2	VAR-M3	VAR-M4	VAR-M4
$\mu_t$	const	5.351	-3.511	-10.293	-10.340	-3.436	-11.694	-10.041	-4.393	0.927	-5.445	-5.445
	$load_t$	19.663	0.245	-10.293	0.190	18.216	0.227	0.191	0.297	0.227	0.227	0.227
	$coast_t$	2.266	2.252	24.160	2.790	2.400	3.067	2.969	2.081	2.739	10.195	8.580
	$gas_t$	8.748	0.273	14.422	0.452	9.312	0.451	0.477	0.222	7.219	15.119	0.086
	$co_2_t$	0.506	0.618	20.469	0.654	15.258	0.739	0.701	0.552	7.988	5.749	0.518
	$hold_t$	-1.271	-2.924	0.839	0.369	-6.227	0.296	0.472	-0.448	0.599	7.665	3.095
	$fwind_t$	-0.200	-35.186	-0.147	-18.077	-18.531	-0.152	-0.140	-0.147	0.107	0.415	0.737
	$fsolart$	0.092	11.721	0.092	12.103	0.091	1.038	0.009	0.295	0.091	1.900	-13.529
	$\mu_t$	const	43.763	2.510	12.691	1.873	8.916	1.810	2.358	10.827	3.224	0.988
	$load_t$	1.772	-0.054	-16.162	0.069	43.964	-0.058	1.695	2.309	-0.052	0.015	0.225
	$coast_t$	0.008	-0.484	2.085	0.057	-14.228	-0.011	-0.063	-0.062	-12.610	0.237	0.097
	$gas_t$	0.029	5.976	8.221	0.061	11.428	0.033	6.807	0.023	3.591	0.017	0.670
	$co_2_t$	0.074	11.727	0.088	0.066	6.970	0.086	0.059	0.052	4.349	0.010	0.775
	$hold_t$	0.388	10.995	0.495	0.556	12.401	0.380	0.526	0.373	10.454	0.373	0.365
	$fwind_t$	0.019	23.080	0.021	0.023	24.372	0.020	0.021	0.019	18.659	0.020	18.779
	$fsolart$	const	-11.181	5.064	4.535	0.002	0.444	0.003	0.908	0.021	3.072	3.755
	$\mu_t$	const	-2.966	-12.288	3.727	-2.805	-10.837	4.482	-2.640	2.988	0.026	0.021
	$load_t$	const	5.374	0.072	0.096	4.229	2.313	0.094	3.948	1.772	0.001	0.067
	$coast_t$	const	-0.628	-4.051	-0.603	-4.233	-0.609	-0.590	-4.045	0.034	0.153	3.511
	$gas_t$	const	-0.188	-7.093	-0.214	-7.972	-0.174	-0.219	-6.162	-0.221	0.173	0.442
	$co_2_t$	const	-0.180	-3.927	-0.156	-3.415	-0.160	-0.138	-2.807	-0.050	-0.260	-2.179
	$hold_t$	const	-1.255	-4.655	-1.399	-5.400	-1.204	-1.368	-4.971	-0.004	-0.233	-1.318
	$fwind_t$	const	-0.025	-4.590	-0.030	-5.614	-0.023	-0.029	-5.034	-0.026	-0.039	-5.380
	$fsolart$	const	1.051	14.531	2.023	13.881	0.059	0.059	-0.238	-0.073	-1.690	-0.675
	$\mu_t$	const	12.171	12.171	2.023	13.881	0.059	0.059	-0.238	0.037	0.783	-0.292
	$load_t$	2.251	12.171	2.023	13.881	14.767	2.263	12.134	2.283	0.519	2.424	-0.111
	$coast_t$	const	1.531	1.030	1.089	1.089	1.089	1.409	0.985	2.170	13.391	0.009
	$gas_t$	const	-0.045	-1.756	-0.045	-1.756	-0.045	-1.392	-0.036	3.821	1.726	1.726
	$co_2_t$	const	-0.118	-2.676	-0.118	-2.676	-0.118	-0.948	-0.714	-0.034	-0.714	-2.366
	$hold_t$	const	0.555	1.770	0.555	1.770	0.555	1.697	0.084	0.084	0.084	0.927
	$fwind_t$	const	0.022	2.435	0.022	2.435	0.022	2.431	-0.292	-0.292	-0.292	-3.440
	$fsolart$	const	-0.012	-6.110	-0.012	-6.110	-0.012	-6.110	0.516	0.516	1.409	1.409
	$\mu_t$	const	0.155	2.491	0.155	2.491	0.155	2.491	0.155	2.491	0.155	2.491
	$load_t$	const	0.013	0.186	0.013	0.186	0.013	0.186	0.013	0.186	0.013	0.186
	$coast_t$	const	-0.203	-0.750	-0.203	-0.750	-0.203	-0.750	-0.203	-0.750	-0.203	-0.750
	$gas_t$	const	0.009	0.205	0.009	0.205	0.009	0.205	0.009	0.205	0.009	0.205

Table 12: MFST Progressive Modelling for HP3.

Eq.	drivers	HOU12											
		MI	M2	M3	M4	AR-M1	AR-M2	AR-M3	AR-M4	VAR-M2	VAR-M3	VAR-M4	
$\mu_t$	drivers	16.316	14.688	15.556	14.017	4.345	14.017	8.248	8.248	13.536	18.705	18.506	3.581
	const	0.188	0.197	0.204	0.215	0.322	0.215	0.279	0.279	0.222	0.183	0.227	0.183
	load <sub>t-1</sub>	2.306	2.368	2.665	2.736	3.175	2.736	3.072	3.072	2.825	3.266	3.266	0.183
	coal <sub>t-1</sub>	0.483	0.460	0.505	0.471	0.393	0.471	0.344	0.344	0.398	0.602	0.602	0.183
	gas <sub>t-1</sub>	13.707	13.078	13.233	12.384	8.823	12.384	8.823	8.823	8.823	15.888	15.888	0.183
	coal <sub>t-1</sub>	0.570	0.572	0.685	0.698	0.779	0.698	0.634	0.634	0.696	1.255	1.255	0.183
	hol <sub>t-1</sub>	-13.118	-12.243	-13.328	-12.419	-7.059	-12.419	-8.000	-8.000	-12.294	-6.868	-6.868	0.183
	fwind <sub>t</sub>	-0.266	-0.249	-0.183	-0.253	-0.193	-0.253	-0.191	-0.191	-0.253	-0.178	-0.178	0.183
	fsolar <sub>t</sub>	-0.242	-0.233	-0.242	-0.234	-0.213	-0.234	-0.207	-0.207	-0.232	-0.234	-0.234	0.183
	$\mu_t$	0.115	0.114	0.093	0.088	0.076	0.088	0.031	0.031	0.340	0.085	0.085	0.183
	$\mu_t$												
	$\log(\sigma_t)$	const	1.750	1.851	1.760	1.597	1.544	1.597	1.419	1.419	1.601	1.676	1.676
load <sub>t-1</sub>			-0.009	-0.032	-0.021	-0.006	-0.021	-0.001	-0.001	-0.008	-0.012	-0.012	0.003
coal <sub>t-1</sub>			0.041	0.041	0.047	0.035	0.035	0.039	0.039	0.025	0.035	0.035	0.003
gas <sub>t-1</sub>			0.004	0.004	0.001	0.025	0.025	0.003	0.003	0.002	0.035	0.035	0.003
coal <sub>t-1</sub>			0.004	0.004	0.001	0.025	0.025	0.003	0.003	0.002	0.035	0.035	0.003
hol <sub>t-1</sub>			-0.044	-0.044	-0.079	-0.054	-0.054	0.040	0.040	-0.058	0.191	0.191	0.003
fwind <sub>t</sub>			0.000	0.000	0.002	0.000	0.000	-1.348	-1.348	0.000	0.002	0.002	0.003
fsolar <sub>t</sub>			-0.002	-0.002	-0.002	-0.002	-0.002	-1.848	-1.848	-0.002	-0.002	-0.002	0.003
$\mu_t$													
$\mu_t$													
$\mu_t$													
$\nu_t$		const	0.085	0.089	0.455	0.455	3.513	0.455	1.895	1.895	0.097	0.473	0.473
	load <sub>t-1</sub>		-0.046	-0.046	-0.106	-0.141	-0.106	-0.145	-0.145	-0.157	-0.157	-0.157	0.003
	coal <sub>t-1</sub>		0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.003
	gas <sub>t-1</sub>		-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	0.003
	coal <sub>t-1</sub>		-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	-0.017	0.003
	hol <sub>t-1</sub>		-2.300	-2.300	-2.300	-2.300	-2.300	-2.300	-2.300	-2.300	-2.300	-2.300	0.003
	fwind <sub>t</sub>		-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	-0.028	0.003
	fsolar <sub>t</sub>		-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011	0.003
	$\mu_t$												
	$\mu_t$												
	$\mu_t$												
	$\log(\tau_t)$	const	1.877	2.097	2.353	14.946	2.353	14.946	2.353	2.353	2.135	14.684	14.684
load <sub>t-1</sub>			0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.004
coal <sub>t-1</sub>			0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.004
gas <sub>t-1</sub>			-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	0.004
coal <sub>t-1</sub>			-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	-0.013	0.004
hol <sub>t-1</sub>			-1.092	-1.092	-1.092	-1.092	-1.092	-1.092	-1.092	-1.092	-1.092	-1.092	0.004
fwind <sub>t</sub>			-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	-0.020	0.004
fsolar <sub>t</sub>			-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	0.004
$\mu_t$													
$\mu_t$													
$\mu_t$													

Table 13: MFST Progressive Modelling for HP12.





	R-sqr		Global Deviance			AIC			SBC			
	Base	AR	VAR	Base	AR	VAR	Base	AR	VAR	Base	AR	VAR
Hour 1												
M1	0.7996	0.7818		15151	15362		15173	15384		15237	15448	
M2	0.8377	0.8217	0.8223	14613	14848	14838	14647	14884	14878	14746	14989	14995
M3	0.8466	0.8326	0.8360	14469	14686	14634	14515	14736	14696	14649	14882	14878
M4	0.8476	0.8337	0.8378	14451	14670	14606	14509	14734	14694	14679	14921	14951
Hour 2												
M1	0.7684	0.7591		15580	15673		15602	15695		15666	15760	
M2	0.8250	0.8174	0.8185	14866	14967	14952	14900	15003	14992	14999	15109	15109
M3	0.8360	0.8283	0.8330	14700	14810	14739	14746	14860	14801	14880	15006	14982
M4	0.8386	0.8320	0.8398	14659	14755	14633	14717	14819	14721	14887	15006	14978
Hour 3												
M1	0.7405	0.7284		15919	16029		15941	16051		16005	16115	
M2	0.8077	0.7988	0.7995	15153	15264	15255	15187	15300	15295	15287	15405	15411
M3	0.8193	0.8115	0.8152	14996	15098	15047	15042	15148	15109	15176	15294	15290
M4	0.8227	0.8153	0.8186	14946	15046	15000	15004	15110	15088	15173	15297	15345
Hour 4												
M1	0.6922	0.6817		16335	16413		16357	16435		16421	16500	
M2	0.7714	0.7625	0.7632	15576	15667	15659	15610	15703	15699	15709	15808	15816
M3	0.7855	0.7769	0.7811	15414	15508	15460	15460	15558	15522	15594	15704	15703
M4	0.7888	0.7801	0.7864	15374	15470	15397	15432	15534	15485	15601	15721	15742
Hour 5												
M1	0.6987	0.6888		16194	16271		16216	16293		16280	16357	
M2	0.7721	0.7646	0.7651	15483	15558	15554	15517	15594	15594	15616	15700	15711
M3	0.7855	0.7797	0.7867	15328	15390	15307	15374	15440	15369	15508	15586	15551
M4	0.7889	0.7734	0.7898	15287	15462	15270	15345	15526	15358	15514	15713	15615
Hour 6												
M1	0.7668	0.7609		15634	15688		15658	15712		15728	15782	
M2	0.8188	0.8165	0.8165	14990	15014	15013	15028	15054	15057	15139	15171	15186
M3	0.8334	0.8312	0.8325	14776	14801	14781	14828	14857	14849	14980	15021	15047
M4	0.8371	0.8341	0.8368	14719	14757	14716	14785	14829	14812	14978	15039	15092
Hour 7												
M1	0.7729	0.7673		16701	16753		16725	16777		16795	16847	
M2	0.8056	0.8082	0.8092	16304	16259	16246	16342	16299	16290	16453	16416	16419
M3	0.8248	0.8318	0.8344	16039	15925	15886	16091	15981	15954	16243	16144	16152
M4	0.8288	0.8339	0.8374	15981	15893	15838	16047	15965	15934	16240	16176	16215
Hour 8												
M1	0.8045	0.8056		17540	17516		17564	17540		17635	17610	
M2	0.8197	0.8224	0.8228	17334	17285	17278	17372	17325	17322	17483	17442	17451
M3	0.8382	0.8460	0.8525	17058	16922	16812	17110	16978	16880	17262	17142	17078
M4	0.8420	0.8487	0.8577	16997	16877	16720	17063	16949	16816	17256	17159	17097
Hour 9												
M1	0.7957	0.7998		17610	17545		17634	17569		17704	17640	
M2	0.8077	0.8092	0.8106	17455	17423	17404	17493	17463	17448	17604	17580	17577
M3	0.8241	0.8333	0.8427	17227	17079	16930	17279	17135	16998	17431	17299	17197
M4	0.8286	0.8404	0.8485	17162	16969	16835	17228	17041	16931	17421	17251	17212
Hour 10												
M1	0.7901	0.7949		17346	17275		17370	17299		17440	17369	
M2	0.8006	0.8013	0.8048	17215	17195	17150	17253	17235	17194	17364	17351	17322
M3	0.8126	0.8139	0.8349	17057	17028	16722	17109	17084	16790	17261	17248	16989
M4	0.8195	0.8222	0.8401	16961	16911	16640	17027	16983	16736	17220	17193	17017
Hour 11												
M1	0.8039	0.8034		17143	17140		17167	17164		17237	17234	
M2	0.8150	0.8122	0.8176	16995	17023	16948	17033	17063	16992	17144	17179	17121
M3	0.8328	0.8261	0.8450	16737	16827	16533	16789	16883	16601	16941	17047	16800
M4	0.8379	0.8322	0.8443	16658	16736	16545	16724	16808	16641	16917	17018	16921
Hour 12												
M1	0.8132	0.8106		17079	17107		17103	17131		17174	17201	
M2	0.8215	0.8192	0.8241	16965	16988	16918	17003	17028	16962	17114	17145	17091
M3	0.8341	0.8367	0.8432	16778	16729	16626	16830	16785	16694	16981	16949	16892
M4	0.8367	0.8380	0.8428	16736	16708	16633	16802	16780	16729	16995	16990	17009

Table 15: Informative Statistics of Enlarged Models. R-sqr is the ‘‘Cox-Snell’’ or Nagelkerke’s R squared, Global Deviance is  $GD = -2\mathcal{LL}$ , AIC and SBC are the Akaike and Schwarz Bayesian Information Criteria for estimated models, as formulated in eqs 2-7 and described therein.

	R-sqr		Global Deviance			AIC			SBC			
	Base	AR	VAR	Base	AR	VAR	Base	AR	VAR	Base	AR	VAR
Hour 13												
M1	0.8262	0.8222		16825	16876		16849	16900		16919	16970	
M2	0.8345	0.8311	0.8345	16700	16745	16693	16738	16785	16737	16849	16902	16865
M3	0.8510	0.8421	0.8549	16433	16573	16358	16485	16629	16426	16637	16793	16625
M4	0.8526	0.8515	0.8559	16405	16417	16340	16471	16489	16436	16663	16699	16717
Hour 14												
M1	0.8321	0.8282		16845	16896		16869	16920		16939	16990	
M2	0.8381	0.8357	0.8382	16752	16781	16742	16790	16821	16786	16901	16938	16915
M3	0.8590	0.8579	0.8644	16400	16411	16293	16452	16467	16361	16604	16631	16559
M4	0.8639	0.8631	0.8705	16309	16316	16176	16375	16388	16272	16568	16599	16552
Hour 15												
M1	0.8267	0.8227		16870	16920		16894	16944		16964	17014	
M2	0.8328	0.8297	0.8316	16779	16817	16789	16817	16857	16833	16928	16974	16962
M3	0.8541	0.8540	0.8605	16431	16425	16309	16483	16481	16377	16635	16644	16576
M4	0.8608	0.8612	0.8705	16311	16296	16120	16377	16368	16216	16570	16579	16497
Hour 16												
M1	0.8129	0.8111		16826	16843		16850	16867		16920	16937	
M2	0.8200	0.8186	0.8205	16728	16739	16713	16766	16779	16757	16877	16895	16886
M3	0.8365	0.8359	0.8429	16482	16483	16372	16534	16539	16440	16686	16703	16639
M4	0.8463	0.8478	0.8589	16324	16292	16099	16390	16364	16195	16582	16574	16476
Hour 17												
M1	0.7924	0.7919		16972	16971		16996	16995		17066	17066	
M2	0.8017	0.8001	0.8009	16855	16869	16859	16893	16909	16903	17004	17026	17032
M3	0.8176	0.8187	0.8227	16642	16620	16563	16694	16676	16631	16846	16839	16830
M4	0.8214	0.8217	0.8258	16589	16577	16518	16655	16649	16614	16848	16860	16895
Hour 18												
M1	0.7465	0.7442		17881	17898		17905	17922		17975	17992	
M2	0.7683	0.7657	0.7666	17652	17674	17664	17690	17714	17708	17801	17831	17836
M3	0.7858	0.7831	0.8006	17451	17477	17262	17503	17533	17330	17655	17696	17529
M4	0.7990	0.7965	0.8021	17289	17314	17243	17355	17386	17339	17548	17596	17620
Hour 19												
M1	0.7489	0.7417		17829	17895		17853	17919		17923	17989	
M2	0.7714	0.7654	0.7726	17589	17650	17569	17627	17690	17613	17739	17806	17742
M3	0.7915	0.7866	0.7895	17354	17408	17373	17406	17464	17441	17558	17627	17640
M4	0.8040	0.8001	0.8052	17196	17241	17176	17262	17313	17272	17455	17523	17553
Hour 20												
M1	0.7223	0.7156		17585	17640		17609	17664		17679	17734	
M2	0.7457	0.7413	0.7494	17361	17399	17317	17399	17439	17361	17510	17556	17490
M3	0.7695	0.7641	0.7658	17111	17163	17145	17163	17219	17213	17315	17383	17411
M4	0.7784	0.7727	0.7766	17010	17068	17024	17076	17140	17120	17269	17351	17401
Hour 21												
M1	0.7553	0.7494		16424	16478		16448	16502		16518	16572	
M2	0.7712	0.7673	0.7716	16252	16290	16242	16290	16330	16286	16401	16447	16415
M3	0.7805	0.7776	0.7882	16146	16174	16050	16198	16230	16118	16350	16393	16317
M4	0.7878	0.7854	0.7945	16060	16083	15973	16126	16155	16069	16319	16366	16350
Hour 22												
M1	0.7862	0.7732		15464	15608		15486	15630		15550	15695	
M2	0.7996	0.7894	0.7935	15299	15419	15369	15333	15455	15409	15432	15560	15526
M3	0.8138	0.8032	0.8155	15111	15246	15082	15157	15296	15144	15291	15442	15325
M4	0.8177	0.8070	0.8154	15058	15196	15082	15116	15260	15170	15285	15447	15427
Hour 23												
M1	0.8082	0.8013		15032	15118		15054	15140		15119	15204	
M2	0.8182	0.8123	0.8138	14897	14972	14952	14931	15008	14992	15030	15113	15109
M3	0.8335	0.8292	0.8298	14671	14732	14722	14717	14782	14784	14852	14928	14965
M4	0.8330	0.8304	0.8330	14679	14714	14674	14737	14778	14762	14906	14965	15019
Hour 24												
M1	0.8286	0.8191		14656	14788		14678	14810		14743	14874	
M2	0.8438	0.8365	0.8382	14419	14531	14504	14453	14567	14544	14552	14672	14661
M3	0.8556	0.8500	0.8528	14219	14312	14264	14265	14362	14326	14400	14508	14507
M4	0.8548	0.8500	0.8564	14233	14310	14200	14291	14374	14288	14460	14561	14545

Table 16: Informative Statistics of Enlarged Models. R-sqr is the ‘‘Cox-Snell’’ or Nagelkerke’s R squared, Global Deviance is  $GD = -2\mathcal{LL}$ , AIC and SBC are the Akaike and Schwarz Bayesian Information Criteria for estimated models, as formulated in eqs 2-7 and described therein.

### 6.4.3. Residuals Analysis

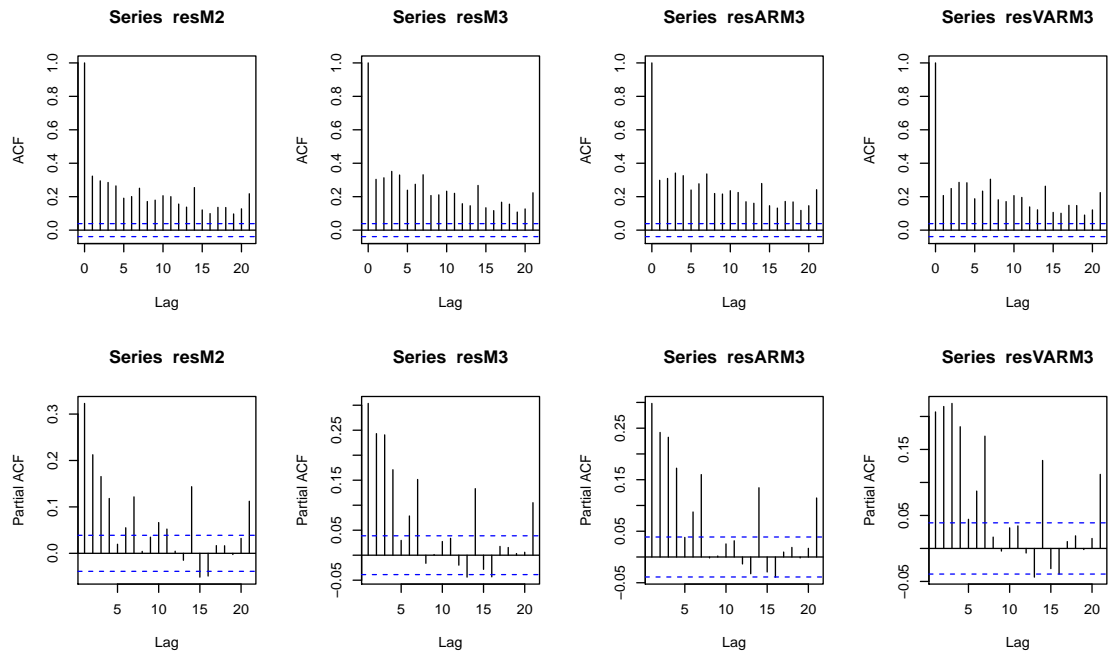


Figure 11: Autocorrelation and Partial autocorrelation Functions for Models M2, M3, ARM3 and VARM3 for hour 3.

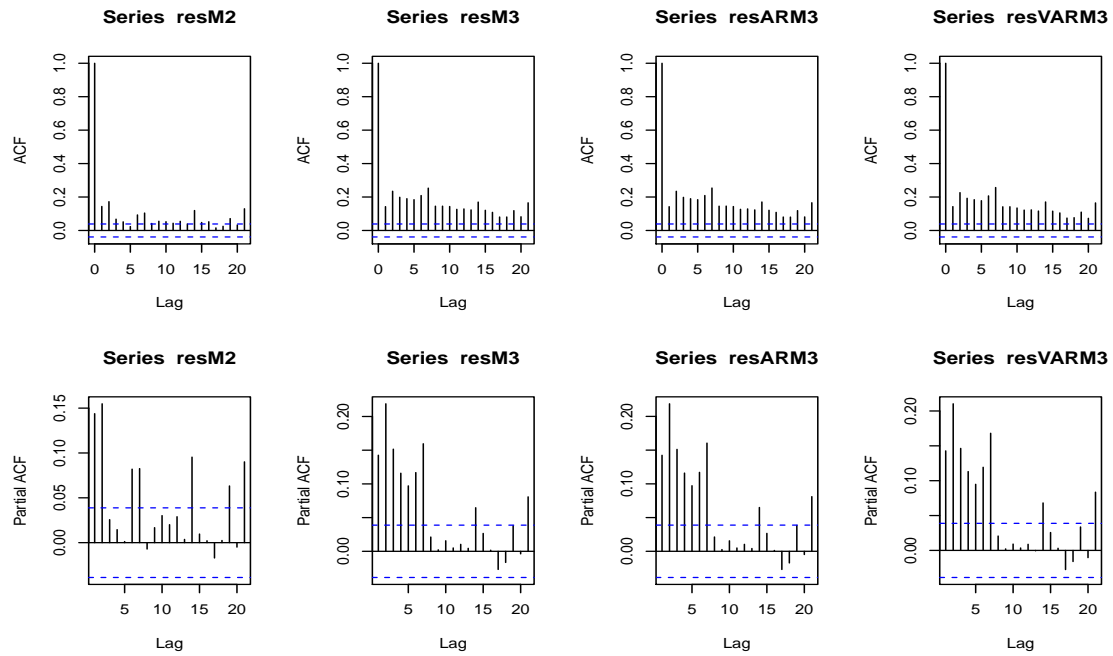


Figure 12: Autocorrelation and Partial autocorrelation Functions for Models M2, M3, ARM3 and VARM3 for hour 12.



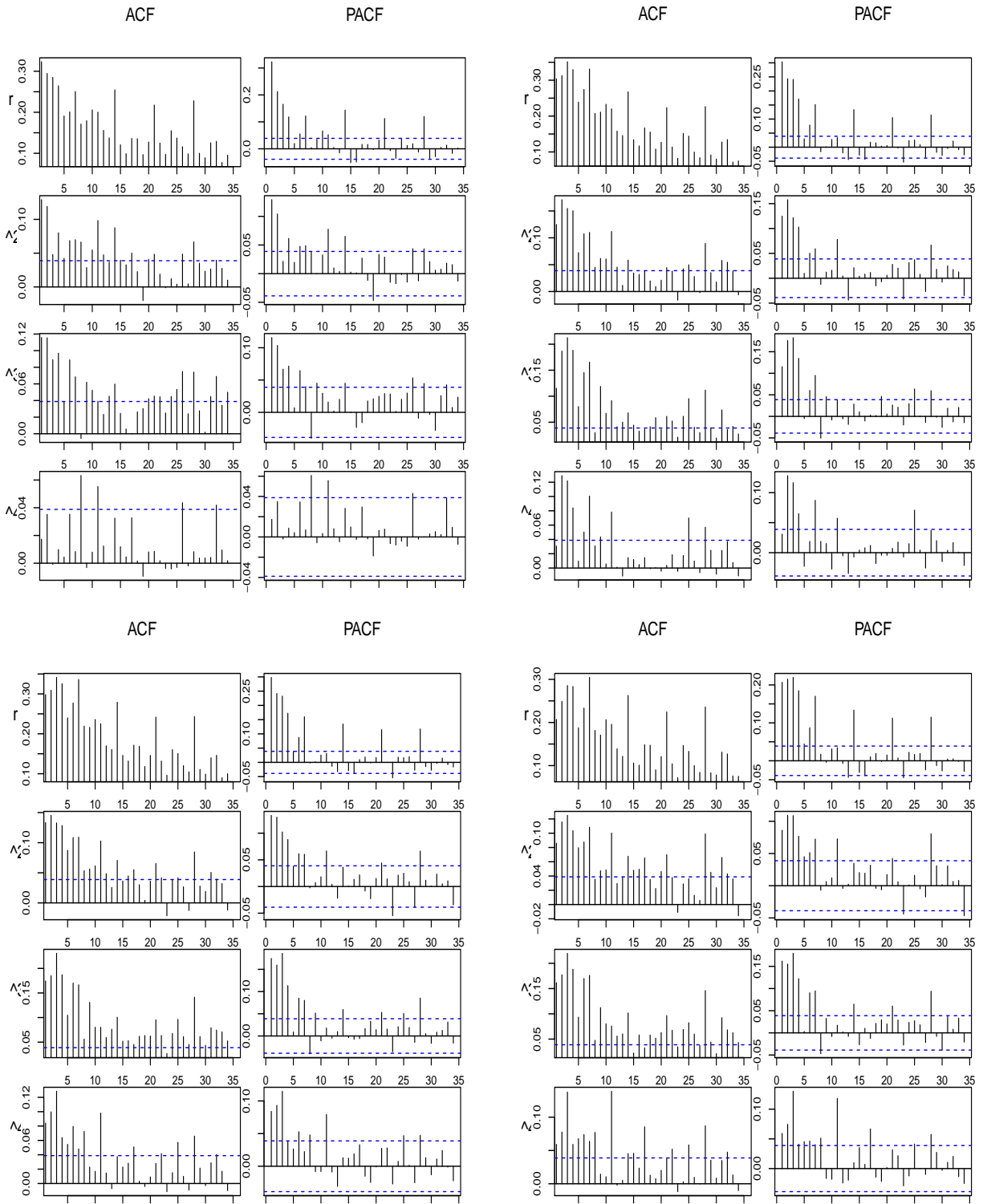


Figure 13: ACF and PACF for Residuals of Models M2 (top-left), M3 (top-right), ARM3 (bottom-left) and VARM3 (bottom-right) for hour 3. Levels of residuals on first rows,  $r_t^2$  on second rows,  $r_t^3$  on third rows and finally  $r_t^4$  on last rows.

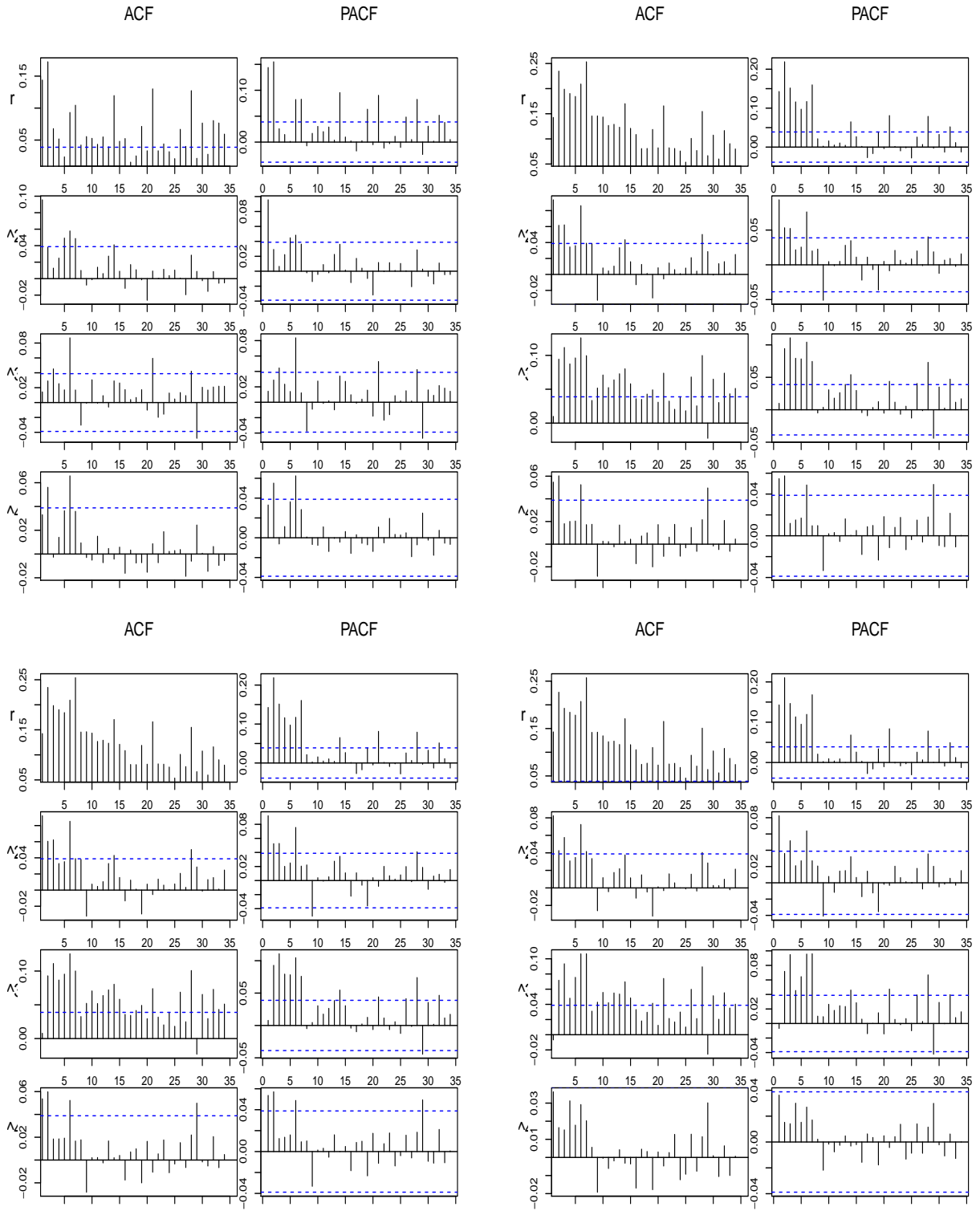


Figure 14: ACF and PACF for Residuals of Models M2 (top-left), M3 (top-right), ARM3 (bottom-left) and VARM3 (bottom-right) for hour 12. Levels of residuals on first rows,  $r_t^2$  on second rows,  $r_t^3$  on third rows and finally  $r_t^4$  on last rows.

		Base				AR				VAR			
		Mean	Var	Skew	Kurt	Mean	Var	Skew	Kurt	Mean	Var	Skew	Kurt
Hour 3													
JSU	M1	-0.004	1.001	-0.061	3.055	-0.002	0.999	-0.075	3.085				
	M2	-0.029	1.007	0.027	2.955	-0.029	1.007	0.025	2.965	-0.028	1.006	0.024	2.963
	M3	-0.029	1.011	0.026	2.941	-0.030	1.010	0.024	2.973	-0.029	1.007	0.025	2.981
	M4	-0.036	0.994	-0.017	3.210	-0.033	0.997	0.007	3.084	-0.029	0.989	-0.034	3.139
JSU <sub>o</sub>	M1	-0.002	0.998	-0.068	2.994	-0.002	0.998	-0.084	3.020				
	M2	-0.002	0.996	0.033	3.272	-0.002	0.996	0.032	3.325	-0.002	0.995	0.005	3.334
	M3	-0.001	0.997	0.036	2.908	-0.001	0.998	0.050	2.868	-0.001	0.998	0.005	2.889
	M4	-0.002	0.993	0.139	3.505	-0.001	0.996	-0.013	3.411	-0.001	0.994	0.053	3.272
ST1	M1	-0.006	1.001	-0.055	2.835	-0.008	1.000	-0.068	2.830				
	M2	-0.008	0.988	0.113	3.232	-0.009	0.987	0.117	3.255	-0.010	0.986	0.108	3.241
	M3	-0.009	0.974	-0.019	3.226	-0.012	0.971	-0.032	3.279	-0.014	0.958	-0.019	3.378
	M4	-0.009	0.978	-0.033	3.143	-0.016	0.972	-0.026	3.224	-0.027	0.974	-0.055	3.058
ST2	M1	-0.004	0.995	-0.058	2.876	-0.005	0.993	-0.068	2.886				
	M2	-0.009	0.992	0.091	3.189	-0.009	0.990	0.094	3.210	-0.011	0.988	0.088	3.205
	M3	-0.011	0.977	-0.027	3.165	-0.014	0.973	-0.041	3.222	-0.016	0.960	-0.028	3.337
	M4	-0.013	0.976	-0.045	3.125	-0.020	0.967	-0.019	3.223	-0.028	0.964	-0.031	3.092
SN1	M1	0.002	1.068	-10.506	> 240	0.001	1.067	-10.271	> 230				
	M2	-0.001	0.991	-0.068	4.254	-0.003	0.990	-0.052	4.222	-0.004	0.987	-0.054	4.113
	M3	0.007	0.982	-0.258	4.141	0.004	0.977	-0.251	4.035	0.000	0.962	-0.237	4.087
NO	M1	0.000	1.000	-10.527	> 240	0.000	1.000	-10.296	> 230				
	M2	-0.044	0.998	-0.855	5.024	-0.044	0.998	-0.810	4.861	-0.041	0.999	-0.815	4.874
Hour 12													
JSU	M1	0.000	0.999	0.054	3.189	0.001	0.999	0.065	3.199				
	M2	0.001	0.999	0.040	3.144	-0.003	0.999	0.043	3.136	0.004	0.999	0.049	3.131
	M3	-0.001	1.002	0.017	3.104	-0.004	1.002	0.016	3.085	0.000	1.004	0.027	3.094
	M4	0.006	0.973	0.014	3.287	-0.005	0.973	0.018	3.188	-0.003	1.007	0.003	3.050
JSU <sub>o</sub>	M1	0.000	1.000	0.054	3.093	0.000	1.000	0.067	3.100				
	M2	0.000	1.000	0.037	3.032	0.000	1.000	0.067	3.031	0.000	1.000	0.022	3.028
	M3	0.000	0.997	0.005	3.103	0.001	0.997	-0.002	3.148	0.001	0.996	-0.015	3.205
	M4	0.000	0.997	0.095	3.309	0.000	0.997	0.057	3.356	0.001	0.995	-0.053	3.553
ST1	M1	0.000	1.001	0.008	3.079	0.000	1.001	0.021	3.080				
	M2	0.000	1.002	0.010	3.059	-0.001	1.002	0.028	3.051	0.000	1.002	0.009	3.052
	M3	0.012	0.984	0.127	3.220	0.016	0.980	0.377	3.536	0.024	0.980	0.350	3.527
	M4	0.012	0.973	0.483	3.889	0.004	0.968	0.503	3.860	0.011	0.970	0.395	3.512
ST2	M1	0.001	1.001	0.039	3.085	0.001	1.001	0.056	3.090				
	M2	0.001	1.002	0.035	3.064	0.001	1.002	0.053	3.059	0.001	1.002	0.038	3.063
	M3	0.010	0.985	0.146	3.202	0.016	0.980	0.357	3.492	0.023	0.981	0.337	3.473
	M4	0.000	0.974	0.355	3.619	0.007	0.973	0.482	3.889	0.012	0.970	0.389	3.441
SN1	M1	-0.002	0.968	0.309	5.880			0.250	5.334				
	M2			0.134	4.705			0.100	4.104	0.000	1.003	0.092	5.079
	M3			0.114	3.784	-0.008	0.980	0.328	4.824	0.002	0.991	0.077	4.275
NO	M1	inf				inf							
	M2	inf				inf				inf			
Hour 19													
JSU	M1	0.000	0.997	0.096	3.203	0.000	0.998	0.110	3.227				
	M2	0.012	1.002	0.027	3.063	0.011	1.002	0.030	3.074	0.010	1.002	0.021	3.031
	M3	0.007	1.006	0.016	3.110	0.005	1.005	0.003	3.167	0.004	1.004	0.000	3.134
	M4	0.013	1.004	0.040	2.909	-0.001	0.991	0.027	2.871	0.005	0.996	0.040	2.907
JSU <sub>o</sub>	M1	0.001	0.999	0.115	3.136	0.001	0.999	0.130	3.155				
	M2	0.003	0.988	0.097	4.500	0.003	0.989	0.081	4.151	0.002	0.997	-0.087	3.489
	M3	0.002	0.992	0.407	3.831	0.002	0.990	0.380	3.780	0.002	0.993	0.260	3.499
	M4	-0.001	0.992	0.252	3.621	-0.001	0.991	0.256	3.554	-0.001	0.989	0.246	3.714
ST1	M1	0.001	1.003	0.063	2.971	0.001	1.003	0.074	2.976				
	M2	0.005	0.995	-0.086	3.209	0.008	0.991	-0.112	3.282	0.003	0.998	-0.071	3.142
	M3	-0.001	0.969	-0.077	3.325	0.003	0.955	-0.136	3.377	-0.001	0.965	-0.100	3.280
	M4	0.030	0.947	-0.007	3.447	0.014	0.920	0.307	3.647	0.017	0.960	-0.078	3.139
ST2	M1	0.005	0.994	0.086	2.983	0.005	0.993	0.100	2.983				
	M2	0.007	0.995	-0.062	3.152	0.010	0.992	-0.085	3.209	0.005	0.998	-0.050	3.094
	M3	0.033	0.957	0.504	3.624	0.026	0.959	0.484	3.629	0.023	0.959	0.497	3.660
	M4	0.016	0.924	0.352	3.850	0.012	0.922	0.295	3.630	0.013	0.921	0.269	3.728
SN1	M1			1.593	10.244	-0.004	0.940	1.615	10.361				
	M2	0.006	0.987	0.042	4.423	0.010	0.982	-0.004	4.128	0.001	0.996	0.030	4.025
	M3	-0.013	0.973	0.329	4.274	-0.011	0.977	0.351	3.976	-0.006	0.989	0.091	4.143
NO	M1	inf				inf							
	M2	0.023	1.000	0.643	4.870	0.028	1.000	0.533	4.491	0.013	1.000	0.553	4.306

Table 17: Descriptive Statistics of (Randomized Quantile) Residuals for Enlarged Models and selected hours.

### 6.5. Coverage Tests

The formulated models in Tables 18-26, without parameter indications and under the skew Student-t distribution unless diversely specified, are

- with just the first moment:
  - M1:  $\mu_t = c + \sum_{i=1}^7 y_{t-i} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ ;
  - ARM1:  $\mu_t = c + \mu_{t-1} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$  with  $\mu_{t-1}$  filtered from M1;
  - QReg:  $Q_q(y_t) = \alpha^q + \sum_{i=1}^7 \gamma_i^q y_{t-i} + \beta_1^q hol_t + \beta_2^q load_{t-1} + \beta_3^q fwind_t + \beta_4^q fsolar_t + \beta_5^q coal_{t-1} + \beta_6^q gas_{t-1} + \beta_7^q co2_{t-1}$ ;
- with the first two moments:
  - M2st:  $\mu_t$  as in M1 and  $\log(\sigma_t) = hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ ;
  - M2jsu: as M2 but with the Johnson's  $S_U$  distribution;
  - M2Ser:  $\mu_t = c + y_{t-1} + y_{t-2} + y_{t-7} + miny_{t-1} + load_t + load_t^2 + load_t^3 + \sum_{i=1}^6 d_i$  and  $\log(\sigma_t) = c + y_{t-1} + abs(y_{t-1} - y_{t-2}) + \sum_{i=1}^6 d_i$  under the Johnson's  $S_U$ ;
  - ARM2:  $\mu_t$  as in ARM1, and  $\log(\sigma_t) = c + \log(\sigma_{t-1}) + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$  with  $\mu_{t-1}$  and  $\log(\sigma_{t-1})$  filtered from M2;
  - VARM2:  $\mu_t = \log(\sigma_t) = c + \mu_{t-1} + \log(\sigma_{t-1}) + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ , with  $\mu_{t-1}$  and  $\log(\sigma_{t-1})$  filtered from M2;
  - AR-EGARCH-st and -sst: as in eqs. (9) and (10) under the Student-t and the skew Student-t distributions;
- with the three moments:
  - M3:  $\mu_t = c + y_{t-1} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ , and  $\log(\sigma_t) = \nu_t = c + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ ;
  - ARM3:  $\mu_t$  and  $\log(\sigma_t)$  as in ARM1 and ARM2,  $\nu_t = c + \nu_{t-1} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$  with  $\mu_{t-1}$ ,  $\log(\sigma_{t-1})$  and  $\nu_{t-1}$  filtered from M3;
  - VARM3:  $\mu_t = \log(\sigma_t) = \nu_t = c + \mu_{t-1} + \log(\sigma_{t-1}) + \nu_{t-1} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ , with  $\mu_{t-1}$ ,  $\log(\sigma_{t-1})$  and  $\nu_{t-1}$  filtered from M3;
- with four moments:
  - M4:  $\mu_t$ ,  $\log(\sigma_t)$ , and  $\nu_t$  as in M3, and with  $\log(\tau_t) = c + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ ;
  - ARM4:  $\mu_t$ ,  $\log(\sigma_t)$  and  $\nu_t$  as in ARM3,  $\log(\tau_t) = c + \tau_{t-1} + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$  with  $\mu_{t-1}$ ,  $\log(\sigma_{t-1})$ ,  $\nu_{t-1}$  and  $\log(\tau_{t-1})$  filtered from M4;
  - VARM4:  $\mu_t = \log(\sigma_t) = \nu_t = \log(\tau_t) = c + \mu_{t-1} + \log(\sigma_{t-1}) + \nu_{t-1} + \log(\tau_{t-1}) + hol_t + load_{t-1} + fwind_t + fsolar_t + coal_{t-1} + gas_{t-1} + co2_{t-1}$ , with  $\mu_{t-1}$ ,  $\log(\sigma_{t-1})$ ,  $\nu_{t-1}$  and  $\log(\tau_{t-1})$  filtered from M4.





Years	Models	Q <sub>95</sub>			Q <sub>98</sub>			Q <sub>99</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000420	0.001309	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.030591	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.030591	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	VARM2	0.000000	0.000000	0.030591	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	EGARCHst	0.001886	0.000005	0.000000	0.021708	0.000001	0.000000	0.473190	0.113910	0.000000
	M3	0.000000	0.000001	0.055849	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	ARM3	0.000000	0.000001	0.055789	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	VARM3	0.000244	0.000176	0.018630	0.000146	0.000737	0.622249	0.007389	0.027654	0.939256
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2012	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.026103	0.000120	0.000615	0.603163	0.006681	0.025263	0.934247
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.050591	0.003063	0.012432	0.783078	0.097586	0.252834	0.988034
	VARM2	0.000001	0.000005	0.088280	0.000120	0.000615	0.603163	0.006681	0.025263	0.934247
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000171	0.000798	0.022039	0.003063	0.012432	0.793918	0.006681	0.025263	0.934247
	ARM3	0.000037	0.000193	0.004777	0.003063	0.012432	0.789655	0.006681	0.025263	0.934247
	VARM3	0.002044	0.007509	0.050295	0.000120	0.000615	0.603163	0.006681	0.025263	0.934247
	M4	0.000002	0.000000	0.000000	0.000092	0.000000	0.000000	0.000000	0.000003	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000002	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2013	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.026569	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.026569	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	VARM2	0.000000	0.000000	0.048856	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000667	0.000000	0.000000	0.068612	0.008689	0.000000	0.724226	0.042852	0.000000
	ARM3	0.014147	0.000003	0.000000	0.068612	0.008689	0.000000	0.342459	0.630242	0.000000
	VARM3	0.000007	0.000002	0.000067	0.019025	0.063250	0.000121	0.342459	0.630242	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2014	M1	0.952019	0.000001	0.000000	0.054567	0.000000	0.000000	0.257954	0.110944	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.026569	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.117696	0.256373	0.000000
	ARM2	0.000000	0.000000	0.026569	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	VARM2	0.000000	0.000000	0.026569	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000000	0.000000	0.051774	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	ARM3	0.000001	0.000005	0.084953	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	VARM3	0.000007	0.000038	0.125103	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000033	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2015	M1	0.079311	0.000998	0.000000	0.910088	0.866199	0.000000	0.724226	0.916521	0.000141
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.001381	0.000478	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.051908	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.856117	0.940933	0.814626
	ARM2	0.000000	0.000000	0.051899	0.003122	0.012651	0.796703	0.006756	0.025518	0.934814
	VARM2	0.000000	0.000000	0.051923	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000007	0.000038	0.157226	0.003122	0.012651	0.797083	0.006756	0.025518	0.934814
	ARM3	0.000007	0.000038	0.157750	0.003122	0.012651	0.796869	0.098483	0.254687	0.992637
	VARM3	0.005822	0.000670	0.003326	0.003122	0.012651	0.797131	0.006756	0.025518	0.934814
	M4	0.000683	0.000086	0.000000	0.011592	0.002554	0.000000	0.048057	0.004252	0.000000
	ARM4	0.002710	0.000167	0.000000	0.000088	0.000029	0.000000	0.000033	0.000017	0.000000
VARM4	0.000013	0.000001	0.000000	0.000003	0.000000	0.000000	0.000000	0.000000	0.000000	
2016	M1	0.180970	0.008472	0.000004	0.175408	0.386258	0.013229	0.097586	0.252834	0.981391
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.026103	0.000120	0.000615	0.603163	0.006681	0.025263	0.934247
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.005012	0.009360	0.000000	0.860310	0.941947	0.095691
	ARM2	0.000006	0.000002	0.000324	0.003063	0.012432	0.781960	0.097586	0.252834	0.988763
	VARM2	0.000006	0.000002	0.000330	0.003063	0.012432	0.789155	0.097586	0.252834	0.991279
	EGARCHst	0.000001	0.000000	0.000000	0.000009	0.000019	0.000000	0.000139	0.000144	0.000000
	M3	0.005637	0.007916	0.231153	0.003063	0.012432	0.778046	0.097586	0.252834	0.976308
	ARM3	0.029983	0.050783	0.506537	0.003063	0.012432	0.779610	0.097586	0.252834	

Years	Models	Q <sub>1</sub>			Q <sub>2</sub>			Q <sub>5</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.362478	0.653153	0.999860	0.077043	0.204213	0.982854	0.131899	0.228489	0.747415
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.755217	0.928583	0.000151	0.046625	0.029370	0.001323	0.100637	0.000106	0.000000
	VARM2	0.755217	0.928583	0.000153	0.176038	0.046094	0.004131	0.038200	0.000166	0.000000
	EGARCHst	0.000001	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.822449	0.088426	0.002268	0.176038	0.003981	0.000002	0.100637	0.000814	0.000002
	ARM3	0.238900	0.107340	0.040831	0.176038	0.003981	0.000002	0.154972	0.000648	0.000000
	VARM3	0.473190	0.113910	0.017902	0.093767	0.039186	0.001123	0.100637	0.000814	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	2012	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2st		0.720414	0.042658	0.000001	0.358469	0.002189	0.000000	0.127009	0.000053	0.000000
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM2		0.720414	0.042658	0.000000	0.802449	0.000608	0.000000	0.017599	0.000000	0.000000
VARM2		0.720414	0.042658	0.000000	0.342897	0.002194	0.000000	0.005374	0.000000	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.048753	0.000148	0.000000	0.053625	0.000000	0.000000	0.000073	0.000000	0.000000
ARM3		0.048753	0.000148	0.000000	0.109291	0.000006	0.000000	0.001447	0.000004	0.000000
VARM3		0.018014	0.000096	0.000000	0.005012	0.000001	0.000000	0.000006	0.000000	0.000000
M4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2013		M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.098483	0.254687	0.991249	0.019025	0.063250	0.883629	0.049070	0.001101	0.000000
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.048057	0.000002	0.000000	0.000729	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM2	0.048057	0.000002	0.000000	0.000029	0.000000	0.000000	0.000000	0.000000	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.001823	0.000072	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM3	0.000515	0.000039	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM3	0.000135	0.000018	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	2014	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2st		0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.002117	0.000148	0.000004
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM2		0.006756	0.025518	0.934814	0.003122	0.012651	0.717610	0.060904	0.000002	0.000000
VARM2		0.006756	0.025518	0.934814	0.019025	0.001033	0.000000	0.060904	0.000002	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.342459	0.010290	0.000000	0.068612	0.008689	0.000000	0.678752	0.007428	0.000474
ARM3		0.342459	0.010290	0.000000	0.068612	0.008689	0.000001	0.761472	0.099267	0.032507
VARM3		0.342459	0.010290	0.000000	0.068612	0.008689	0.000001	0.857958	0.004694	0.000115
M4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	0.000000
ARM4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2015		M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000515	0.001687	0.000000	0.001938	0.003608	0.000000	0.382296	0.249397	0.046475
	M2st	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.049059
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000001	0.000005	0.092642
	VARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000001	0.000005	0.092690
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.006756	0.025518	0.934814	0.003122	0.012651	0.794360	0.000667	0.002814	0.126549
	ARM3	0.006756	0.025518	0.934814	0.003122	0.012651	0.794842	0.005822	0.019076	0.113599
	VARM3	0.006756	0.025518	0.934814	0.003122	0.012651	0.794574	0.184689	0.266163	0.255936
	M4	0.117696	0.083839	0.000061	0.054567	0.004209	0.000000	0.029350	0.000897	0.000021
	ARM4	0.017711	0.002318	0.000000	0.000729	0.000079	0.000000	0.009509	0.008970	0.001904
	VARM4	0.000002	0.000001	0.000000	0.000003	0.000000	0.000000	0.000013	0.000001	0.000000
	2016	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000000	0.000001	0.000000	0.000003	0.000001	0.000000	0.009882	0.000807	0.000000
M2st		0.006681	0.025263	0.934247	0.000120	0.000615	0.603163	0.000006	0.000036	0.155612
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM2		0.097586	0.252834	0.992890	0.067621	0.183640	0.968604	0.180970	0.000038	0.000008
VARM2		0.097586	0.252834	0.992952	0.175408	0.035337	0.005011	0.107839	0.003364	0.011703
EGARCHst		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.097586	0.252834	0.989362	0.018707	0.062327	0.912695	0.573304	0.783853	0.013882
ARM3		0.097586	0.252834	0.990810	0.018707	0.062327	0.914305	0.414556	0.622290	0.1



Years	Models	Q <sub>25</sub>			Q <sub>50</sub>			Q <sub>75</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.124615	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.194493	0.000000	0.000000	0.004950	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.371055	0.000001	0.000000	0.022693	0.000000	0.000000	0.000997	0.000000	0.000000
	M2jsu	0.000000	0.000000	0.000000	0.063756	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.002501	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.830988	0.000000	0.000000	0.006855	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM2	0.347979	0.000000	0.000000	0.003537	0.000000	0.000000	0.000000	0.000000	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.003537	0.002722	0.000000	0.076328	0.095002	0.000000
	M3	0.124688	0.000000	0.000000	0.152811	0.000000	0.000000	0.000001	0.000000	0.000000
	ARM3	0.058685	0.000000	0.000000	0.711017	0.000000	0.000000	0.000001	0.000000	0.000000
	VARM3	0.024857	0.000000	0.000000	0.491384	0.000000	0.000000	0.000069	0.000000	0.000000
	M4	0.003241	0.000000	0.000000	0.368170	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.002214	0.000000	0.000000	0.185609	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM4	0.000997	0.000000	0.000000	0.266242	0.000000	0.000000	0.000000	0.000000	0.000000
	2012	M1	0.000000	0.000000	0.000000	0.008854	0.000001	0.000020	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000556	0.000000	0.000000	0.753801	0.000017	0.000000	0.015538	0.000001	0.000000
M2st		0.015538	0.000022	0.000002	0.006475	0.000000	0.000013	0.000003	0.000000	0.000000
M2jsu		0.000000	0.000000	0.000000	0.011984	0.000000	0.000023	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.021296	0.000004	0.000001	0.000000	0.000000	0.000000
ARM2		0.011241	0.000002	0.000000	0.834382	0.000002	0.000000	0.000036	0.000000	0.000000
VARM2		0.011241	0.000004	0.000000	0.530459	0.000104	0.000000	0.000036	0.000000	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.173952	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.002743	0.000001	0.000000	0.008854	0.000000	0.000000	0.000000	0.000000	0.000000
ARM3		0.085083	0.000012	0.000000	0.006475	0.000000	0.000000	0.000000	0.000000	0.000000
VARM3		0.050541	0.000482	0.000000	0.001160	0.000000	0.000000	0.000000	0.000000	0.000000
M4		0.000022	0.000000	0.000000	0.753801	0.000272	0.000000	0.000000	0.000000	0.000000
ARM4		0.000008	0.000000	0.000000	0.530459	0.000041	0.000000	0.000000	0.000000	0.000000
VARM4		0.000000	0.000000	0.000000	0.916739	0.002957	0.004808	0.000000	0.000000	0.000000
2013		M1	0.000000	0.000000	0.000000	0.793540	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.637565	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000019	0.000000	0.000000	0.958256	0.000000	0.000000	0.001676	0.000000	0.000000
	M2jsu	0.000000	0.000000	0.000000	0.714061	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.793540	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000011	0.000000	0.000000	0.104463	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM2	0.000001	0.000000	0.000000	0.271553	0.000000	0.000000	0.000000	0.000000	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.228484	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.002464	0.000000	0.000000	0.000292	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM3	0.001676	0.000000	0.000000	0.000193	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM3	0.000082	0.000000	0.000000	0.005452	0.000000	0.000000	0.000000	0.000000	0.000000
	M4	0.000001	0.000000	0.000000	0.432309	0.000004	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000001	0.000000	0.000000	0.319867	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM4	0.000000	0.000000	0.000000	0.496173	0.000011	0.000000	0.000000	0.000000	0.000000
	2014	M1	0.000000	0.000000	0.000000	0.000292	0.000001	0.000002	0.000019	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.046912	0.000016	0.000000	0.875223	0.000218	0.000000	0.101772	0.000084	0.000000
M2st		0.061428	0.000003	0.000000	0.000646	0.000005	0.000036	0.001566	0.000007	0.000211
M2jsu		0.000000	0.000000	0.000000	0.000126	0.000002	0.000011	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.002793	0.000038	0.000000	0.000000	0.000000	0.000000
ARM2		0.103177	0.000000	0.000000	0.000013	0.000000	0.000000	0.000000	0.000000	0.000000
VARM2		0.079241	0.000000	0.000000	0.000008	0.000000	0.000000	0.000000	0.000000	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.010249	0.000000	0.000000
M3		0.489975	0.000008	0.000000	0.000052	0.000000	0.000000	0.000000	0.000000	0.000000
ARM3		0.651793	0.000000	0.000000	0.000052	0.000000	0.000000	0.000000	0.000000	0.000000
VARM3		0.026430	0.000000	0.000000	0.005452	0.000000	0.000000	0.000000	0.000000	0.000000
M4		0.026430	0.000001	0.000000	0.190510	0.000000	0.000000	0.000002	0.000000	0.000000
ARM4		0.001676	0.000000	0.000000	0.041022	0.000000	0.000000	0.000004	0.000000	0.000000
VARM4		0.001676	0.000000	0.000000	0.319867	0.000000	0.000000	0.000002	0.000000	0.000000
2015		M1	0.000000	0.000000	0.000000	0.157394	0.008526	0.001411	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.489975	0.018289	0.000399	0.714061	0.717797	0.012691	0.003580	0.006926	0.000003
	M2st	0.000007	0.000035	0.000290	0.052583	0.042368	0.001929	0.785058	0.753309	0.000176
	M2jsu	0.000000	0.000000	0.000000	0.083902	0.058584	0.000400	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.001968	0.008298	0.013985	0.000000	0.000000	0.000000
	ARM2	0.446381	0.079471	0.024716	0.958256	0.054159	0.000097	0.376452	0.002840	0.000055
	VARM2	0.693254	0.492014	0.024584	0.373476	0.023611	0.000007	0.522952	0.008893	0.000466
	EGARCHst	0.000000	0.000000	0.000000	0.319867	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.353223	0.033368	0.000082	0.190510	0.000005	0.000000	0.002464	0.000000	0.000000
	ARM3	0.243885	0.001565	0.000000	0.875223	0.000000	0.000000	0.000749	0.000000	0.000000
	VARM3	0.000031	0.000000	0.000000	0.496173	0.000000	0.000000	0.002464	0.000000	0.000000
	M4	0.832815	0.205723	0.175900	0.958256	0.289652	0.042589	0.019498	0.000129	0.000002
	ARM4	0.651793	0.018469	0.050663	0.373476	0.146708	0.009501	0.005143	0.000031	0.000001
	VARM4	0.243885	0.001194	0.000195	0.637565	0.000133	0.000042	0.019498	0.000073	0.000000
	2016	M1	0.000002	0.000000	0.000000	0.016056	0.000062	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.762107	0.005903	0.000034	0.094183	0.000000	0.000000	0.000556	0.000010	0.000000
M2st		0.000340	0.000000	0.000000	0.016056	0.000273	0.000000	0.136865	0.001989	0.000000
M2jsu		0.000000	0.000000	0.000000	0.059663	0.001201	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.003358	0.004402	0.008863	0.000000	0.000000	0.000000
ARM2		0.198896	0.000007	0.000000	0.001160	0.000000	0.000000	0.000000	0.000000	0.000000
VARM2		0.125125	0.000015	0.000001	0.000542	0.000000	0.000000	0.000000	0.000000	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.000542	0.000000	0.000000	0.005683	0.000000	0.000000
M3		0.210474	0.000950	0.000000	0.250018	0.000000	0.000000	0.000000	0.000000	0.000000
ARM3		0.050541	0.000015	0.000000	0.173952	0.000000	0.000000	0.000000	0.000000	

Years	Models	Q <sub>95</sub>			Q <sub>98</sub>			Q <sub>99</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.131899	0.228489	0.189578	0.003639	0.014543	0.811099	0.007389	0.027654	0.939256
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000213	0.000001	0.000000	0.176038	0.000000	0.000000	0.238900	0.107340	0.000000
	VARM2	0.000213	0.000000	0.000000	0.093767	0.000000	0.000000	0.238900	0.107340	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.009491	0.018702	0.000000	0.238900	0.450950	0.000008
	M3	0.000018	0.000000	0.000000	0.000195	0.000001	0.000000	0.015421	0.042117	0.000000
	ARM3	0.000008	0.000000	0.000000	0.001519	0.000000	0.000000	0.106849	0.079249	0.000000
	VARM3	0.000939	0.000000	0.000000	0.009491	0.000260	0.000000	0.001520	0.000755	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2012	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.867459	0.006110	0.000071	0.358469	0.002189	0.000000	0.720414	0.042658	0.000000
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.002832	0.000001	0.000000	0.109291	0.000269	0.000000	0.119098	0.000001	0.000000
	VARM2	0.009882	0.000005	0.000000	0.342897	0.000109	0.000000	0.119098	0.000001	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.277538	0.000461	0.000000	0.904210	0.016419	0.000000	0.504858	0.002671	0.000000
	ARM3	0.389106	0.000299	0.000000	0.904210	0.016419	0.000000	0.860310	0.001019	0.000000
	VARM3	0.000161	0.000004	0.000000	0.802449	0.000016	0.000000	0.504858	0.002671	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	
2013	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.049070	0.000176	0.000000	0.362159	0.615798	0.938763	0.342459	0.630242	0.966196
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.000000	0.011592	0.000287	0.000000	0.257954	0.110944	0.000009
	VARM2	0.000000	0.000000	0.000000	0.011938	0.000001	0.000000	0.017711	0.002973	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000000	0.000000	0.000000	0.001938	0.000001	0.000000	0.048057	0.004252	0.000000
	ARM3	0.000000	0.000000	0.000000	0.000729	0.000001	0.000000	0.017711	0.000145	0.000000
	VARM3	0.000000	0.000000	0.000000	0.000729	0.000001	0.000000	0.017711	0.002973	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2014	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000069	0.000289	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000178	0.000828	0.134085	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.184689	0.085040	0.003581	0.003122	0.012651	0.740891	0.006756	0.025518	0.934814
	VARM2	0.030817	0.052103	0.033297	0.003122	0.012651	0.792868	0.006756	0.025518	0.934814
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.005157	0.000812	0.000001	0.068612	0.185837	0.004056	0.006756	0.025518	0.934814
	ARM3	0.001381	0.000478	0.000000	0.177586	0.385466	0.034533	0.006756	0.025518	0.934814
	VARM3	0.000683	0.000104	0.000000	0.019025	0.063250	0.833024	0.006756	0.025518	0.934814
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000001	0.000003	0.000000	0.000000	0.000000	0.000000	0.000002	0.000004	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2015	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000013	0.000001	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000007	0.000038	0.143988	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000039	0.000201	0.245507	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	VARM2	0.000039	0.000201	0.245598	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.014147	0.039241	0.518372	0.003122	0.012651	0.796835	0.006756	0.025518	0.934814
	ARM3	0.014147	0.039241	0.518013	0.003122	0.012651	0.797138	0.006756	0.025518	0.934814
	VARM3	0.000667	0.002767	0.214394	0.000123	0.000627	0.605281	0.006756	0.025518	0.934814
	M4	0.000013	0.000004	0.000000	0.000001	0.000003	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000005	0.000000	0.000000	0.000029	0.000052	0.000000	0.000000	0.000002	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000	
2016	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000345	0.001066	0.000000	0.000092	0.000338	0.000000	0.000034	0.000106	0.000000
	M2st	0.000171	0.000798	0.047675	0.000120	0.000615	0.603163	0.006681	0.025263	0.934247
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000015	0.000000
	ARM2	0.414556	0.236078	0.020227	0.175408	0.381984	0.995920	0.006681	0.025263	0.934247
	VARM2	0.180970	0.083389	0.006599	0.175408	0.381984	0.995911	0.006681	0.025263	0.934247
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.030336	0.017291	0.000011	0.003063	0.012432	0.794777	0.006681	0.025263	0.934247
	ARM3	0.030336	0.005067	0.000001	0.003063	0.012432	0.794100	0.007586	0.252834	

Years	Models	Q <sub>1</sub>			Q <sub>2</sub>			Q <sub>5</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.105957	0.269935	0.993641	0.003639	0.014543	0.811919	0.007528	0.010491	0.337196
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000420	0.000318	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.105957	0.269935	0.992711	0.195891	0.414024	0.061076	0.017930	0.027863	0.045510
	VARM2	0.105957	0.269935	0.992861	0.195891	0.414024	0.054235	0.216771	0.013229	0.001150
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.362478	0.653153	0.999797	0.077043	0.204213	0.978866	0.074224	0.023396	0.002994
	ARM3	0.822449	0.088426	0.000000	0.957655	0.290410	0.000011	0.216771	0.099144	0.016069
	VARM3	0.755217	0.928583	0.999995	0.657748	0.817914	0.999631	0.970981	0.572167	0.507888
	M4	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000
	ARM4	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2012	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.340027	0.627392	0.660684	0.904210	0.000004	0.000000	0.942492	0.000001	0.000000
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.006681	0.025263	0.934247	0.067621	0.000035	0.000000	0.000643	0.000000	0.000006
	VARM2	0.006681	0.025263	0.934247	0.018707	0.001015	0.000000	0.005637	0.000022	0.000089
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.260387	0.000059	0.000000	0.904210	0.000004	0.000000	0.526512	0.001788	0.000001
	ARM3	0.720414	0.000174	0.000000	0.175408	0.000413	0.000000	0.191077	0.000650	0.000000
	VARM3	0.720414	0.000174	0.000000	0.611055	0.007128	0.000028	0.277538	0.000333	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2013	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.006756	0.025518	0.934814	0.019025	0.063250	0.903307	0.110310	0.000274	0.000163
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.006756	0.025518	0.934814	0.003122	0.012651	0.795806	0.184689	0.011080	0.000180
	VARM2	0.006756	0.025518	0.934814	0.003122	0.012651	0.794222	0.421216	0.005021	0.000782
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.342459	0.630242	0.999735	0.910088	0.016521	0.000432	0.952019	0.000308	0.000002
	ARM3	0.098483	0.254687	0.992894	0.177586	0.385466	0.991246	0.421216	0.005021	0.000137
	VARM3	0.098483	0.254687	0.993119	0.362159	0.095224	0.313273	0.761472	0.018236	0.000442
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2014	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.050568
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.026569
	VARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.051838
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.006756	0.025518	0.934814	0.003122	0.012651	0.744981	0.000667	0.000644	0.076085
	ARM3	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000667	0.000925	0.003962
	VARM3	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.005822	0.008170	0.100350
	M4	0.000135	0.000506	0.000000	0.000260	0.000757	0.000039	0.000069	0.000000	0.000000
	ARM4	0.000033	0.000152	0.000000	0.000088	0.000123	0.000000	0.000069	0.000000	0.000000
VARM4	0.000000	0.000000	0.000000	0.000009	0.000043	0.000000	0.000013	0.000000	0.000000	
2015	M1	0.017711	0.047812	0.000008	0.000729	0.003300	0.000033	0.000005	0.000023	0.000001
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000029	0.000052	0.000000	0.005157	0.000812	0.000000
	M2st	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.026569
	M2jsu	0.000033	0.000152	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.026569
	VARM2	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.000000	0.000000	0.026569
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.001381	0.000006	0.000000
	ARM3	0.006756	0.025518	0.934814	0.003122	0.012651	0.772641	0.000000	0.000000	0.000000
	VARM3	0.006756	0.025518	0.934814	0.000123	0.000627	0.605281	0.123862	0.000001	0.000000
	M4	0.048057	0.118387	0.000007	0.338885	0.477187	0.066598	0.678752	0.913119	0.000021
	ARM4	0.005937	0.017125	0.000029	0.107486	0.181850	0.001892	0.952019	0.391156	0.001540
VARM4	0.001823	0.004809	0.000000	0.011592	0.037040	0.000000	0.123862	0.019919	0.000001	
2016	M1	0.000002	0.000000	0.000000	0.000001	0.000000	0.000000	0.000032	0.000007	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000345	0.000001	0.000000
	M2st	0.006681	0.025263	0.934247	0.000120	0.000615	0.603163	0.000001	0.000005	0.092709
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.097586	0.252834	0.992478	0.003063	0.012432	0.795178	0.000006	0.000002	0.012444
	VARM2	0.097586	0.252834	0.992716	0.003063	0.012432	0.795202	0.000001	0.000005	0.092210
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.006681	0.025263	0.934247	0.000120	0.000615	0.603163	0.000001	0.000005	0.088045
	ARM3	0.006681	0.025263	0.934247	0.000120	0.000615	0.603163	0.000643	0.000620	0.1



Years	Models	Q <sub>95</sub>			Q <sub>98</sub>			Q <sub>99</sub>		
		UC	CC	DC	UC	CC	DC	UC	CC	DC
2011	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000453	0.000000	0.000000	0.392781	0.102259	0.001235	0.105957	0.269935	0.991296
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.001520	0.000000	0.000000
	VARM2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000420	0.000000	0.000000
	EGARCHst	0.074224	0.002021	0.000620	0.392781	0.102259	0.001184	0.822449	0.088426	0.001801
	M3	0.003671	0.000001	0.000000	0.957655	0.000409	0.000000	0.473190	0.000019	0.000000
	ARM3	0.000213	0.000016	0.000000	0.749709	0.354551	0.014937	0.362478	0.653153	0.000000
	VARM3	0.000939	0.000109	0.000000	0.093767	0.161552	0.003770	0.473190	0.720013	0.000001
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000
	VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	2012	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000073	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2st		0.000345	0.000000	0.000000	0.011879	0.000001	0.000000	0.001864	0.000000	0.000000
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM2		0.000000	0.000000	0.000000	0.000753	0.000000	0.000000	0.048753	0.000002	0.000000
VARM2		0.000000	0.000000	0.000000	0.000092	0.000000	0.000000	0.000139	0.000000	0.000000
EGARCHst		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.017599	0.000000	1.000000	0.802449	0.810113	1.000000	0.097586	0.252834	1.000000
ARM3		0.001447	0.000001	1.000000	0.611055	0.794848	1.000000	0.097586	0.252834	1.000000
VARM3		0.000032	0.000000	0.000000	0.200579	0.273041	0.987808	0.504858	0.746917	0.999937
M4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM4		0.000002	0.000000	1.000000	0.000000	0.000000	1.000000	0.000000	0.000000	1.000000
VARM4		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
2013		M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2st	0.000000	0.000000	0.000000	0.197757	0.048298	0.002166	0.098483	0.254687	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000515	0.000370	0.000000
	VARM2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000135	0.000018	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.005937	0.012184	0.000015
	ARM3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.048057	0.051865	0.001088
	VARM3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.001823	0.000858	0.000000
	M4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	2014	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.000005	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2st		0.060904	0.107162	0.047806	0.003122	0.012651	0.772962	0.006756	0.025518	0.934814
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM2		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.856117	0.087289	0.000636
VARM2		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.856117	0.087289	0.000607
EGARCHst		0.000153	0.000000	0.000000	0.000029	0.000052	0.000000	0.005937	0.012184	0.000000
M3		0.000005	0.000000	0.000000	0.003122	0.012651	0.796369	0.006756	0.025518	0.934814
ARM3		0.000153	0.000000	0.000000	0.019025	0.063250	0.918321	0.006756	0.025518	0.934814
VARM3		0.857958	0.004694	0.000000	0.003122	0.012651	0.796569	0.006756	0.025518	0.934814
M4		0.000005	0.000003	0.000000	0.000003	0.000003	0.000000	0.000000	0.000000	0.000000
ARM4		0.000005	0.000007	0.000000	0.000003	0.000001	0.000000	0.000000	0.000000	0.000000
VARM4		0.000013	0.000012	0.000000	0.000003	0.000014	0.000000	0.000000	0.000000	0.000000
2015		M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	QReg	0.005157	0.000037	0.000000	0.000003	0.000001	0.000000	0.000000	0.000000	0.000000
	M2st	0.079311	0.004414	0.000000	0.362159	0.095224	0.002892	0.006756	0.025518	0.934814
	M2jsu	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	M2Ser	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	ARM2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.501312	0.000019	0.000000
	VARM2	0.000000	0.000000	0.000000	0.338885	0.048191	0.000000	0.342459	0.010290	0.000000
	EGARCHst	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000002	0.000009	0.000000
	M3	0.000000	0.000000	0.000000	0.338885	0.048191	0.000000	0.342459	0.630242	0.976142
	ARM3	0.000000	0.000000	0.000000	0.000260	0.000000	0.000000	0.856117	0.940933	0.001518
	VARM3	0.000153	0.000000	0.000000	0.177586	0.385466	0.027653	0.342459	0.630242	0.991392
	M4	0.000069	0.000001	0.000000	0.000003	0.000000	0.000000	0.000002	0.000000	0.000000
	ARM4	0.000153	0.000015	0.000000	0.000729	0.000542	0.000000	0.000008	0.000003	0.000000
	VARM4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
	2016	M1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
ARM1		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
QReg		0.526512	0.061445	0.000726	0.000753	0.000555	0.000000	0.000139	0.000019	0.000000
M2st		0.414556	0.036122	0.177217	0.611055	0.007128	0.000004	0.006681	0.025263	0.934247
M2jsu		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M2Ser		0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000001	0.000000
ARM2		0.000000	0.000000	0.000000	0.026521	0.000327	0.000000	0.720414	0.914928	0.999998
VARM2		0.389106	0.083226	0.000001	0.904210	0.000377	0.000000	0.860310	0.001019	0.000000
EGARCHst		0.000032	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
M3		0.191077	0.000073	0.000000	0.067621	0.008562	0.010455	0.006681	0.025263	0.934247
ARM3		0.000000	0.000000	0.000000	0.904210	0.000377	0.000000	0.097586	0.252834	









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