uc3m | Universidad Carlos III de Madrid

e-Archivo

This is a postprint version of the following published document:

Peña, J. I., Rodríguez, R., & Mayoral, S. (2020). Tail risk of electricity futures. *Energy Economics*, 91, p. 104886.

DOI: 10.1016/j.eneco.2020.104886

© Elsevier, 2020

This work is licensed under a Creative Commons Attribution-NonCommercialNoDerivatives 4.0 International License.

Tail Risk of Electricity Futures

Juan Ignacio Peña[a], Rosa Rodríguez[b]

and Silvia Mayoral[c]

Abstract

This paper compares the in-sample and out-of-sample performance of several models for computing the tail risk of one-month and one-year electricity futures contracts traded in the NordPool, French, German, and Spanish markets in 2008-2017. As measures of tail risk, we use the Value-at-Risk (VaR) and the Expected Shortfall (ES). Overall, and with VaR, the AR (1)-GARCH (1,1) model with Student-t distribution is the best model with 88% cases in which their adequacy is accepted, with a higher success rate in the left tail (94%) than in the right tail (81%). By markets, this model passes the test of model adequacy in the 100% of the cases in the NordPool and German markets, but only in the 88% and 63% of the cases in the Spanish and French markets. With ES, this model passes the test of model adequacy in 100% of cases in all markets. Historical Simulation and Quantile Regression-based approaches misestimate tail risks. The right-hand tail of the returns is more difficult to model than the left-hand tail and therefore financial regulators and the administrators of futures markets should take these results into account when setting regulatory capital requirements and margin account regulations.

Keywords: Electricity markets; Futures markets; Value-at-Risk; Expected Shortfall; Backtesting

JEL Codes: C51; G13; L94; Q40

a. Corresponding author. Universidad Carlos III de Madrid, Department of Business Administration, c/ Madrid 126, 28903 Getafe (Madrid, Spain). ypenya@eco.uc3m.es; *b.* Universidad Carlos III de Madrid, Department of Business Administration, c/ Madrid 126, 28903 Getafe (Madrid, Spain). rosa.rodriguez@uc3m.es *c*. Department of Business Administration, c/ Madrid 126, 28903 Getafe (Madrid, Spain). *c.* Universidad Carlos III de Madrid, Department of Business Administration, c/ Madrid 126, 28903 Getafe (Madrid, Spain). silvia.mayoral@uc3m.es . Department of Business Administration, c/ Madrid 126, 28903 Getafe (Madrid, Spain).
We acknowledge financial support from FUNCAS, through grant PRELEC2020-2017/00085/001 and from DGICYT, through grant ECO2016-77807-P.

Tail Risk of Electricity Futures

Highlights

- Nordpool, Germany, France, and Spain electricity futures prices are analyzed
- We forecast VaR and ES of one-month and one-year electricity futures contracts
- AR (1)-GARCH (1,1) with Student-t distributions best forecast VaR and ES in all cases
- Historical Simulation and Quantile Regression misestimate tail risks
- Tail risk is higher for short positions than for long positions

1. Introduction

The liberalization of electricity markets generates competition coupled with price uncertainty. Both factors create powerful incentives to carry out effective management of the market risk of electricity prices. Consider a portfolio of an energy trading company. If it trades in gas and power, it may have positions in many locations. Each location is characterized by its forward price and volatility curves. Thus, the firm may face hundreds of portfolio value drivers[1]. Given this high dimensionality, mapping the changes in portfolio value on a reduced set of principal risk factors is common practice in the industry, Eydeland, and Wolyniec (2003). Electricity futures contracts prices are key risk factors and we need thus methods for representing their distribution for the computation of tail risk measures of complex portfolios using Monte Carlo simulation or delta-gamma approaches.

The right assessment of the tail risk of the price of electricity futures contracts is crucial when setting the size of the buffer designed to protect the futures market's clearinghouse from losses caused by defaults in traders' positions. Most futures markets erect at least two consecutive safeguards. First, the exchange's own default fund and second, the clearinghouse members' default fund. If, when setting the size of both default funds, they underestimate losses because of extreme movements in futures prices, the exchange and its members may face significant liquidity (and perhaps solvency) problems. A recent event illustrates this situation. On September 13, 2018, the Financial Times (2018), reported that in the Nasdaq's Nordic futures power market the losses incurred by just one trader[2] wiped

[1] Eydeland and Wolyniec (2003) suggest that in the US the firm may face several thousand possible value drivers.

[2] The trader, an individual member of the Nasdaq Clearing firm, could clear his own trades without going through a bank. He based his strategy on betting on a narrowing of the price differential between German and Norpool electricity prices. When implementing this strategy, he likely bought Norpool futures and sold Germany's EEX futures. German prices augmented because of increases in carbon prices and, at the same time, Nordic prices fell because of wetter than previously expected weather expanded the hydropower supply. Both

out all the exchange's own default fund of €7 million and an additional €107 million, or 64%, of the member's default fund of €166 million. These losses prompted Nasdaq to ask the members of the clearinghouse to make compensating payments to the funds within 48 hours.

Although research exists (Byström, 2005, Westgaard et al., 2019b) about what method provides better forecasts of tail risk in day-ahead electricity prices, little is known about this issue with longer-maturity contract prices (monthly, quarterly and yearly). The scarcity of research on these matters implies a lack of convincing evidence on how well alternative models measure the tail risk of the electricity futures price. In this paper, we aim to fill this gap in the literature, by comparing the in-sample and out-of-sample performance of several models and markets and suggesting policy recommendations, based on the empirical evidence provided.

The non-storability of electricity and the physical and reliability constraints in its transmission manifest itself in complex price distributions, as measured by time-dependent volatility, skewness, kurtosis, and quantiles. Although research on the distributional characteristics of spot and day-ahead electricity prices is available (e.g. Escribano et al., 2011), we know little about the tail risk of futures prices with maturities longer than one day and its implications for risk management. In this paper, we compare the in-sample and out-of-sample performance of several models for computing the tail risk of electricity futures contracts with one month and one year to maturity traded in the NordPool, French, German and Spanish markets in 2008-2017. As measures of tail risk, we use Value-at-Risk and Expected Shortfall. Our findings support the conclusion that the AR(1)-GARCH-t model

legs of the strategy generated huge losses simultaneously and, unable to meet the margin calls, the trader declared bankruptcy.

performs better than other models in predicting VaR and ES in all markets. Overall, and with VaR, the AR(1)-GARCH(1,1) model with Student-t distribution is the best model with 88% cases in which their adequacy is accepted, with a higher success rate in the left tail (94%) than in the right tail (81%). This model works better for monthly contracts than for yearly contracts and passes the test of model adequacy in the 100% of the cases in the Nordpoool, and German markets, and in 88% of the cases in the Spanish market, but only in the 63% of the cases when predicting VaR in the French market. We report persistent risk misestimation in widely used methods in the industry, such as Historical Simulation or methods that seem to work well in other energy markets, such as Quantile Regression. The right-hand tail of the returns is more difficult to model than the left-hand tail.

This study makes several contributions to existing literature. First, while several studies (e.g. Byström, 2005, Chan and Grey, 2006) have addressed the performance of VaR forecasting models in electricity prices, few papers have focused on the estimation of extreme high and low quantiles for the prices of electricity futures contracts. With this paper, we aim to fill this gap in the literature. This is important because producers and retailers of electricity pursuing active risk management policies use futures contracts of different maturities (monthly, quarterly, yearly) when they become available (Sanda et al., 2013, Boroumand et al., 2015). In contrast with Gonzalez-Pedraz et al. (2014) who studied the tail risk of monthly futures contracts in one market (NYMEX), we study monthly and yearly maturities in several markets. Second, we model the tail risk both for long positions in futures contracts, typically held by retailers and for short positions in a futures contract, typically held by producers. Third, earlier studies focused on the NordPool or German markets. We study those markets, but we also include the French and Spanish markets, which have received limited attention in the literature so far. Fourth, we study an array of competing models, from

the simple historical simulation to quantile regression. Fifth, we study the extent to which the model's out-of-sample performance matches its in-sample fitting. Also, besides VaR, this paper presents the forecast and backtesting of ES, which is becoming the tail risk measure of choice for regulators.

We organize the rest of this paper as follows. Section 2 reviews the literature. After describing the methodology in Section 3, we present data in Section 4. Section 5 discusses the empirical results. Section 6 concludes.

2. Literature Review

Literature has addressed optimal hedging strategies in those markets using financial contracts, Deng and Oren (2006). Vehviläinen and Keppo (2003) studied the optimal hedging strategy of spot price risk by using futures contracts. Most papers investigating the tail risk of electricity prices focus on the spot or day-ahead price and study hourly prices or their daily averages. However, we cannot translate the results directly to the prices of futures contracts with longer maturities. Spot or day-ahead prices trade seven days a week and the average value and the volatility differ between hours and between weekdays and weekends. Also, these prices present strong seasonality, regime-switching, large price spikes, time-varying daily volatility (Knittel and Roberts, 2005, Escribano et al., 2011, Paraschiv et al., 2016), complex marginal distributions with significant skewness and excess kurtosis (Benth et al., 2008) and negative prices (Fanone et al., 2013). Futures prices trade five days a week and are always non-negative, the seasonal variation is less salient, price spikes are less frequent and smaller, the average price increases with maturity and the volatility (Samuelson effect), skewness and kurtosis decrease with maturity (Blanco et al., 2018), but they may present regime-switching and non-Gaussian marginal distributions (Andresen et al., 2010).

As Quinn, et al. (2005) argue, futures prices are a function of market expectations of demand and cost conditions during the delivery period. The current market situation (i.e. spot prices) may or may not influence these expectations and as a result, the tail risk may be different for spot and futures prices.

Most papers investigating the tail risk in electricity futures prices focus on day-ahead prices. Henney and Keers (1999) suggest the Historical Simulation (HS) in the case of established electricity markets. Leong and Siddiqi (1999) compute the VaR of electricity spot prices assuming a normal distribution for electricity prices. Dahlgren et al. (2003) apply the historical simulation method to the computation of VaR and ES of day-ahead electricity prices. Byström (2005) studies hourly day-ahead Nord Pool prices using a GARCH-EVT framework and recommends the generalized Pareto distribution. Liu and Wu (2007) use the delta-normal method to calculate the value of VaR of day-ahead electricity prices. Keles et al. (2016) report similar results to Byström, (2005) in the case of the German market (EPEX). Chan and Grey (2006) analyze day-ahead prices from five markets using and EGARCH-EVT specification that performs well in forecasting out-of-sample VaR in comparison to several models. Bunn et al. (2016) study UK day-ahead prices and conclude that a linear quantile regression model outperforms skewed GARCH-t and CAViaR models in out-of-sample forecasts of VaR. Hagfors et al. (2016) analyze extreme positive and negative price occurrences in the German day-ahead market. Paraschiv et al. (2014, 2016) show the improvements got in forecasting the tail risk of day-ahead prices by using fundamental variables, and Hagfors et al. (2016a) using quantile regression techniques show that the sensitivities to fundamentals may depend on market conditions. Hagfors et al. (2016b) analyze extreme positive and negative price occurrences in the German day-ahead market by using non-linear methods. Westgaard et al. (2019b) present a detailed analysis of the

performance of VaR forecasts of hourly day-ahead prices in the German market, using fundamental explanatory variables and six different models: QR, EWQR, EWDKQR, GARCH-T, SAV CAViaR and AS CAViaR. Although the best-performing model varies across trading periods and depending on the evaluation criteria, the authors recommend the EWQR based on selected fundamentals as the best model overall.

With futures with longer maturities, as far as we know, the evidence on the relative performance of tail risk measures is scarce. Gonzalez Pedraz et al. (2014) analyze PJM electricity futures with monthly maturity (M1, the front contract) traded in the NYMEX market in an energy portfolio analysis and report that the best VaR forecasting model is a GARCH model with a Student t distribution. Westgaard et al. (2019a) investigate the in-sample performance of estimates of one-day-ahead VaR got from three univariate models (EWMA, FHS, QR) of the prices of nine European energy futures front (M1) contracts, for oil, gas, coal, and M1, M2 and M3 contracts for electricity. They conclude that VaR forecasts made by the QR model present the best conditional and unconditional performance, followed by the FHS, whereas EWMA's forecast is the poorest. Also, the modeling of the right-hand tail is more challenging in all cases, suggesting that the tail risk attributable to short positions is more difficult to assess.

3. Methodology

This section presents the various approaches to calculating VaR(α,t) and ES(α,t) for quantile α and period *t* examined in this paper. These distribution-based risk measures are estimates of the capital reserve (as required by the regulator or set by the firm) as protection against fluctuations in the value of a financial asset. We focus on one-step-ahead estimates of VaR(α,t) and ES(α,t) calculated with data up to period *t* -1 and based on daily returns for

long ($\alpha = 0.05, 0.01$) and short ($\alpha = 0.95, 0.99$) positions. Let r_j be the asset return series where $j = t\text{-}1,\ldots,1$. We define the left-hand side VaR(α,t), measuring the tail risk of long futures positions, as

$$\Pr[r(t) < VaR(\alpha, t)] = \alpha \ ; \ \alpha < 0.5 \tag{1}$$

The right-hand side VaR(α,t), measuring the tail risk of short futures positions, is

$$\Pr[r(t) > VaR(\alpha, t)] = 1 - \alpha \ ; \ \alpha \geq 0.5 \tag{2}$$

In the same way, we define the left-hand side ES(α,t) as

$$ES(\alpha, t) = E[r(t) | \, r(t) < VaR(\alpha, t)] \ ; \ \alpha < 0.5 \tag{3}$$

And the right-hand side ES(α,t) as

$$ES(\alpha, t) = E[r(t) | \, r(t) > VaR(\alpha, t)] \ ; \ \alpha \geq 0.5 \tag{4}$$

Regarding the computation of ES(α,t), we apply two methods. First, if the model we use allows a closed-form for its computation, we use it. Second, if there is no closed-form available, we rely on the representation of ES as integrated VaR as presented in Acerbi and Tasche (2002)

$$ES(\alpha, t) = \frac{1}{\alpha} \int_0^{\alpha} VaR(u) du \tag{5}$$

and apply the discretization suggested in Emmer et al. (2015)

$$ES(\alpha,t) \cong \frac{1}{4}(VaR(\alpha,t) + VaR(0.75\alpha + 0.25I(\alpha),t) + VaR(0.5\alpha + 0.5I(\alpha),t) + VaR(0.25\alpha + 0.75I(\alpha),t) \qquad I(\alpha) = \begin{cases} 1 & \alpha \geq 0.5 \\ 0 & \alpha < 0.5 \end{cases} \tag{6}$$

Intuitively (6) suggests that an estimate of ES could be considered reliable if estimates of the four VaR are reliable[3]. Backtesting ES could be done by simultaneously backtesting multiple VaR estimates at different levels.

As methods for the computation of those risk measures, we apply two non-parametric models. First, we consider the Historical Simulation (HS) method because of Perignon and Smith (2010) report that one-day-ahead VaR(0.01) based on historical simulation is the standard in the case of international commercial banks. Second, we apply the Boudoukh-Richardson-Whitelaw (Boudoukh et al., 1998) method of exponentially declining weights of historical returns because Taylor (2008) commends this method as an equivalent to Exponentially Weighted Quantile Regression (EWQR) with one intercept and no regressors and shows that they may be able to outperform GARCH-based methods and CAViaR models. We also apply parametric approaches based on AR(1)-GARCH(1,1), AR(1)-EGARCH(1,1) or AR(1)-GJR(1,1) models with Student t distributions which are considered as standard benchmarks for the computation of risk measures (e.g. Du and Escanciano, 2017). Also, we apply quantile regression (QR) models which have been used successfully in modeling extreme quantiles in electricity markets by Hagfors et al. (2016) among others. Table 1A

[3] For instance, ES(0.05) should be based on estimates of VaR(0.05), VaR(0.0375), VaR(0.025) and VaR(0.0125)

presents the models.

[INSERT TABLE 1A HERE]

Next, we present the backtesting methods for VaR (Bin, POF, CCI, and DQ) and ES (UN-N, and UN-t) [4]. The following Table 1B summarizes their principal characteristics

[INSERT TABLE 1B HERE]

With VaR, two tests (Bin, POF) focus on the proportion of failures (unconditional failure) and two tests on conditional failure for clustering (CCI, DQ). Besides results from traditional individual tests (e.g., POF, CCI), and to give an overall perspective of the results from the VaR backtesting exercise we present a combined p-value test for multiple hypothesis testing. This procedure follows the same principle of the mixed coverage test, Haas (2001). We use Fisher's product test combining p-values to test the global null hypothesis H_0 that each of n component null hypotheses, H_1, …, H_n is true versus the alternative that at least one of H_1,…, H_n is false. As Zhang et al. (2013) show, Fisher's test is more powerful than classical multiple tests such as the Bonferroni test and the Simes tests, especially when n is not large. The combined p-value test is based on the notion that several non-significant results together may suggest significance and hence detect departures from H_0. The test is

$$F = -2\sum_{i=1}^{n} \ln(p_i) \tag{7}$$

[4] The technical details on models and backtesting test are in Appendix A.

that follows a χ^2_{2n} distribution under H_0 and the assumption that the tests are independent.

With ES, backtesting is more difficult than with VaR, Hull, and White (2014). ES estimates rely on a smaller number of observations than VaR estimates and are thus less stable, especially when the return distribution has fat tails (Yamai and Yoshiba, 2002). For instance, in the current Basel III regulatory framework, ES estimators are based on only 2.5% of the sample size used for estimating the VaR[5]. With ES, both unconditional backtests (UN-N and UN-t) compare observed and expected ES, but assuming different reference distributions (Normal and Student-t). The expected value for the UN test statistic is zero, and it is negative when there is evidence of risk underestimation. To determine how negative it should be to reject the model, we need critical values, based on distributional assumptions (Normal, Student-t) for the price returns. We check the consistency of the tests' outcomes and report the p-value of each UN test separately. Notice that consistency implies that (i) if the UN-N test shows no undervaluation, the UN-t test must match, (ii) if the UN-t test suggests undervaluation, the UN-N test must match. An inconsistency arises when the UN-N test shows no undervaluation but the UN-t test says the opposite.

4. Data

We collect daily prices of baseload futures contracts with one-month and one-year maturity in the period from January 2, 2008, to September 25, 2017, from the German, French, Spanish and NordPool markets. Price time series are continuous and computed as perpetually linked series[6]. For instance, in the case of the month series, the first data point on January 2,

[5] Standard back-testing periods of 250 days are routinely recommended by regulators. Using the 2.5% confidence limit gives 250*0.025= 6.25 failures.

[6] Month contracts cease trading at the close of business, one Business Day prior to the last calendar day of the contract's delivery period. However, usually there is hardly any trading volume after the day before the first

2008, corresponds to the price of the front contract M1 to supply electricity during February 2008. On February 1, 2008, the price in the continuous series corresponds to the price of the front contract M1 to supply electricity during March 2008, and so on. Table 1C has a contract definition, codes, and sample period of all contracts and markets.

[INSERT TABLE 1C HERE]

In what follows, we consider the full sample period[7] (January 2, 2008, to September 25, 2017), the in-sample period for model estimation (January 2, 2008, to December 31, 2014) and the out-of-sample period for backtesting purposes (January 2, 2015, to September 25, 2017). Figure 1 displays the prices of the futures contracts in the full sample, Panel A contains M1 contracts and Panel B shows Y1 contracts.

[INSERT FIGURE 1 HERE]

After steep increases during 2009, the prices of the month contract show a downward trend in the German market and, to a lesser extent, in the French and NordPool markets, but are steady in the Spanish market. Noticeable price increases, including price spikes, are apparent in the French market during November 2016 because of the combination of low temperatures and shortages in nuclear production because of extensive revisions in many facilities during this period (Commission de Régulation de L'Énergie, 2017). Prices of year contracts follow similar patterns to month contracts but are less volatile and spiky. The behavior across

calendar day of the delivery month. Year contracts cease trading at the close of business, two Business Days prior to the first calendar day of the delivery year.

[7] The number of data points in each sample varies across markets, due to national holidays and other market-specific events. For instance, in Germany (NordPool) the figures for the full-sample, in-sample, and out-of-sample are 2470 (2438), 1772 (1756), and 698 (688) respectively.

markets is alike, peaking around mid-2008, and then rapidly decreasing in all markets, bottoming near the end of 2009, in coincidence with the financial crisis 2007-2009. Then a stable period ensues until 2013 where a downward trend manifests in the French, German, and NordPool markets, bottoming out at the end of 2015. Prices in the Spanish market present a steadier pattern.

We compute daily returns as the first difference in log prices[8]. Figure 2 describes the log returns over the full sample period and Panel A contains M1 contracts and Panel B shows Y1 contracts.

[INSERT FIGURE 2 HERE]

The graphs of the return series suggest time-varying volatility and volatility clustering around supply and demand shocks, for instance, in the French market during November 2016 or in the Spanish market during January 2014. Several positive and negative spikes are apparent, these features being more extreme in the case of the month series. Notice that a positive (negative) spike in the return series is caused by a positive (negative) level change in the price series. The literature usually relates the reasons justifying these jumps to events in the industry deemed to have a lasting impact on prices. For instance, on March 13, 2011, Angela Merkel, the German chancellor, ordered an emergency safety check at all Germany's

[8] In the continuous price series, a level change may appear on the days when trading activity moves from the old contract to the fresh one. This "rolling" event sometimes brings forth a jump in the return series, generating high volatility. Therefore, to avoid this artificial consequence, in days with "rolling" effects, we set the returns on these days equal to zero, as is usual in the literature (e.g. Westgaard et al., 2019a, Blanco et al., 2018). Notice that those jumps are spurious outcomes induced by the definition of the continuous series, but they are void of economic consequences because the trader does not receive the return between old contracts and fresh ones. Specifically, with month contracts, we assume traders close their positions in the old contract the last Business day before the delivery period, and they take positions in the new contract on the first day of the delivery period. Therefore, we set the return on that day equal to zero. With year contracts, and following the same logic, we set the return on the first day of the delivery period equal to zero.

17 nuclear power stations in the wake of the Japanese earthquake (Financial Times, 2011a), and on March 15, 2011 (Financial Times, 2011b) she announced a decree to make seven of the country's 17 nuclear plants idle. The German M1 and Y1 returns series show positive spikes on March 15, 2011, of 15% and 6% respectively, suggesting an expectation of permanent increases in electricity prices during the corresponding delivery periods because of lower supply. Interestingly, in the French market, the month contract also shows a spike of 12% on the same date, but the year contract does not present an extreme return. Jumps are also apparent in the French market during November 2016, corresponding to the contract with delivery during December 2016 and related to lasting decreases in supply, as discussed above. In the Spanish market during December 2013 and January 2014 some positive and negative jumps bunch together, due to reduced supply in four out of the eight nuclear plants available, followed by unprecedented increases in Eolic production (CNMC, 2014).

Table 2 provides descriptive statistics of the returns in all markets and contracts for the full sample in Panel A, the in-sample in Panel B, and the out-of-sample in Panel C.

[INSERT TABLE 2 HERE]

In Panel A, we may observe that the average return is small and negative in all cases, suggesting a persistent decrease in futures prices. Month contracts present higher price volatility than year contracts, as expected. Daily return volatility in month contracts is highest in NordPool (2.9%), followed by the French (2.6%), Spanish (1.7%), and German (1.6%) markets, and with year contracts results are alike. Although returns are negatively skewed in the French and Spanish markets, and positively skewed in Germany and the NordPool, all of them are leptokurtic with the Spanish month contract having the largest

coefficient (18.5) and the NordPool year contract having the smaller (7.18). All the returns series reject the null hypotheses of the Jarque-Bera Normality test. Tail risk in month contracts as measured by the 1% and 99% quantiles is more extreme in the NordPool (-0.079, 0.080) and French (-0.063, 0.082) markets than in the German (-0.045, 0.044) and Spanish (-0.050, 0.042) markets. The risk varies between the right and left tails, for instance, the French month contract presents a higher (0.082) right tail risk than left tail risk (-0.063). Year contracts present a lower tail risk than month contracts, as expected. The Ljung-Box test with 10 and 20 lags suggests auto-correlated returns in all cases. Results in the in-sample and out-of-sample periods are similar. The overall picture indicates that the market generating more extreme returns is NordPool, followed closely by the French market, whereas the German and Spanish markets exhibit fewer extreme returns.

We now summarize how the return distribution changes over time. We have split our data set by years. Detailed results are in Table 1A in the Appendix. The key takeaway from Table 1A is that the shape of the distribution of the return changes over time in all contracts and markets, suggesting a time-dependent tail risk. Figure 3 shows the time evolution of the volatility, skewness, and kurtosis of the month and year contracts, usually the latter presenting fewer extreme values of these statistics than the former.

[INSERT FIGURE 3 HERE]

With month contracts, we may see the volatility changing over time and reaching a peak in 2014 in Spain, in 2015 in NordPool and in 2016 in France and Germany. These peaks are possibly associated with shortages in nuclear production in Spain, Germany, and France during those years, as discussed above. Regarding skewness and kurtosis, the events of 2011

in the German market are associated with peaks in skewness and kurtosis in Germany and France, suggesting an overall increase in the risk of the month futures prices in these markets during this period. Asymmetry changes sign over time in all markets and kurtosis peaked in 2008 in Spain, in 2011 in Germany, 2014 in France, and 2015 in NordPool. All these changes point to changes also in tail risk over time[9].

5. Results and discussion

In this section, we present the results of the models used to generate VaR and ES forecasts and study their performance as measured by the backtesting tests[10]. A summary of the results is in Table 3, panels A1(VaR) and B1(ES) for all contracts and markets together, A2 and B2 for VaR with M1 and Y1 contracts, panels C2 and D2 for ES, also for M1 and Y1 contracts, and panels E1 and E2 for VaR and ES by markets, respectively[11]. Table 3 shows the number of times and percentages that data do not reject the overall Fisher test of model adequacy for all models, contracts, and markets. GT is the total for both tails. GTL is the total for the left tail (5%, 1%). GTR is the total for the right tail (95%, 99%).

[INSERT TABLE 3 HERE]

With VaR (Panel A1), the best model is GARCH with 88% cases in which their adequacy is accepted by the Fisher test in both tails, with a higher success rate in the left tail (94%) than in the right tail (81%). The worst model is the HS with an acceptance rate of 22%, also showing a differential success rate between the left (31%) and the right (13%) tail. Regarding

[9] **Data Availability**

Datasets related to this article can be found at EEX, OMIP, and NASDAQ OMX, hosted at http://www.eex.com, www.omipo.pt, and http://www.nasdaqomx.com/

[10] Models' estimated parameters and residual analysis are in the Appendix A, Tables 1 and 2.

[11] Detailed results on results of individual test are in Appendix A.

the other models, the ranking is EGARCH, GJR, EWQR, and QR with overall success rates of 81%, 75%, 44%, and 28% respectively, although the success rate is higher in the left tail than in the right tail. With ES (Panel B1), the best models are three GARCH-type models with an acceptance rate of 100% in both tails. The worst model is QR-COM, accepted in 33% of cases whereas HS and EWQR present a success rate of 63%. By contracts, Panel A2 presents VaR results for M1 and Panel B2 for Y1. GARCH and EGARCH models do equally well in both contracts, with a success rate of 88% and 81% respectively, but other models do better for M1 than for Y1. For instance, EWQR has a success rate of 56% in M1 but 31% in Y1. Thus, although the volatility of the returns of Y1 contracts is lower than the ones of M1 returns, the Y1 contract's VaR is more difficult to forecast. Panel C2 and D2 present ES results for M1 and Y1, respectively. GARCH-type models have a 100% success rate in both cases. However, other models present better performance with M1 than with Y1. For instance, EWQR and HS do pretty well with M1 (100% and 88%) but less so with Y1 (25% and 38%). Panels E1 and E2 present aggregate results by markets. With VaR, GARCH, EGARCH, and GJR have a success rate of 100% in the NordPool. In Germany, GARCH, and EGARCH present a rate of 100%. However, in the and Spanish and French markets, the success rate of the best GARCH model is 88% and 63% respectively. The performance of all models in the French market is worse than in the other three markets, excepting HS, that is rejected in all cases in the NordPool market. With ES the GARCH-type models are not rejected in 100% of cases in all markets.

An important point is whether the model's rejection arises because of risk underestimation or overestimation. In Table 4, panels A-E we compare the expected number of VaR failures with actual failures in every market and contract (eight cases). We compute the deviation defined as (Observed Failures – Expected Failures)/Expected Failures. A positive (negative)

figure shows that the model underestimates (overestimates) tail risk.

[INSERT TABLE 4 HERE]

The summary results in Panel E indicates that the HS method underestimates risk, with an average deviation of 34.56% (M1) and 62.24% (Y1). The EWQR method also underestimates the risk with an average deviation of 25.64% (M1) and 37.10% (Y1). The QR-COM, underestimate risk with average deviations of 78.81% (M1) and 148.44% (Y1). The GARCH and EGARCH models misestimate risk between -0.25% and 6.54% whereas GJR overestimates risk by -2.99% (M1) and -10.83% (Y1). Risk misestimation in most cases is stronger for Y1 contracts than for M1 contracts, which agrees with similar results in Table 3.

In summary, the GARCH model presents the leading forecasting performance among the models considered, followed closely by EGARCH and then by GJR while the EWQR, HS, and QR-COM models are least accurate.

As an illustration of the reasons why GARCH-type models outperform the other models, the following Figure 4 presents the VaR(1%) forecast in the out-of-sample (o-o-s) period with all models for the M1 contract in the German market. The results for ES(1%) are very similar and available on request.

[INSERT FIGURE 4]

The graph in the upper left-hand side labeled “Backtesting GARCHs” shows the results for

AR(1)-GARCH(1,1), AR(1)-EGARCH(1,1), and AR(1)-GJR(1,1). The shape of the forecast is similar across the three models and follows closely the temporal evolution of the returns. When a relatively large return appears, the VaR forecast moves up (in absolute terms) after a one-day lag and then goes back to normal levels quickly. If a cluster of extreme returns appears, the forecast adjusts to that accordingly. This fast adaptability is an embedded feature of GARCH models and one of the reasons for their popularity. In contrast, HS models produce a constant VaR forecast, that changes only when very large returns appear. After that, the VaR forecast remains at the new level for the number of days (e.g. 250) in that the rolling window contains that extreme return, even when consecutive returns are small. Therefore, the HS method tends, at first, to underestimate risk and, after one big return, to overestimate risk. Given that HS only relies on the recent (one year) unconditional distribution of the risk factors, is likely to misestimate the changes in conditional risk (Pritsker, 2006). Besides, the VaR forecast generated by the HS model is largely insensitive to volatility clustering if the returns in the cluster are not very high. Similar behavior to HS is produced by the EWQR, although this model presents more adaptability to volatility clustering. Finally, the Quantile Regression (QR-COM) model generates almost constant VaR forecasts because the regressors have very low explanatory power, and therefore hardly impact the VaR forecast. Table 3 in the Appendix shows the correlations between the returns and the explanatory variables. They range from -0.12 to 0.05 and are statistically not different from zero.

In summary, the distribution of electricity futures returns exhibit heavier-than-normal tails. The tails of the return distribution decay in a power-law speed instead of the exponential speed as in that of the normal distribution. The GARCH model with Student-t innovations captures volatility clustering by modeling the dynamic of volatility, leading to a time-

dependent estimate of the VaR and ES. Besides, the GARCH-type models capture the heavy tails, see Davis and Mikosch (2009), because GARCH processes have power-law marginal tails. In Table 4 in the Appendix, we present robust estimates of the tail index assuming the GARCH(1,1) Student-t model, and estimates of the empirical tail index in the right (95%) and left (5%) tail using the empirical distribution of returns. The average deviation between the GARCH estimate of the tail index and the empirical estimate is 3.83% with the quantile 5% and 7.10% with the quantile 95%. Therefore, in most cases, the GARCH model's implied tails are close to the empirical ones, especially with the 5% quantile. This is the reason GARCH-t models capture the tail risk so well. On average the GARCH estimate is 1.47, higher than the empirical estimate (95%) which is 1.18 and (5%), 1.28. This shows that empirical tails decay more slowly than predicted by GARCH models, especially beyond the 95% quantile. This suggests that the right-hand tail is more difficult to model than the left-hand tail. As a result, GARCH models are more adequate to investors taking long positions in electricity futures, a situation that also applies to other European energy futures markets, as documented in Westgaard et al. (2019a).

6. Conclusion

Agents in the deregulated electricity markets are well aware of the high volatility of prices and so have an incentive in implementing risk management policies, for instance, using futures contracts of different maturities. Thus, research on the tail risk associated with the prices of those futures contracts may help market participants in the design and implementation of their hedging and trading strategies. This paper examines some parametric and non-parametric approaches to forecasting VaR and ES in four markets (Norpool, Germany, France, and Spain) in the period 2008-2017 for the futures price of two contracts extensively used by market participants, monthly and yearly contracts.

The empirical evidence suggests that AR(1)-GARCH(1,1) models with t distributions present better performance than historical simulation, EWQR, and quantile regression models when predicting the VaR and ES in all markets and contracts. The reasons explaining this result are the ability of GARCH models of simultaneously capturing volatility clustering and fitting the heavy tails of the distribution of returns. However, the right-hand tail risk is more difficult to model than the left-hand tail. As a result, GARCH models are more adequate to investors taking long positions in electricity futures, a situation that also applies to other European energy futures markets. In addition to that, the performance of GARCH models in the NordPool and German markets is better than in the Spanish and French markets. Therefore, agents taking long positions in the NordPool, and German markets are advised to use GARCH-type models as a way of gauging the tail risk as well as a way of computing regulatory capital requirements and setting the size of default funds. In the Spanish market and especially in the French market, more study is needed before a recommendation can be done.

.

Popular methods used in the industry such as the Historical Simulation method and more innovative methods such as those based on Quantile Regression misestimate the tail risk of electricity futures returns. The reason is that HS models produce a constant VaR forecast, that changes only when very large returns appear. After that, the VaR forecast remains at the new level for the number of days contained in the rolling window. Therefore, the HS method tends, at first, to underestimate risk and, after one big return, to overestimate risk. Furthermore, the VaR forecast generated by the HS model is largely insensitive to volatility clustering. Similar behavior to HS is produced by the EWQR, although this model presents more adaptability to volatility clustering. Finally, the Quantile Regression (QR-COM) model

generates almost constant VaR forecasts because the regressors have very low explanatory power, and therefore their changes hardly impact the VaR forecast. The regressors (fuel prices and backward-looking volatility measures) have been applied in other commodity markets with some success, but in this case, their explanatory power turns out to be low. Searching for other explanatory variables useful in the case of electricity futures is an interesting avenue for future research.

The policy recommendation to financial market regulators is that risk weights, and the associated capital ratios to be required to investments in long positions these contracts should be computed using GARCH-type methods. The tail risk in short positions is more difficult to assess, and therefore more conservative capital requirements should be required. Widely used methods such as HS produce lower capital buffers, increasing the risk of financial distress for the incumbent firms. As an added policy recommendation to the administrators of futures markets, in charge of setting margin account regulations, is that, although the volatility of the yearly contract's returns is lower than the volatility of monthly contract returns, forecasting the VaR of the yearly contract is more difficult. Thus, margin requirements should be increased to account for this.

Looking forward, to improve this study, more general GARCH-type models could be studied, allowing more flexible distribution for the innovations such as the skewed-t, Extreme Value Theory-based, and the Normal Inverse Gaussian. We also acknowledge that our empirical results apply for only a one-day-ahead time horizon. Thus, assessing the VaR and ES performance of the models for other time horizons (weekly, monthly) may provide useful information to market participants and regulators. Considering additional backtesting procedures, especially for ES in the line of Du and Escanciano (2017) is another promising area of study, that we left for future research.

References

Acerbi, C. and D. Tasche, 2002. On the coherence of expected shortfall. *Journal of Banking and Finance*, 26, 1487-1503.

Acerbi, C. and Székely, B., 2014. Backtesting expected shortfall. *Asia Risk*, (Dec 2014/Jan 2015): 42-47.

Andresen, A., Koekebakker, S., and S. Westgaard, S., 2010. Modeling electricity forward prices using the multivariate normal inverse Gaussian distribution. *The Journal of Energy Markets*, 3, 3–25.

Benth, F.E., J. Šaltyte-Benth, and S. Koekebakker (2008). *Stochastic modelling of electricity and related markets*. World Scientific Publishing.

Blanco, I., Peña, J.I, and Rodriguez, R., 2018. Modeling Electricity Swaps with Stochastic Forward Premium Models. *The Energy Journal*, 39,2, 1-33.

Boudoukh, J., M. Richardson, and R. F. Whitelaw., 1998. The Best of Both Worlds. *Risk,* 11, May, 64–67.

Boroumand, R. H., Goutte, S., Porcher, S., and Porcher. T., 2015. Hedging strategies in energy markets: The case of electricity retailers. *Energy Economics*, 51, 503-509.

Bunn, D., Andresen, A., Chen, D., and Westgaard, S., 2016. Analysis and Forecasting of Electricity Price Risk with Quantile Factor Models. *The Energy Journal*, 37,1, 101-122.

Byström, H.N., 2005. Extreme value theory and extremely large electricity price changes. *International Review of Economics and Finance*, 14, 1, 41–55.

Chan, K.F., and Gray, P., 2006. Using extreme value theory to measure value-at-risk for daily electricity spot prices. *International Journal of Forecasting*, 22, 283–300.

Christoffersen, P., 1998. Evaluating Interval Forecasts. *International Economic Review*, 39, 841–862

Commission de Régulation de L'Énergie, 2017. Surveillance Rapport 2016-2017. Le fonctionnement des marchés de gros de l'électricité, du CO2 et du gaz natural. https://www.cre.fr/Documents/Publications/Rapports-thematiques/Rapport-sur-le-fonctionnement-des-marches-de-gros-2016-2017.

CNMC, 2014. Informes de supervisión de mercados a plazo de Energía Eléctrica en España (Diciembre 2013, Enero 2014). Comisión Nacional de los Mercados y la Competencia. https://www.cnmc.es/ambitos-de-actuacion/energia/mercado-electrico.

Dahlgren, R., Liu, C.-C., Lawarree, J., 2003. Risk assessment in energy trading. *IEEE Transactions on Power Systems* 18, 503–511.

Davis, R. A., and Mikosch, T., 2009. Extreme value theory for GARCH processes. *Handbook of Financial Time Series*, 187-200.

Deng, S., Oren, S. 2006. Electricity derivatives and risk management. *Energy*, 31, 940–953

Du, Z., and Escanciano, J. C., 2017. Backtesting Expected Shortfall: Accounting for Tail Risk. *Management Science*, 63, 4, 940-958.

Emmer, S., Kratz, M., and Tasche, D., 2015. What Is the Best Risk Measure in Practice? A Comparison of Standard Measures. *Journal of Risk* 18, 2, 31-60.

Escribano, Á., Peña, J. I., and Villaplana, P., 2011. Modeling Electricity Prices: International Evidence. *Oxford Bulletin of Economics and Statistics*, 73,5, 622- 650.

Eydeland, A., and Wolyniec, K., 2003. *Energy and Power Risk Management*. Wiley Finance.

Fanone, E., Gamba, A., Prokopczuk, M., 2013. The case of negative day-ahead electricity prices. *Energy Economics*, 35, 22-34.

Ferro, C. A. T., and Segers, J., 2003. Inference for clusters of extreme values. *Journal of the Royal Statistical Society, Series B*, 65, 545–556.

Financial Times, 2011a. Germany orders safety review at nuclear plants. https://www.ft.com/content/842c725e-4d81-11e0-85e4-00144feab49a.

Financial Times, 2011b. Merkel attacked over nuclear stance. https://www.ft.com/content/18adf5a8-50a5-11e0-9e89-00144feab49a.

Financial Times, 2018. Trader blows a €100m hole in Nasdaq's Nordic power market. https://www.ft.com/content/43c74e02-b749-11e8-bbc3-ccd7de085ffe.

Hull, J.C., and White, A., 2014. The shortfalls of expected shortfall. *Risk*, November, 10-12.

González-Pedraz, C., Moreno, M., and Peña, J. I., 2014. Tail Risk in Energy portfolios. *Energy Economics*, 46, 422-434.

Haas, M., 2011. New Methods in Backtesting. Financial Engineering, Research Center Caesar, Bonn.

Hagfors, L. I., Bunn D., Kristoffersen, E., Staver, T. T. and Westgaard, S., 2016a. Modeling the UK electricity price distributions using quantile regression. *Energy*, 102, 231-243.

Hagfords, L.I., Kamperud, H. H., Paraschiv, F., Prokopczuk, M., Sator, A., and Westgaard, S., 2016b. Prediction of extreme price occurrences in the German day-ahead electricity market. *Quantitative Finance*, 16, 1929-1948.

Haugom, E., Ray, R., Ullrich, C. J., Veka, S., and Westgaard, S., 2016. A parsimonious quantile regression model to forecast day-ahead value-at-risk. *Finance Research Letters*, 16, 196–207.

Henney, A., Keers, G., 1999. Managing total corporate electricity / energy market risks. *The Electricity Journal*,11, 36–46.

Ioannidis J. P. A., 2005. Why most published research findings are false. *PLoS Med* 2(8): e124.

Jorion, P., 2011. *Financial Risk Manager Handbook*. 6th Edition. Wiley Finance.

Keles, D., Hadzi-Mishev, R., and F. Paraschiv, 2016. Extreme value theory for heavy tails in electricity prices. *Journal of Energy Markets*, 9, 2, 21-50.

Knittel, C. R., and Roberts, M., 2005. An empirical examination of restructured electricity prices. *Energy Economics*, 27, 791–817.

Koenker R., and Bassett G., 1978. Regression quantiles. *Econometrica*, 46, 1, 33-50.

Kupiec, P., 1995. Techniques for Verifying the Accuracy of Risk Management Models. *Journal of Derivatives*, 3, 73–84.

Leong, K., and Siddiqi, R., 1999. Value at risk for power markets. In *Energy Risk Management*, P.C. Fusaro, ed. McGraw Hill.

Liu M., Wu F. F., Ni Y.X., 2006. A survey on risk management in electricity markets. The proceedings of the 2006 IEEE PES General Meeting. Montreal.

Liu, M., and Wu, F. F., 2007. Risk management in a competitive electricity market. *Electrical Power and Energy Systems,* 29, 690-697.

McNeil, A. J., and Frey, R., 2000. Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of Empirical Finance*, 7, 271-300.

McNeil, A. J., Frey, R., and Embrechts, P., 2010. *Quantitative Risk Management: Concepts, Techniques, and Tools*. Princeton University Press.

Mikosch. T. and Starica, C., 2000. Limit theory for the sample autocorrelations and extremes of a GARCH(1, 1) process. *Annals of Statistics*, 28, 1427-1451.

Paraschiv, F., Erni, D., and Pietsch, R., 2014. The impact of renewable energies on EEX day-ahead electricity prices. *Energy Policy*, 73, 196-210.

Paraschiv, F., Hadzi-Mishev, R., and Keles, D., 2016. Extreme Value Theory for Heavy Tails in Electricity Prices. *Journal of Energy Markets*, 9, 21-50.

Pérignon, C., and Smith, D. R., 2010. The level and quality of Value-at-Risk disclosure by commercial banks. *Journal of Banking and Finance*, 34, 362-377.

Pritsker, M., 2006. The hidden dangers of historical simulation. *Journal of Banking and Finance* 30, 561–582.

Quinn, J.A., J.D. Reitzes, J.D., and Schumacher, A. C., 2005. Forward and spot prices in electricity and gas markets. In *Obtaining the Best from Regulation and Competition*, Crew, M.A. and M. Spiegel (Eds.): 109–134. Springer-Verlag.

Sanda, G.E., Tandberg Olsen, E. and Fleten, S.-E., 2013. Selective hedging in hydro-based electricity companies. *Energy Economics*, 40, 326-338.

Taylor, J. W., 2008. Using Exponentially Weighted Quantile Regression to Estimate Value at Risk and Expected Shortfall. *Journal of Financial Econometrics*, 6, 3, 382-406.

Vehviläinen I. and Keppo J. 2003. Managing electricity market price risk. *European Journal of Operational Research* 145, (1), 136–147.

Westgaard, S., Århus, G. H., Frydenberg, M., and Frydenberg, S., 2019a. Value-at-risk in the European energy market: a comparison of parametric, historical simulation, and quantile regression value-at-risk. *The Journal of Risk Model Validation*, 13, 4, 43-69.

Westgaard, S., Paraschiv, F., Ekern, L. L., Naustdal, I., 2019b. Forecasting Price Distributions in the German Electricity Market. *International Financial Markets*, 11-35. Routledge.

Yamai, Y. and Yoshiba T., 2002. Comparative Analysis of Expected Shortfall and Value at Risk: Their Estimation Error, Decomposition, and Optimization. *Monetary and Economic Studies*, January, 87–121

Zhang, S., Chen, H-S, and Pfeiffer, R. M., 2013. A combined p-value test for multiple hypothesis testing. *Journal of Statistical Planning and Inference*, 143, 764-770.

Tables

Table 1A: Models

Model	Short Code	Parameters and Equation
Historical Simulation	HS	Window size of 250 data points
Exponentially Weighted Quantile Regression	EWQR	λ = 0.97 and 0.99
Autoregressive model of order 1 and Generalized Autoregressive Conditional Heteroskedastic model of order (1,1) with Student-t innovations with ν degrees of freedom	AR(1)-GARCH(1,1)	$r_j = \phi_0 + \phi_1 r_{j-1} + \sigma_j \varepsilon_j = \mu_j + \sigma_j \varepsilon_j; \quad \varepsilon_j \sim t(\nu)$ $\sigma_j^2 = \omega_0 + \omega_1 \sigma_{j-1}^2 + \omega_2 \varepsilon_{j-1}^2$
Autoregressive model of order 1 and Exponential Generalized Autoregressive Conditional Heteroskedastic model of order (1,1) with Student-t innovations with ν degrees of freedom	AR(1)-EGARCH(1,1)	$r_j = \phi_0 + \phi_1 r_{j-1} + \sigma_j \varepsilon_j = \mu_j + \sigma_j \varepsilon_j; \quad \varepsilon_j \sim t(\nu)$ $\ln(\sigma_j^2) = \beta_0 + \beta_1 \varepsilon_{j-1} + \beta_2 \ln(\sigma_{j-1}^2) + \beta_3 (\varepsilon_{j-1} - E\lvert\varepsilon_{j-1}\rvert)$
Autoregressive model of order 1 and Glosten-Jagannathan-Runkle GARCH model of order (1,1) with Student-t innovations with ν degrees of freedom	AR(1)-GJR(1,1)	$r_j = \phi_0 + \phi_1 r_{j-1} + \sigma_j \varepsilon_j = \mu_j + \sigma_j \varepsilon_j; \quad \varepsilon_j \sim t(\nu)$ $\sigma_j^2 = \kappa_0 + \kappa_1 \varepsilon_{j-1}^2 + \kappa_2 I_{j-1}(\varepsilon_{j-1} < 0) \varepsilon_{j-1}^2 + \kappa_3 \sigma_{j-1}^2$
Quantile Regression model for quantile α with fuel prices and daily, weekly, and monthly backward-looking volatility measures as explanatory variables	QR-COM	$Q_\alpha(r_j) = \omega_{\alpha,0} + \sum_{m=1}^{M} \delta_{\alpha,m} VolX_{j,m} + \sum_{k=1}^{K} \beta_{\alpha,k} FuelPX_{j,k} + \eta_{\alpha,j}$

Table 1B: VaR and ES Backtesting methods

Method	Risk Measure	Short Code	Comments
Binomial test (Jorion, 2011)	VaR	Bin	The Bin assesses if the number of failures is consistent with the VaR confidence level.
The proportion of failures test (Kupiec, 1995)	VaR	POF	The POF tests if the proportion of failures is consistent with the VaR confidence level
Conditional coverage independence test (Christoffersen, 1998)	VaR	CCI	The CCI assesses the independence of failures on consecutive time periods.
Dynamic Quantile test (Engle and Manganelli, 2004)	VaR	DQ	The DQ evaluates the existence of a correlation between failures, their lagged values, and the contemporaneous VaR estimate
Unconditional Test under the Normal distribution (Acerbi and Székely, 2014)	ES	UN-N	The UN-Normal tests if the average of the ES-scaled losses beyond VaR is consistent with the tails of a Normal distribution
Unconditional Test under the Student-t distribution (Acerbi and Székely, 2014)	ES	UN-t	The UN-t tests if the average of the ES-scaled losses beyond VaR is consistent with the tails of a Student-t distribution with 3 degrees of freedom

Table 1C: Futures contracts code and sample period

Country	Short Code	Market	Long Code	Sample
Germany	F1BM	EEX	Phelix-DE/AT Base Month Future	02.01.2008-25.09.2017
Germany	F1BY	EEX	Phelix-DE/AT Base Year Future	02.01.2008-25.09.2017
France	F2BM	EEX	French Base Month Future	02.01.2008-23.11.2011
France	F2BY	EEX	French Basel Year Future	02.01.2008-23.11.2011
France	F7BM	EEX	French Base Month Future	24.11.2011-25.09.2017
France	F7BY	EEX	French Base Year Future	24.11.2011-25.09.2017
Spain	FEBM	EEX	Spanish Base Month Future	01.04.2014-25.09.2017
Spain	FEBY	EEX	Spanish Base Year Future	01.04.2014-25.09. 2017
Spain	FTBM	OMIP	Spanish Base Month Future	02.01.2008-31.03.2014
Spain	FTBY	OMIP	Spanish Base Year Future	02.01.2008-31.03.2014
NordPool	ENOYC1	Nasdaq OMX	Oslo ASA Euro ENO Yearly Contract Energy Future	02.01.2008-25.09.2017
NordPool	ENOMC1	Nasdaq OMX	Oslo ASA Euro ENO Monthly Contract Energy Future	02.01.2008-25.09.2017

Table 2: Descriptive statistics returns

This table reports descriptive statistics of the eight series of futures price returns. The sample period is 02.01.2008-25.09.2017. JB is the p-value of the Jarque-Bera normality test. Q is the Ljung-Box test with 10 and 20 lags and pvQ is the corresponding p-value

Panel A: Full Sample								
	M1				**Y1**			
	FR	**GE**	**SP**	**NP**	**FR**	**GE**	**SP**	**NP**
Mean (%)	-0.060%	-0.074%	-0.137%	-0.082%	-0.014%	-0.027%	-0.020%	-0.016%
Std_dev	0.026	0.016	0.017	0.029	0.011	0.011	0.007	0.015
Minimum	-0.263	-0.122	-0.134	-0.167	-0.132	-0.059	-0.050	-0.090
Maximum	0.202	0.163	0.162	0.215	0.089	0.065	0.055	0.099
Skewness	-0.333	0.275	-0.020	0.193	-0.481	0.179	-0.271	-0.006
Kurtosis	15.789	10.670	18.539	7.329	16.873	7.203	10.978	7.187
Quantile 1	-0.063	-0.045	-0.050	-0.079	-0.033	-0.030	-0.022	-0.044
Quantile 5	-0.038	-0.026	-0.026	-0.046	-0.016	-0.017	-0.012	-0.025
Quantile 95	0.035	0.024	0.021	0.043	0.017	0.016	0.011	0.023
Quantile 99	0.082	0.044	0.042	0.080	0.030	0.030	0.022	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	149.240	85.987	59.872	37.454	50.441	33.925	65.513	11.732
pvQ_10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.303
Q_20	176.440	96.031	90.332	47.375	98.801	61.210	79.199	24.946
pvQ_20	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.204
obsv	2469	2470	2463	2438	2469	2470	2463	2444
Panel B: In-sample								
	M1				**Y1**			
	FR	**GE**	**SP**	**NP**	**FR**	**GE**	**SP**	**NP**
Mean (%)	-0.099%	-0.135%	-0.177%	-0.127%	-0.027%	-0.048%	-0.032%	-0.026%
Std_dev	0.023	0.016	0.017	0.028	0.010	0.010	0.008	0.015
Minimum	-0.131	-0.122	-0.133	-0.167	-0.056	-0.059	-0.050	-0.090
Maximum	0.202	0.163	0.162	0.127	0.060	0.065	0.055	0.092
Skewness	0.441	0.346	0.011	-0.047	-0.006	0.184	-0.228	-0.109
Kurtosis	10.006	13.132	19.356	5.759	7.912	8.677	10.188	7.318
Quantile 1	-0.061	-0.044	-0.052	-0.080	-0.033	-0.030	-0.026	-0.044
Quantile 5	-0.038	-0.026	-0.026	-0.046	-0.015	-0.015	-0.014	-0.024
Quantile 95	0.034	0.023	0.020	0.043	0.015	0.015	0.012	0.023
Quantile 99	0.068	0.043	0.041	0.076	0.029	0.029	0.025	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	48.488	57.228	44.393	27.964	34.202	37.535	44.985	18.066
pvQ_10	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.054
Q_20	52.020	65.288	88.838	38.979	49.374	51.663	56.098	29.137
pvQ_20	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.085
obsv	1771	1772	1762	1756	1771	1772	1762	1756
Panel C: Out-of-sample								
	M1				**Y1**			
	FR	**GE**	**SP**	**NP**	**FR**	**GE**	**SP**	**NP**
Mean (%)	0.039%	0.078%	-0.036%	0.032%	0.019%	0.026%	0.011%	0.008%
Std_dev	0.031	0.017	0.016	0.030	0.014	0.012	0.005	0.016
Minimum	-0.263	-0.074	-0.134	-0.146	-0.132	-0.050	-0.030	-0.063
Maximum	0.167	0.081	0.124	0.215	0.089	0.049	0.027	0.099
Skewness	-1.147	0.097	-0.093	0.695	-0.995	0.122	-0.328	0.238
Kurtosis	18.005	5.641	16.510	10.334	21.909	5.000	7.716	6.854
Quantile 1	-0.089	-0.050	-0.040	-0.073	-0.034	-0.031	-0.015	-0.044
Quantile 5	-0.041	-0.025	-0.026	-0.047	-0.019	-0.020	-0.008	-0.025
Quantile 95	0.042	0.028	0.021	0.043	0.020	0.020	0.009	0.023
Quantile 99	0.095	0.049	0.049	0.087	0.036	0.034	0.015	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	112.000	38.868	31.032	21.230	50.212	17.240	32.941	12.313
pvQ_10	0.000	0.000	0.001	0.020	0.000	0.069	0.000	0.265
Q_20	147.920	55.229	39.324	40.272	102.470	38.016	47.028	30.761
pvQ_20	0.000	0.000	0.006	0.005	0.000	0.009	0.001	0.058
obsv	698	698	701	688	698	698	701	688

Table 3: Summary of backtesting results

This table reports a summary of the backtesting results. The table shows the number of times and percentages that data do not reject the overall Fisher test for all VaR models, contracts, and countries. GT is the total for both tails and %GT is the proportion of no rejections (e.g. 0.13 means that in 13 out of 100 cases the Fisher test does not reject the null of model adequacy). GTL is the total for the left tail (5%, 1%). GTR is the total for the right tail (95%, 99%). With ES, we present the number of times and proportions UN-N and UN-t test does not reject the null of model adequacy. We check the consistency of the tests' outcomes.

Panel A1: VaR (All contracts)

	Grand Total	% GT	GTL	%GTL	GTR	%GTR
HS	7	0.22	5	0.31	2	0.13
AR(1)-GARCH(1,1)	28	0.88	15	0.94	13	0.81
AR(1)-EGARCH(1,1)	26	0.81	13	0.81	13	0.81
AR(1)-GJR(1,1)	24	0.75	13	0.81	11	0.69
EWQR	14	0.44	9	0.56	5	0.31
QR-COM	9	0.28	9	0.56	0	0.00

Panel B1: ES (All contracts)

	Grand Total	% GT	GTL	%GTL	GTR	%GTR
HS	40	0.63	25	0.78	15	0.47
AR(1)-GARCH(1,1)	64	1.00	32	1.00	32	1.00
AR(1)-EGARCH(1,1)	64	1.00	32	1.00	32	1.00
AR(1)-GJR(1,1)	64	1.00	32	1.00	32	1.00
EWQR	40	0.63	24	0.75	16	0.50
QR-COM	21	0.33	18	0.56	3	0.09

Panel A2: VaR (M1)

	Grand Total	%GT	GTL	%GTL	GTR	%GTR
HS	4	0.25	4	0.50	0	0.00
AR(1)-GARCH(1,1)	14	0.88	8	1.00	6	0.75
AR(1)-EGARCH(1,1)	13	0.81	7	0.88	6	0.75
AR(1)-GJR(1,1)	13	0.81	8	1.00	5	0.63
EWQR	9	0.56	6	0.75	3	0.38
QR-COM	6	0.38	6	0.75	0	0.00

Panel B2: VaR (Y1)

	Grand Total	%GT	GTL	%GTL	GTR	%GTR
HS	3	0.19	1	0.13	2	0.25
AR(1)-GARCH(1,1)	14	0.88	7	0.88	7	0.88
AR(1)-EGARCH(1,1)	13	0.81	6	0.75	7	0.88
AR(1)-GJR(1,1)	11	0.69	5	0.63	6	0.75
EWQR	5	0.31	3	0.38	2	0.25
QR-COM	3	0.19	3	0.38	0	0.00

Panel C2: ES (M1)

	Grand Total	%GT	GTL	%GTL	GTR	%GTR
HS	28	0.88	15	0.94	13	0.81
AR(1)-GARCH(1,1)	32	1.00	16	1.00	16	1.00
AR(1)-EGARCH(1,1)	32	1.00	16	1.00	16	1.00
AR(1)-GJR(1,1)	32	1.00	16	1.00	16	1.00
EWQR	32	1.00	16	1.00	16	1.00
QR-COM	14	0.44	12	0.75	2	0.13

Panel D2: ES(Y1)

	Grand Total	%GT	GTL	%GTL	GTR	%GTR
HS	12	0.38	10	0.63	2	0.13
AR(1)-GARCH(1,1)	32	1.00	16	1.00	16	1.00
AR(1)-EGARCH(1,1)	32	1.00	16	1.00	16	1.00
AR(1)-GJR(1,1)	32	1.00	16	1.00	16	1.00
EWQR	8	0.25	8	0.50	0	0.00
QR-COM	7	0.22	6	0.38	1	0.06

Panel E1: VAR (Markets)

	%GT NP	%GT GE	%GT SP	%GT FR
HS	0.00	0.38	0.38	0.13
AR(1)-GARCH(1,1)	1.00	1.00	0.88	0.63
AR(1)-EGARCH(1,1)	1.00	1.00	0.75	0.50
AR(1)-GJR(1,1)	1.00	0.88	0.75	0.38
EWQR	0.50	0.50	0.50	0.25
QR-COM	0.38	0.38	0.38	0.00

Panel E2: ES (Markets)

	%GT NP	%GT GE	%GT SP	%GT FR
HS	0.69	0.63	0.69	0.50
AR(1)-GARCH(1,1)	1.00	1.00	1.00	1.00
AR(1)-EGARCH(1,1)	1.00	1.00	1.00	1.00
AR(1)-GJR(1,1)	1.00	1.00	1.00	1.00
EWQR	0.75	0.75	0.50	0.50
QR-COM	0.25	0.38	0.44	0.25

Table 4: Out-of-sample VaR violations for each model.

The out-of-sample number of observations is 698 (FR, GE), 701(SP), and 688 (NP). A positive (negative) Deviation implies risk underestimation (overestimation).

Panel A: Nordpool. M1 and Y1		M1			Y1		
	Quantile	Expected	Failures	Deviation (F-E)/E	Expected	Failures	Deviation (F-E)/E
HS				**41.50%**			**69.33%**
	1%	6.82	14	105.28%	6.88	14	103.49%
	5%	34.1	38	11.44%	34.4	45	30.81%
	95%	34.1	35	2.64%	34.4	48	39.53%
	99%	6.82	10	46.63%	6.88	14	103.49%
AR(1)-GARCH(1,1)				**10.70%**			**13.37%**
	1%	6.82	9	31.96%	6.88	10	45.35%
	5%	34.1	32	-6.16%	34.4	31	-9.88%
	95%	34.1	34	-0.29%	34.4	40	16.28%
	99%	6.82	8	17.30%	6.88	7	1.74%
AR(1)-EGARCH(1,1)				**17.30%**			**9.01%**
	1%	6.82	10	46.63%	6.88	8	16.28%
	5%	34.1	35	2.64%	34.4	35	1.74%
	95%	34.1	35	2.64%	34.4	40	16.28%
	99%	6.82	8	17.30%	6.88	7	1.74%
AR(1)-GJR(1,1)				**-1.03%**			**-12.79%**
	1%	6.82	8	17.30%	6.88	6	-12.79%
	5%	34.1	30	-12.02%	34.4	28	-18.60%
	95%	34.1	30	-12.02%	34.4	37	7.56%
	99%	6.82	7	2.64%	6.88	5	-27.33%
EWQR				**29.03%**			**32.99%**
	1%	6.82	11	61.29%	6.88	9	30.81%
	5%	34.1	33	-3.23%	34.4	40	16.28%
	95%	34.1	38	11.44%	34.4	43	25.00%
	99%	6.82	10	46.63%	6.88	11	59.88%
QR-COM				**80.35%**			**127.47%**
	1%	6.82	8	17.30%	6.88	32	365.12%
	5%	34.1	32	-6.16%	34.4	39	13.37%
	95%	34.1	84	146.33%	34.4	64	86.05%
	99%	6.82	18	163.93%	6.88	10	45.35%

Panel B: Germany. M1 and Y1		M1			Y1		
	Quantile	Expected	Failures	Deviation (F-E)/E	Expected	Failures	Deviation (F-E)/E
HS				**41.83%**			**76.22%**
	1%	6.98	9	28.94%	6.98	13	86.25%
	5%	34.9	36	3.15%	34.9	53	51.86%
	95%	34.9	42	20.34%	34.9	53	51.86%
	99%	6.98	15	114.90%	6.98	15	114.90%
AR(1)-GARCH(1,1)				**-10.46%**			**-14.04%**
	1%	6.98	2	-71.35%	6.98	5	-28.37%
	5%	34.9	28	-19.77%	34.9	31	-11.17%
	95%	34.9	47	34.67%	34.9	39	11.75%
	99%	6.98	8	14.61%	6.98	5	-28.37%
AR(1)-EGARCH(1,1)				**-10.46%**			**-15.47%**
	1%	6.98	2	-71.35%	6.98	7	0.29%
	5%	34.9	30	-14.04%	34.9	31	-11.17%
	95%	34.9	45	28.94%	34.9	37	6.02%
	99%	6.98	8	14.61%	6.98	3	-57.02%
AR(1)-GJR(1,1)				**-15.47%**			**-14.76%**
	1%	6.98	2	-71.35%	6.98	5	-28.37%
	5%	34.9	26	-25.50%	34.9	30	-14.04%
	95%	34.9	42	20.34%	34.9	39	11.75%
	99%	6.98	8	14.61%	6.98	5	-28.37%
EWQR				**28.22%**			**54.01%**
	1%	6.98	6	-14.04%	6.98	11	57.59%
	5%	34.9	32	-8.31%	34.9	44	26.07%
	95%	34.9	42	20.34%	34.9	46	31.81%
	99%	6.98	15	114.90%	6.98	14	100.57%
QR-COM				**71.92%**			**307.59%**
	1%	6.98	8	14.61%	6.98	10	43.27%
	5%	34.9	33	-5.44%	34.9	48	37.54%
	95%	34.9	47	34.67%	34.9	101	189.40%
	99%	6.98	24	243.84%	6.98	74	960.17%

Panel C: Spain M1 and Y1		M1			Y1		
	Quantile	Expected	Failures	Deviation (F-E)/E	Expected	Failures	Deviation (F-E)/E
HS				**13.41%**			**34.09%**
	1%	7.01	9	28.39%	7.01	12	71.18%
	5%	35.05	36	2.71%	35.05	39	11.27%
	95%	35.05	33	-5.85%	35.05	39	11.27%
	99%	7.01	9	28.39%	7.01	10	42.65%
AR(1)-GARCH(1,1)				**9.84%**			**-13.69%**
	1%	7.01	6	-14.41%	7.01	6	-14.41%
	5%	35.05	26	-25.82%	35.05	34	-3.00%
	95%	35.05	58	65.48%	35.05	42	19.83%
	99%	7.01	8	14.12%	7.01	3	-57.20%
AR(1)-EGARCH(1,1)				**2.00%**			**-28.67%**
	1%	7.01	5	-28.67%	7.01	4	-42.94%
	5%	35.05	24	-31.53%	35.05	30	-14.41%
	95%	35.05	54	54.07%	35.05	40	14.12%
	99%	7.01	8	14.12%	7.01	2	-71.47%
AR(1)-GJR(1,1)				**5.56%**			**-3.00%**
	1%	7.01	6	-14.41%	7.01	6	-14.41%
	5%	35.05	24	-31.53%	35.05	40	14.12%
	95%	35.05	54	54.07%	35.05	51	45.51%
	99%	7.01	8	14.12%	7.01	3	-57.20%
EWQR				**16.26%**			**28.39%**
	1%	7.01	9	28.39%	7.01	9	28.39%
	5%	35.05	33	-5.85%	35.05	40	14.12%
	95%	35.05	35	-0.14%	35.05	40	14.12%
	99%	7.01	10	42.65%	7.01	11	56.92%
QR-COM				**82.60%**			**31.24%**
	1%	7.01	6	-14.41%	7.01	10	42.65%
	5%	35.05	25	-28.67%	35.05	63	79.74%
	95%	35.05	51	45.51%	35.05	56	59.77%
	99%	7.01	30	327.96%	7.01	3	-57.20%

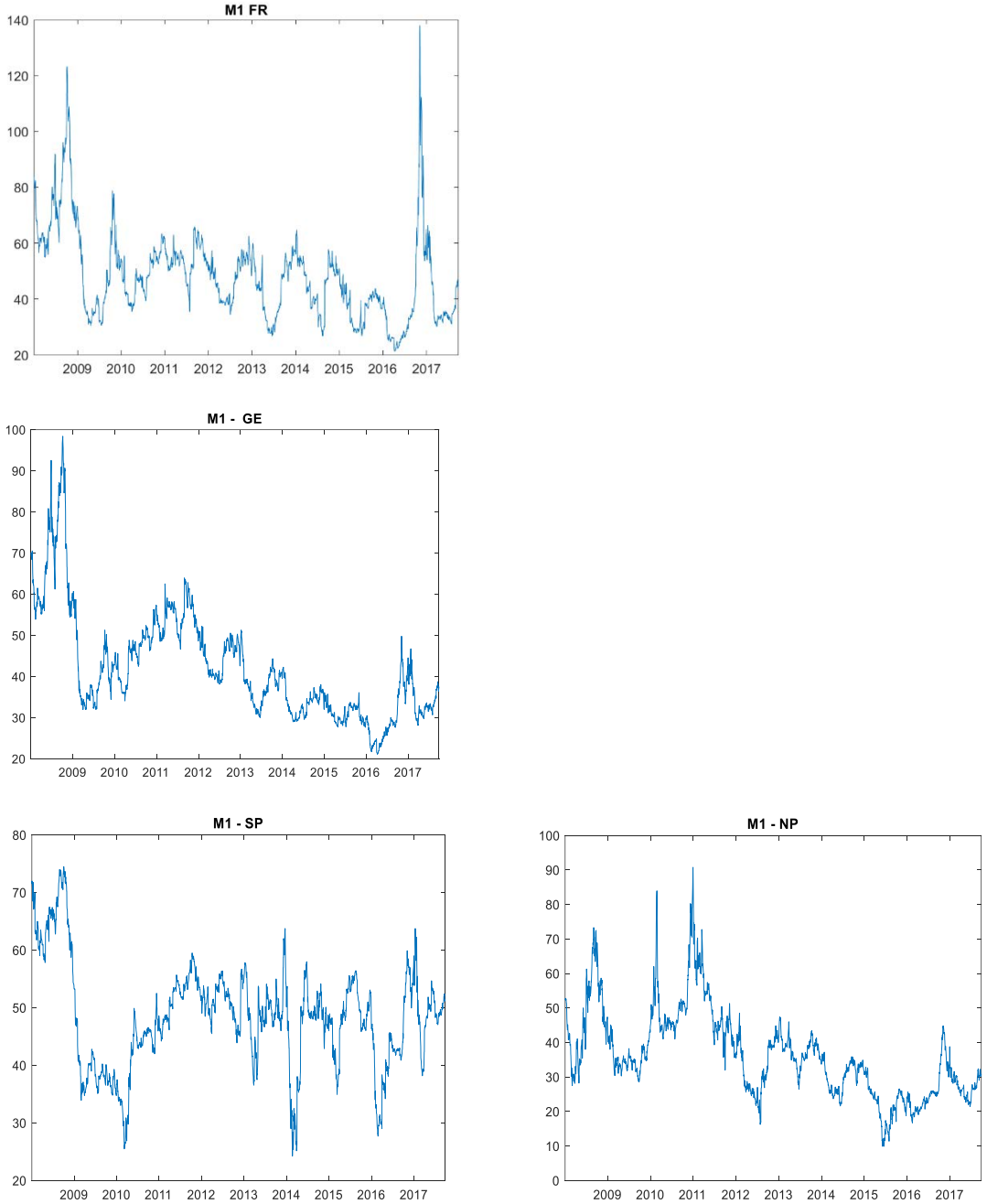
Panel D: France. M1 and Y1		M1			Y1		
	Quantile	Expected	Failures	Deviation (F-E)/E	Expected	Failures	Deviation (F-E)/E
HS				**29.66%**			**86.25%**
	1%	6.98	10	43.27%	6.98	16	129.23%
	5%	34.9	31	-11.17%	34.9	46	31.81%
	95%	34.9	40	14.61%	34.9	59	69.05%
	99%	6.98	12	71.92%	6.98	15	114.90%
AR(1)-GARCH(1,1)				**-7.59%**			**28.22%**
	1%	6.98	5	-28.37%	6.98	9	28.94%
	5%	34.9	27	-22.64%	34.9	36	3.15%
	95%	34.9	52	49.00%	34.9	38	8.88%
	99%	6.98	5	-28.37%	6.98	12	71.92%
AR(1)-EGARCH(1,1)				**16.05%**			**31.09%**
	1%	6.98	6	-14.04%	6.98	10	43.27%
	5%	34.9	31	-11.17%	34.9	38	8.88%
	95%	34.9	51	46.13%	34.9	40	14.61%
	99%	6.98	10	43.27%	6.98	11	57.59%
AR(1)-GJR(1,1)				**46.85%**			**-1.15%**
	1%	6.98	6	-14.04%	6.98	6	-14.04%
	5%	34.9	43	23.21%	34.9	30	-14.04%
	95%	34.9	57	63.32%	34.9	33	-5.44%
	99%	6.98	15	114.90%	6.98	9	28.94%
EWQR				**26.79%**			**73.35%**
	1%	6.98	10	43.27%	6.98	15	114.90%
	5%	34.9	30	-14.04%	34.9	49	40.40%
	95%	34.9	42	20.34%	34.9	48	37.54%
	99%	6.98	11	57.59%	6.98	14	100.57%
QR-COM				**198.71%**			**145.70%**
	1%	6.98	15	114.90%	6.98	18	157.88%
	5%	34.9	122	249.57%	34.9	39	11.75%
	95%	34.9	55	57.59%	34.9	79	126.36%
	99%	6.98	33	372.78%	6.98	27	286.82%

Panel E Averages

	M1	Y1
HS	34.56%	62.24%
AR(1)-GARCH(1,1)	5.20%	-0.25%
AR(1)-EGARCH(1,1)	6.54%	-6.53%
AR(1)-GJR(1,1)	-2.99%	-10.83%
EWQR	25.64%	37.10%
QR-COM	78.81%	148.44%

Figure 1: Prices of electricity futures (€/MWh) of M1 and Y1 contracts for the French (FR), German (GE), Spanish (SP), and Nordpool (NP) markets. The sample period goes from January 2, 2008 to September 25, 2017.

Panel A: M1 Contracts



Panel B: Y1 Contracts

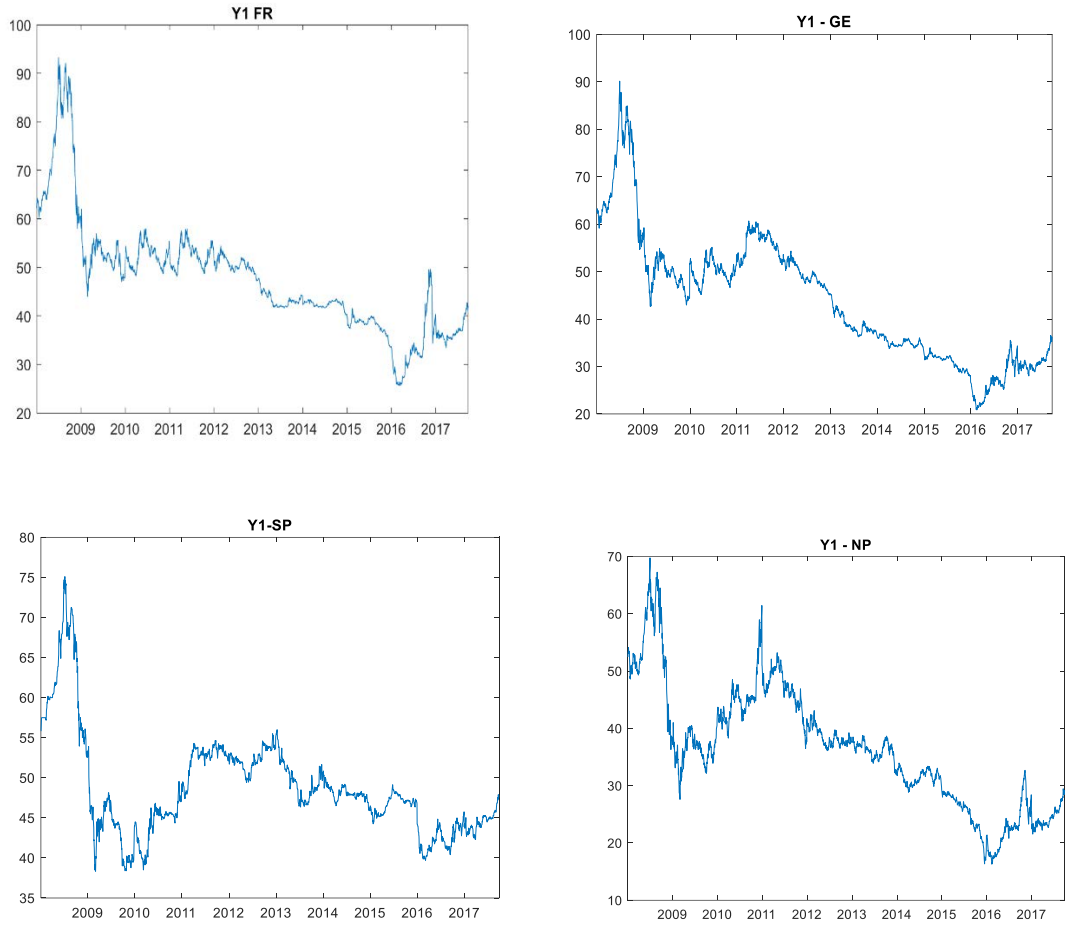
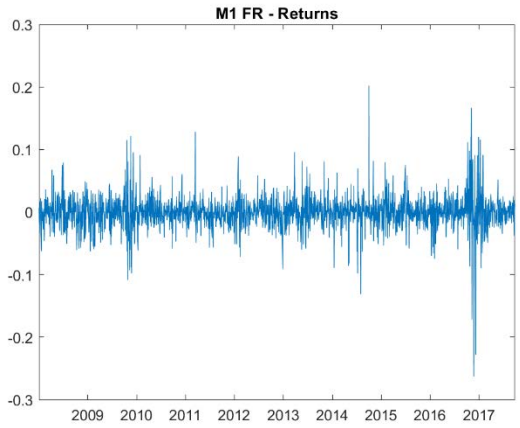
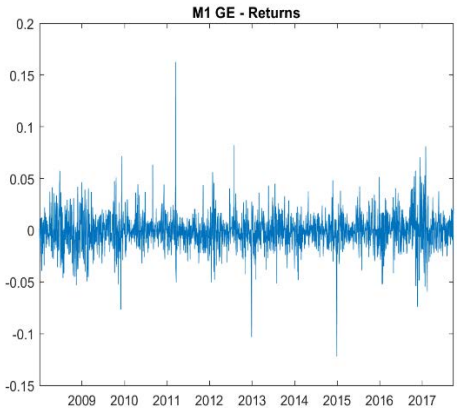
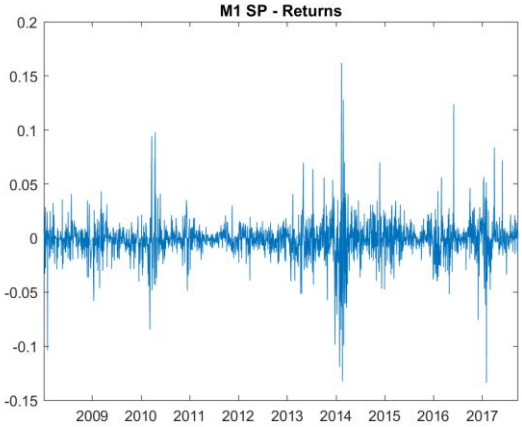


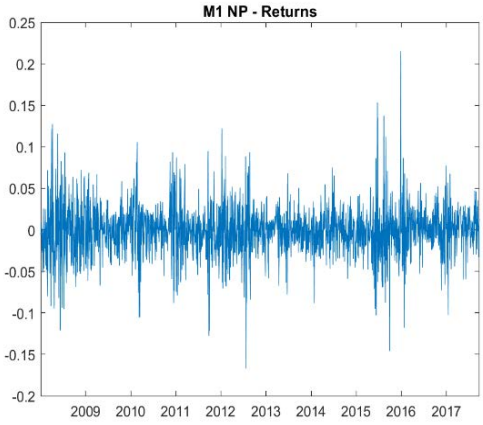
Figure 2: Returns of electricity futures of M1 and Y1 contracts for the French (FR), German (GE), Spanish (SP), and Nordpool (NP) markets. The sample period goes from January 2, 2008 to September 25, 2017.

Panel A: M1 Contracts









Panel B: Y1 Contracts

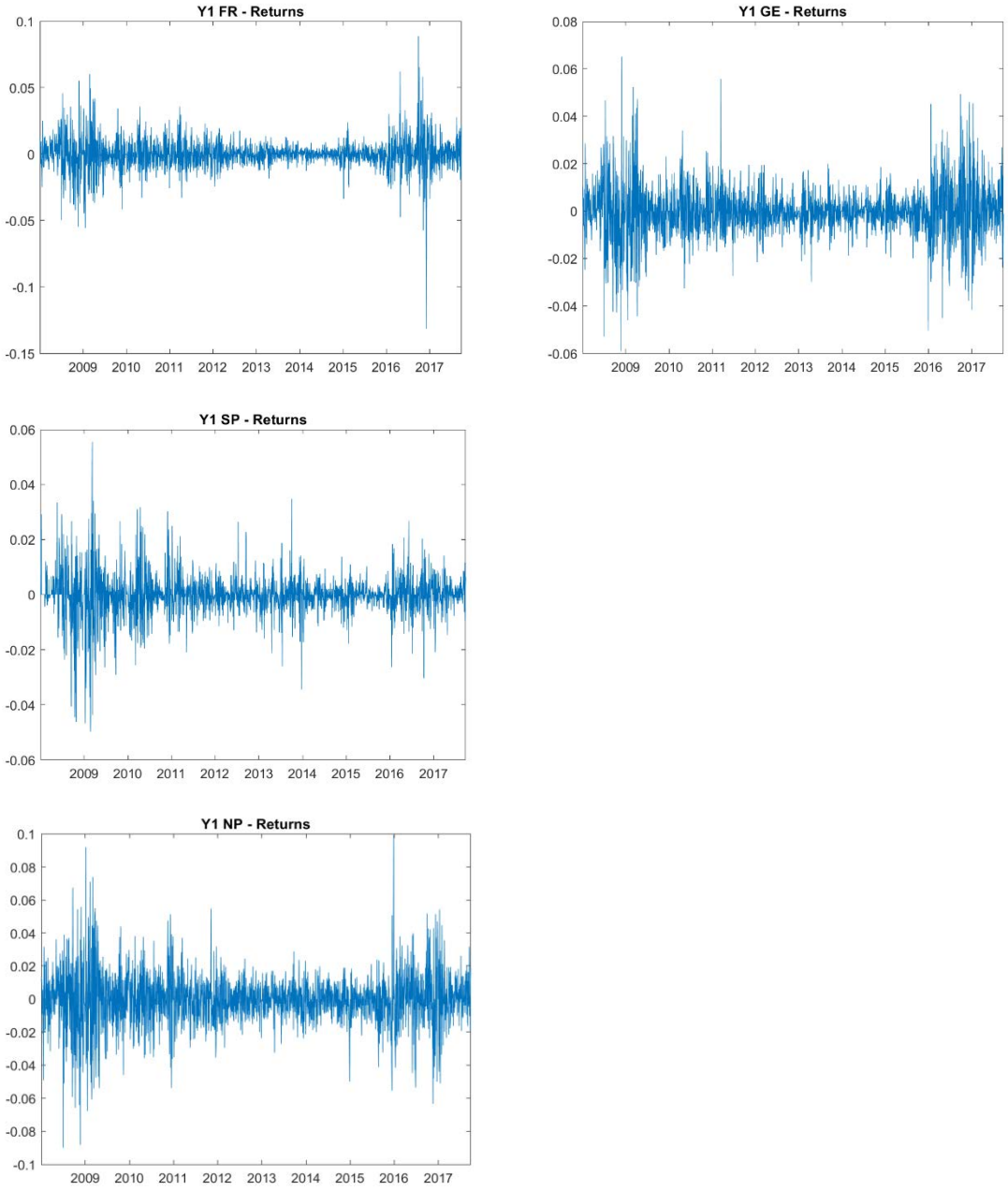
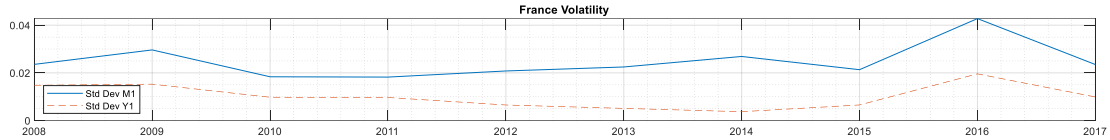
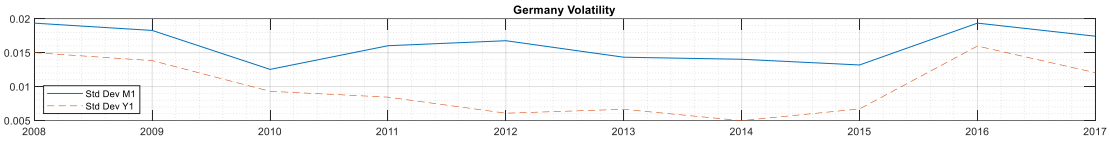
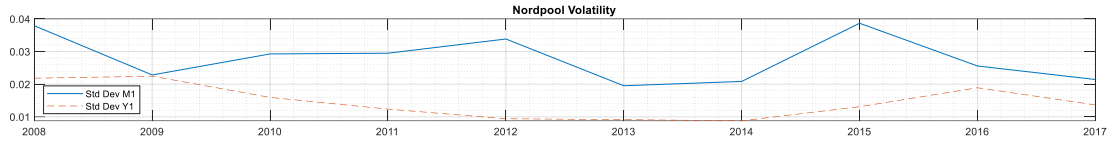
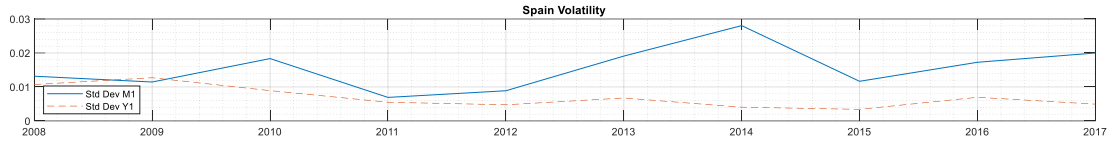


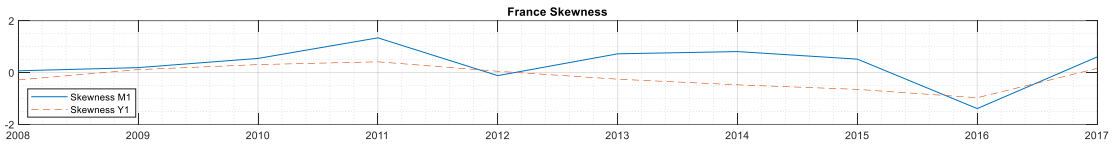
Figure 3: Volatility, Skewness, and Kurtosis of daily returns in all markets by year. Sample period January 2, 2008 – September 25, 2017.

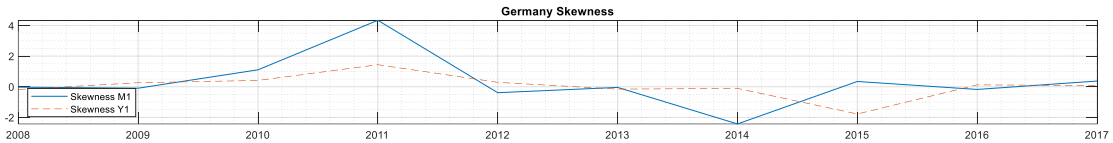

France Volatility
Std Dev M1
Std Dev Y1
0.04
0.02
0
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

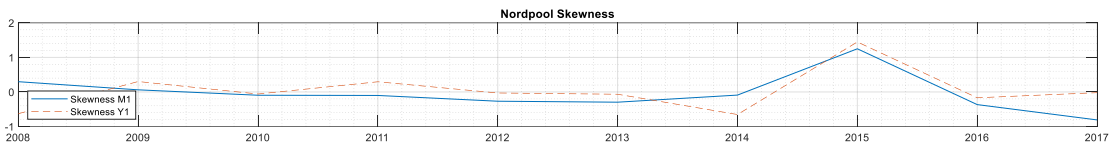

Germany Volatility
Std Dev M1
Std Dev Y1
0.02
0.015
0.01
0.005
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

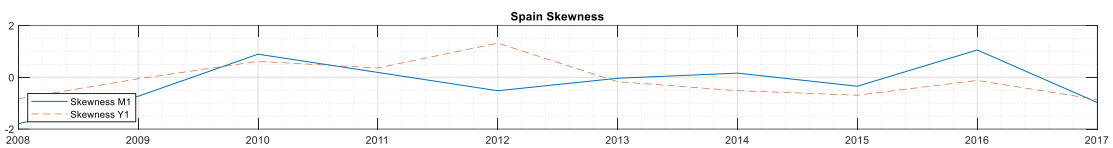

Nordpool Volatility
Std Dev M1
Std Dev Y1
0.04
0.03
0.02
0.01
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


Spain Volatility
Std Dev M1
Std Dev Y1
0.03
0.02
0.01
0
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


France Skewness
Skewness M1
Skewness Y1
2
0
-2
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


Germany Skewness
Skewness M1
Skewness Y1
4
2
0
-2
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


Nordpool Skewness
Skewness M1
Skewness Y1
2
1
0
-1
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017


Spain Skewness
Skewness M1
Skewness Y1
2
0
-2
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

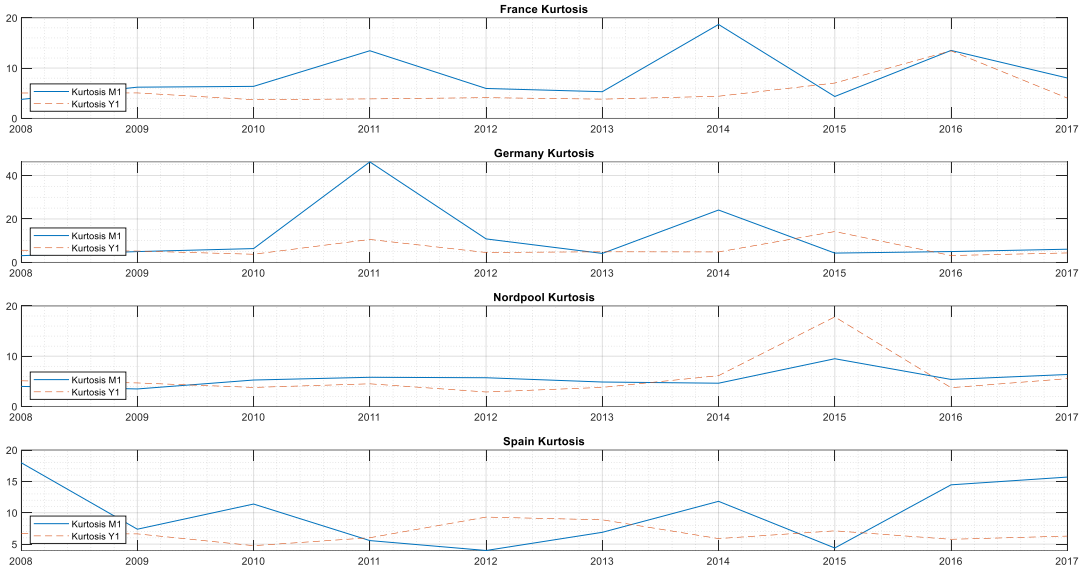
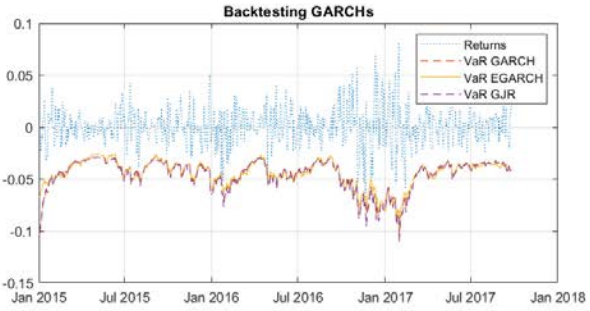
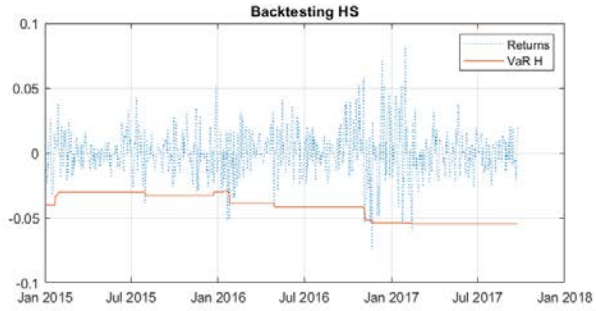
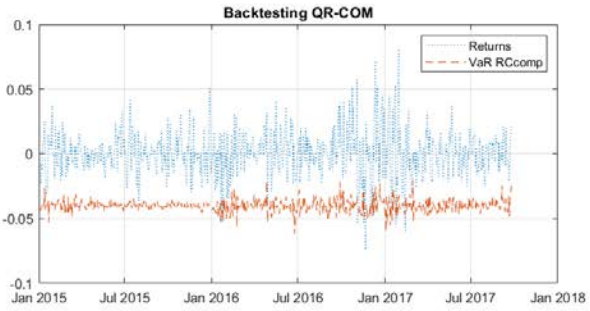
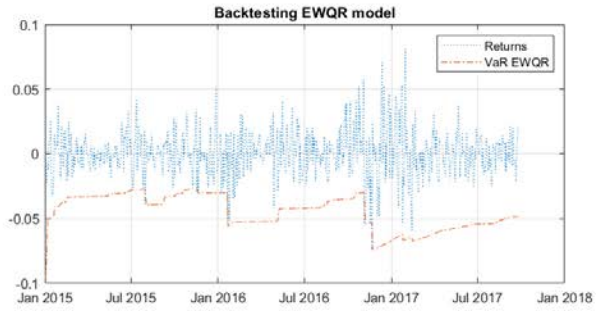

France Kurtosis
Kurtosis M1
Kurtosis Y1
Germany Kurtosis
Kurtosis M1
Kurtosis Y1
Nordpool Kurtosis
Kurtosis M1
Kurtosis Y1
Spain Kurtosis
Kurtosis M1
Kurtosis Y1
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Figure 4: VaR Forecasts with all methods. Contract M1, German market.









Appendix A

A.1 Models

The HS approach exploits the empirical distribution of past returns on the asset of interest. First, the user selects a moving window of size *n* (e.g. last 250 days) of recent periods, and then she computes the risk measures (VaR and ES) using the quantiles (e.g. 1%) of the empirical distribution of historical returns. For example, to compute at time *t*-1 the VaR(α, t) for the next day *t* for quantile α = 1%, one takes the 1% quantile from the distribution of the most-recent *n* observed daily returns (r_j, j = t-1, …,t-n+1). Similarly, to compute ES(α, t), she takes the average of all quantiles beyond VaR. The only assumption of the HS method is stationarity of the return distribution for a one-day horizon. Given that HS only relies on the recent (one or two years) unconditional distribution of the risk factors, is likely to underestimate changes in conditional risk (Pritsker, 2006).

The EWQR method proceeds in three steps. First, taking the most recent *K* returns and assigning a decreasing weight $[(1- \lambda)/(1- \lambda^K)]$,$[(1- \lambda)/(1- \lambda^K)] \lambda$, ..., $[(1- \lambda)/(1- \lambda^K)] \lambda^{K-1}$, respectively ($\lambda < 1$). Note that the constant $[(1-\lambda)/(1- \lambda^K)]$ simply ensures that weights sum to 1. Values of λ are usually set between 0.97 and 0.99. We apply both of them. As results are very similar, in the text we report results with 0.97. Next, the user orders the returns in ascending order. Finally, to obtain the VaR(α,t), of the portfolio, she starts from the lowest return and keeps accumulating the weights until percent α is reached. The intuition is that the most recent returns have higher weights because they influence tomorrow's return more heavily than returns further in the past. Similarly, to compute ES(α, t), she takes the average of all quantiles beyond VaR. In comparison with the HS method, the EWQR reacts more quickly to periods of large (or small) returns.

The parametric AR(1)-GARCH(1,1), AR(1)-EGARCH(1,1) or AR(1)-GJR(1,1) models for the return series *r(j)* with student-t distributions are defined as follows. First, we consider a one-period autoregressive AR(1) model with Student-t innovations $t(\nu)$ where ν are the degrees of freedom

$$r_j = \phi_0 + \phi_1 r_{j-1} + \sigma_j \varepsilon_j = \mu_j + \sigma_j \varepsilon_j; \qquad \varepsilon_j \sim t(\nu) \tag{1}$$

And the volatility can take one the following three specifications, the GARCH(1,1)

$$\sigma_j^2 = \omega_0 + \omega_1 \sigma_{j-1}^2 + \omega_2 \varepsilon_{j-1}^2 \tag{2}$$

The EGARCH(1,1)

$$\ln\left(\sigma_j^2\right) = \beta_0 + \beta_1 \varepsilon_{j-1} + \beta_2 \ln\left(\sigma_{j-1}^2\right) + \beta_3 (\varepsilon_{j-1} - E|\varepsilon_{j-1}|) \tag{3}$$

And the GJR(1,1)

$$\sigma_j^2 = \kappa_0 + \kappa_1 \varepsilon_{j-1}^2 + \kappa_2 I_{j-1}\left(\varepsilon_{j-1} < 0\right)\varepsilon_{j-1}^2 + \kappa_3 \sigma_{j-1}^2 \tag{4}$$

The adoption of an EGARCH and GJR formulations for volatility is motivated by Knittel and Roberts (2005), who suggest a differential impact of positive and negative shocks on spot electricity prices. This gives rise to a leverage effect that can be either positive or negative. This leverage effect has not been previously studied in the case of futures prices, so we

deem it interesting to provide evidence on this subject. We calculate the VaR(α, t) as

$$VaR(\alpha, t) = \mu_t - \sigma_t F^{-1}(\alpha); \;\; \alpha < 0.5 \tag{5}$$

$$VaR(\alpha, t) = -\mu_t + \sigma_t F^{-1}(\alpha); \;\; \alpha \geq 0.5 \tag{6}$$

Where $F^{-1}(x)$ is the inverse of the cumulative density function of a Student-t distribution with ν degrees of freedom and σ_t are volatilities estimated using models (8) – (10). We calculate the ES(α, t) as

$$ES(\alpha, t) = \mu_t + \sigma_t \left(\frac{\nu + \left(F^{-1}(\alpha)\right)^2}{\nu - 1} \right) \left(\frac{\tau\left(F^{-1}(\alpha)\right)}{1 - \alpha} \right) \;\; ; \;\; \alpha \geq 0.5 \tag{7}$$

$$ES(\alpha, t) = \mu_t + \sigma_t \left(\frac{\nu + \left(F^{-1}(\alpha)\right)^2}{\nu - 1} \right) \left(\frac{\tau\left(F^{-1}(\alpha)\right)}{\alpha} \right) \;\; ; \;\; \alpha < 0.5 \tag{8}$$

Where $\tau(x)$ is the density function of a Student-t distribution with ν degrees of freedom (McNeil et al., 2010).

Linear Quantile Regression (QR) was introduced by Koenker and Bassett (1978) to generalize the Ordinary Least Squares (OLS) method by computing a set of regression functions, each corresponding to a different quantile of the conditional distribution of the dependent variable. In contrast with standard OLS regression, QR lines pass through different quantiles of the distributions. Whilst with OLS regression approximately half of

the data set lies above or below the OLS line, for QR regression and extreme quantiles most of the data set will lie above or below the quantile regression line. Employing QR, we can analyze the relationship between the dependent and independent variables across the entire distribution, thus providing a complete picture of the impact of explanatory variables on the dependent variable. So, QR can model the impact of the explanatory variables on the tail risk of the dependent variable thus providing a natural estimate of VaR and ES. The linear QR model for $Q_\alpha(r_j)$, the quantile α of the return distribution r_j is

$$Q_\alpha(r_j) = \delta_{\alpha,0} + \sum_{k=1}^{K} \delta_{\alpha,k} X_{j,k} \; + \eta_{\alpha,j} \tag{9}$$

Where $X_{j,k}$ are the explanatory variables such as fuel prices, carbon prices, and volatility measures. The distribution of $\eta_{\alpha,j}$ is left unspecified because it is not the conventional innovation term in the OLS equations, and its distributional properties are not required to meet the same criteria. The expression for the conditional α quantile is defined as any solution to the minimization problem

$$\min_{\{\delta_{\alpha,0},\, \delta_{\alpha,k}\}} \sum_{j=1}^{t-1} (\alpha - \boldsymbol{I}_{Q_\alpha(r_j) \le \delta_{\alpha,0} + \sum_{k=1}^{K} \delta_{\alpha,k} X_{j,k}})(Q_\alpha(r_j) - (\delta_{\alpha,0} + \sum_{k=1}^{K} \delta_{\alpha,k} X_{j,k})) \tag{10}$$

Where

$$\boldsymbol{I}_{Q_\alpha(r_j) \le \delta_{\alpha,0} + \sum_{k=1}^{K} \delta_{\alpha,k} X_{j,k}} = \begin{cases} 1 & if\ Q_\alpha(r_j) \le \delta_{\alpha,0} + \sum_{k=1}^{K} \delta_{\alpha,k} X_{j,k} \\ 0 & otherwise \end{cases} \tag{11}$$

In the model QR-COM, we consider as explanatory variables fuel prices, as suggested in Hagfors et al. (2016), and daily, weekly, and monthly backward-looking volatility measures, as suggested in Haugom et al. (2016). We calculate the VaR(α, t) of QR as

$$VaR(\alpha, t)|X_{j,k} = \hat{\delta}_{\alpha,0} + \sum_{k=1}^{K} \hat{\delta}_{\alpha,k} X_{j,k} \quad (12)$$

And the computation of ES(α, t) is based on (5) – (6) because no closed-form expression of ES has been published for QR.

We now turn to the definition of the backtesting methods for VaR (Bin, POF, CCI, and DQ) and ES (UN-N, UN-t) applied in this paper. Most tests are based on the hit function I_t. The hit function sequence, (0,0,1,0,0,...,1), shows whether or not a return (r_t) is lower (higher) than the reported VaR(α,t) if $\alpha < 0.5$ (if $\alpha \geq 0.5$) has been realized.

$$I_t = \begin{cases} 1 & if \quad r_t < VaR(\alpha, t) \\ 0 & otherwise \end{cases} \quad (13)$$

The Binomial test (Bin) is based on a normal approximation to a binomial distribution (Jorion, 2011). Given n observations, let $p = 1 - \alpha$ ($\alpha \geq 0.5$) or $p = \alpha$ ($\alpha < 0.5$) the probability of observing a hit (failure) if the model is correct and n_1 is the number of hits. If the hits are independent, then n_1 is distributed as a binomial distribution with parameters n and p. Therefore, the mean and variance of the hit sequence is $E[n_1] = np$, and $Var[n_1] = np(1 - p)$ and the Bin test statistic is the *ZBin*, defined as:

$$ZBin = \frac{n_1 - np}{\sqrt{np(1-p)}} \tag{14}$$

In large samples, the ZBin approximately follows a standard normal distribution under the null hypothesis.

The Proportion of failures (POF) test proposed by Kupiec (1995) is based on a likelihood ratio ($\alpha < 0.5$)

$$POF = -2\ln((1-\alpha)^{n-n_1}\alpha^{n_1}) + 2\ln\left(\left(1-\left(\frac{n_1}{n}\right)\right)^{n-n_1}\left(\frac{n_1}{n}\right)^{n_1}\right) \tag{15}$$

Where *n* is the total number of observations, n_1 is the number of hits and this test statistic is asymptotically distributed as a chi-square distribution with one degree of freedom.

The Conditional coverage independence test (CCI) proposed by Christoffersen (1998) to assess the independence of the hit sequence over time. To define the statistic of the CCI test, we define the following quantities: $n_{0,0}$ (number of periods with no hits followed by a period with no hit), n_{10} (number of periods with hits followed by a period with no hit), n_{01} (number of periods with no hits followed by a period with a hit), and n_{11} (number of periods with hits followed by a period with a hit), and the total number of observations is $n = n_{00} + n_{01} + n_{10} + n_{11}$. Next, we define the conditional probability estimates. They are p_{01} (probability of having a hit on period j, given that there was no hit on period j – 1) and thus $p_{01} = n_{01}/(n_{00} + n_{01})$, and p_{11} (probability of having a hit on period j, given that there was a hit on period j – 1) and thus $p_{11} = n_{11}/(n_{10} + n_{11})$. The unconditional probability estimates of observing a hit is $p_{UC} = (n_{01} + n_{11})/n$. The CCI test is then given by

$$CCI = -2\log\left(\frac{(1-p_{UC})^{n_{0,0}+n_{1,0}}\ (p_{UC})^{n_{0,1}+n_{1,1}}}{(1-p_{0,1})^{n_{0,0}}(p_{0,1})^{n_{0,1}}(1-p_{1,1})^{n_{1,0}}(p_{1,1})^{n_{1,1}}}\right) \quad (16)$$

And this test statistic is asymptotically distributed as a chi-square distribution with one degree of freedom.

The Dynamic Quantile (DQ) test proposed by Engle and Manganelli (2004) evaluates the existence of a correlation between VaR violations, their lagged values, and the contemporaneous VaR estimate, based on logit models. If we define $\Pr\{I_t=1\}=\pi_t$, then

$$\pi_t = \frac{e^{\mu(t)}}{1+e^{\mu(t)}} \quad (17)$$

$$\mu(t) = \beta_0 + \beta_1 I_{t-1} + \beta_2 VaR_t \quad (18)$$

Under the null hypothesis $H_0 = \beta_1 = \beta_2 = 0$, regressors should not have explanatory power and the test is asymptotically Chi-squared distributed with one degree of freedom.

Regarding backtesting methods to ES (i.e., UN-N, UN-t), we consider the proposals in Acerbi, and Székely (2014). The unconditional test (UN) scales the losses by the corresponding ES value.

$$UN = \sum_{t=1}^{n} \frac{r_t I_t}{n\alpha ES(\alpha,t)} + 1 \quad (19)$$

Where n is the sample size, r_t is the return (profit and loss distribution), α is the quantile and I_t is the hit indicator. We employ calculated critical values for the UN test statistic under two distributional assumptions: normal distribution (UN-N), and t distribution with 3 degrees of freedom (UN-t).

A.2 Descriptive statistics and Model Estimation Results

Table 1A contains descriptive statistics of all return series, full sample, in-sample, out-of-sample, and by years. All moments of the distributions vary over time. Table 1B Panels A - H has the results of estimating models (7) – (10) to the M1 and Y1 series of the NordPool, Germany, Spain, and France respectively

[INSERT TABLE 1A HERE]

[INSERT TABLE 1B HERE]

In Nordpool, France, and Spain (year contract) all models present a non-significant constant, but in Germany (month and year contracts) and in Spain's month contract the constant is negative and significant suggesting a negative trend in futures prices. The AR(1) term is positive and significant in in all month contracts, suggesting a short-term momentum in front-month futures prices. In the year contract, the AR(1) coefficient is significant in Spain and Germany. The degrees of freedom of the t distributions range from 3.3 (France, M1) to 11.4 (Spain, Y1), suggesting heavy tails in the return distribution. The leverage effect in EGARCH and GJR is not significant in any case. According to the BIC criterion, the three models present similar in-sample fitting performance.

The results of the backtesting tests applied to the forecast of VaR and ES generated using the models (7) – (19) are in Table 2. Panels A - H has the results of the M1 and Y1 series of the NordPool, Germany, Spain, and France respectively. We discuss the results in the main text.

[INSERT TABLE 2 HERE]

To give further insight into the impact of the independent variables used in the QR models, Table 3 summarizes the correlation between the dependent variable and the explanatory variables.

[INSERT TABLE 3 HERE]

Correlation is near zero in all cases, the highest is -0.12. This fact suggests low explanatory power of the fuel and volatility explanatory variables.

A.3 Estimation of Tail Index

In this paper, we tested the GARCH-t model instead of the most often applied GARCH (1,1)-Normal because the evidence in McNeil and Frey (2000) show that the GARCH model with Student-t innovations is more efficient in forecasting the VaR, whereas the estimates from GARCH models with normal innovation underestimate tail risk (see also Mikosch and Starica, 2000). Next, we present the calculation of the tail index under the GARCH(1,1) model following Davis and Mikosch (2009). Let X_t be the (filtered of AR (1) terms) return series defined as

$$X_t = \sigma_t Z_t \qquad (A.1)$$

Where

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (A.2)$$

Where Z_t is an iid sequence with mean zero and unit variance and the process (R.2) is second-order stationary if (α_1 + β_1) < 1, Nelson (1990). The tails of the marginal distribution of a stationary GARCH(1,1) process have a power-law shape. This implies that there is a tail index *k* >0 and a positive constant *c* such that

$$P(|X| > x) \sim c x^{-2k} \qquad (A.3)$$

The tail index *k* solves the equation

$$E[(\alpha_1 Z^2 + \beta_1)^k] = 1 \qquad (A.4)$$

Equation (A.4) can be solved numerically for *k*, assuming a specific density for *Z* and given values of α_1 and β_1. Given a sample of returns X∗, we can fit a power function gX_*^{-2k*}, to the specific tail (e.g. X∗ = X > Quantile(X, 0.95)) and compare estimates *k* and *k*∗ of the tail index. In the following Table 4 (Appendix), we present robust estimates of *k* assuming the GARCH(1,1) Student-t model with estimated parameters in Table 1B in the Appendix and estimates of *k*∗ in the right (95%) and left (5%) tail using the empirical distribution of returns.

Tables

Table 1A. Descriptive Statistics

Descriptive statistics returns (full sample)								
	M1				Y1			
	FR	GE	SP	NP	FR	GE	SP	NP
Mean (%)	-0.060%	-0.074%	-0.137%	-0.082%	-0.014%	-0.027%	-0.020%	-0.016%
Std_dev	0.026	0.016	0.017	0.029	0.011	0.011	0.007	0.015
Minimum	-0.263	-0.122	-0.134	-0.167	-0.132	-0.059	-0.050	-0.090
Maximum	0.202	0.163	0.162	0.215	0.089	0.065	0.055	0.099
Skewness	-0.333	0.275	-0.020	0.193	-0.481	0.179	-0.271	-0.006
Kurtosis	15.789	10.670	18.539	7.329	16.873	7.203	10.978	7.187
Quantile 1	-0.063	-0.045	-0.050	-0.079	-0.033	-0.030	-0.022	-0.044
Quantile 5	-0.038	-0.026	-0.026	-0.046	-0.016	-0.017	-0.012	-0.025
Quantile 95	0.035	0.024	0.021	0.043	0.017	0.016	0.011	0.023
Quantile 99	0.082	0.044	0.042	0.080	0.030	0.030	0.022	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	149.240	85.987	59.872	37.454	50.441	33.925	65.513	11.732
pvQ_10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.303
Q_20	176.440	96.031	90.332	47.375	98.801	61.210	79.199	24.946
pvQ_20	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.204
obsv	2469	2470	2463	2438	2469	2470	2463	2444
Descriptive statistics returns (in sample)								
	M1				Y1			
	FR	GE	SP	NP	FR	GE	SP	NP
Mean (%)	-0.099%	-0.135%	-0.177%	-0.127%	-0.027%	-0.048%	-0.032%	-0.026%
Std_dev	0.023	0.016	0.017	0.028	0.010	0.010	0.008	0.015
Minimum	-0.131	-0.122	-0.133	-0.167	-0.056	-0.059	-0.050	-0.090
Maximum	0.202	0.163	0.162	0.127	0.060	0.065	0.055	0.092
Skewness	0.441	0.346	0.011	-0.047	-0.006	0.184	-0.228	-0.109
Kurtosis	10.006	13.132	19.356	5.759	7.912	8.677	10.188	7.318
Quantile 1	-0.061	-0.044	-0.052	-0.080	-0.033	-0.030	-0.026	-0.044
Quantile 5	-0.038	-0.026	-0.026	-0.046	-0.015	-0.015	-0.014	-0.024
Quantile 95	0.034	0.023	0.020	0.043	0.015	0.015	0.012	0.023
Quantile 99	0.068	0.043	0.041	0.076	0.029	0.029	0.025	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	48.488	57.228	44.393	27.964	34.202	37.535	44.985	18.066
pvQ_10	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.054
Q_20	52.020	65.288	88.838	38.979	49.374	51.663	56.098	29.137
pvQ_20	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.085
obsv	1771	1772	1762	1756	1771	1772	1762	1756
Descriptive statistics returns (out of sample)								
	M1				Y1			

	FR	GE	SP	NP	FR	GE	SP	NP
Mean (%)	0.039%	0.078%	-0.036%	0.032%	0.019%	0.026%	0.011%	0.008%
Std_dev	0.031	0.017	0.016	0.030	0.014	0.012	0.005	0.016
Minimum	-0.263	-0.074	-0.134	-0.146	-0.132	-0.050	-0.030	-0.063
Maximum	0.167	0.081	0.124	0.215	0.089	0.049	0.027	0.099
Skewness	-1.147	0.097	-0.093	0.695	-0.995	0.122	-0.328	0.238
Kurtosis	18.005	5.641	16.510	10.334	21.909	5.000	7.716	6.854
Quantile 1	-0.089	-0.050	-0.040	-0.073	-0.034	-0.031	-0.015	-0.044
Quantile 5	-0.041	-0.025	-0.026	-0.047	-0.019	-0.020	-0.008	-0.025
Quantile 95	0.042	0.028	0.021	0.043	0.020	0.020	0.009	0.023
Quantile 99	0.095	0.049	0.049	0.087	0.036	0.034	0.015	0.044
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	112.000	38.868	31.032	21.230	50.212	17.240	32.941	12.313
pvQ_10	0.000	0.000	0.001	0.020	0.000	0.069	0.000	0.265
Q_20	147.920	55.229	39.324	40.272	102.470	38.016	47.028	30.761
pvQ_20	0.000	0.000	0.006	0.005	0.000	0.009	0.001	0.058
obsv	698	698	701	682	698	698	701	688

M1FR	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	-0.158%	-0.217%	0.059%	-0.319%	-0.007%	0.111%	-0.159%	0.102%	0.080%	-0.104%
Std_dev	0.024	0.030	0.018	0.018	0.021	0.022	0.027	0.021	0.043	0.023
Minimum	-0.062	-0.109	-0.062	-0.057	-0.091	-0.060	-0.131	-0.058	-0.263	-0.090
Maximum	0.079	0.121	0.091	0.128	0.089	0.096	0.202	0.080	0.167	0.116
Skewness	0.068	0.191	0.547	1.341	-0.117	0.724	0.810	0.519	-1.390	0.602
Kurtosis	3.761	6.198	6.360	13.451	5.942	5.300	18.684	4.347	13.514	8.030
Quantile 1	-0.059	-0.093	-0.047	-0.050	-0.057	-0.052	-0.089	-0.053	-0.170	-0.060
Quantile 5	-0.043	-0.051	-0.027	-0.031	-0.035	-0.031	-0.046	-0.031	-0.051	-0.041
Quantile 95	0.033	0.041	0.032	0.021	0.032	0.041	0.032	0.035	0.069	0.028
Quantile 99	0.067	0.095	0.057	0.042	0.058	0.082	0.069	0.071	0.120	0.086
JB_Test	0.041	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	20.970	18.475	8.921	19.464	16.094	11.078	9.305	31.350	47.763	67.934
pvQ_10	0.021	0.047	0.540	0.035	0.097	0.352	0.503	0.001	0.000	0.000
Q_20	29.391	22.498	15.857	29.620	29.371	26.753	13.924	40.525	86.172	100.102
pvQ_20	0.080	0.314	0.725	0.076	0.081	0.142	0.834	0.004	0.000	0.000
obsv	251	253	258	255	251	250	253	253	257	188

Y1FR	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	0.003%	-0.090%	-0.018%	-0.012%	-0.025%	-0.020%	-0.028%	-0.061%	0.078%	0.044%
Std_dev	0.015	0.015	0.010	0.010	0.007	0.005	0.004	0.007	0.020	0.010
Minimum	-0.055	-0.056	-0.033	-0.033	-0.024	-0.018	-0.013	-0.034	-0.132	-0.034
Maximum	0.055	0.060	0.036	0.036	0.020	0.014	0.013	0.024	0.089	0.031
Skewness	-0.284	0.114	0.308	0.416	0.050	-0.255	-0.473	-0.648	-0.971	0.160
Kurtosis	5.041	5.056	3.706	3.866	4.114	3.814	4.398	7.022	13.435	4.036
Quantile 1	-0.042	-0.041	-0.021	-0.020	-0.018	-0.013	-0.012	-0.023	-0.065	-0.023
Quantile 5	-0.027	-0.029	-0.014	-0.014	-0.010	-0.009	-0.008	-0.012	-0.024	-0.015
Quantile 95	0.025	0.023	0.016	0.017	0.011	0.008	0.005	0.008	0.026	0.019
Quantile 99	0.037	0.042	0.026	0.026	0.017	0.013	0.008	0.018	0.062	0.028

JB_Test	0.001	0.001	0.017	0.005	0.007	0.016	0.001	0.001	0.001	0.018
Q_10	14.047	10.128	14.195	22.098	10.243	7.289	15.297	10.019	28.647	31.739
pvQ_10	0.171	0.429	0.164	0.015	0.419	0.698	0.122	0.439	0.001	0.000
Q_20	26.084	38.989	21.770	28.682	36.677	35.978	21.385	18.255	51.806	40.878
pvQ_20	0.163	0.007	0.353	0.094	0.013	0.015	0.375	0.571	0.000	0.004
obsv	251	253	258	255	251	250	253	253	257	188

M1GE	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	-0.136%	-0.241%	0.060%	-0.236%	-0.106%	-0.113%	-0.173%	0.045%	0.164%	0.006%
Std_dev	0.019	0.018	0.013	0.016	0.017	0.014	0.014	0.013	0.019	0.017
Minimum	-0.053	-0.077	-0.032	-0.051	-0.103	-0.051	-0.122	-0.039	-0.074	-0.059
Maximum	0.057	0.072	0.063	0.163	0.082	0.045	0.048	0.051	0.071	0.081
Skewness	-0.026	-0.095	1.105	4.335	-0.389	-0.043	-2.428	0.344	-0.176	0.372
Kurtosis	3.087	4.971	6.354	46.271	10.808	4.129	24.106	4.279	4.985	6.064
Quantile 1	-0.045	-0.049	-0.026	-0.032	-0.048	-0.038	-0.040	-0.030	-0.054	-0.050
Quantile 5	-0.036	-0.033	-0.018	-0.022	-0.026	-0.024	-0.020	-0.021	-0.029	-0.025
Quantile 95	0.031	0.022	0.026	0.018	0.023	0.023	0.017	0.024	0.036	0.031
Quantile 99	0.046	0.047	0.044	0.043	0.046	0.036	0.032	0.038	0.052	0.050
JB_Test	0.500	0.001	0.001	0.001	0.001	0.007	0.001	0.002	0.001	0.001
Q_10	18.027	22.739	38.283	26.959	7.110	8.308	4.956	18.502	12.451	41.635
pvQ_10	0.055	0.012	0.000	0.003	0.715	0.599	0.894	0.047	0.256	0.000
Q_20	24.050	38.316	42.590	38.814	20.549	23.259	8.869	23.483	22.179	58.987
pvQ_20	0.240	0.008	0.002	0.007	0.424	0.276	0.984	0.266	0.331	0.000
obsv	251	253	258	256	251	250	253	253	257	188

Y1GE	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	-0.026%	-0.104%	-0.033%	-0.001%	-0.064%	-0.076%	-0.032%	-0.072%	0.099%	0.057%
Std_dev	0.015	0.014	0.009	0.008	0.006	0.007	0.005	0.007	0.016	0.012
Minimum	-0.059	-0.046	-0.033	-0.027	-0.022	-0.030	-0.019	-0.050	-0.045	-0.042
Maximum	0.065	0.052	0.034	0.056	0.019	0.020	0.019	0.016	0.049	0.045
Skewness	-0.179	0.261	0.413	1.438	0.289	-0.154	-0.109	-1.777	0.125	0.073
Kurtosis	5.602	5.224	3.744	10.560	4.554	4.878	4.817	14.194	3.150	4.348
Quantile 1	-0.043	-0.034	-0.022	-0.015	-0.017	-0.018	-0.015	-0.020	-0.034	-0.029
Quantile 5	-0.024	-0.026	-0.013	-0.012	-0.010	-0.011	-0.009	-0.011	-0.025	-0.020
Quantile 95	0.023	0.021	0.016	0.013	0.009	0.011	0.008	0.009	0.028	0.021
Quantile 99	0.032	0.043	0.025	0.019	0.016	0.017	0.012	0.013	0.045	0.031
JB_Test	0.001	0.001	0.007	0.001	0.001	0.001	0.001	0.001	0.500	0.006
Q_10	12.161	10.640	17.200	5.022	10.000	19.804	25.532	7.622	14.318	21.285
pvQ_10	0.274	0.386	0.070	0.890	0.440	0.031	0.004	0.666	0.159	0.019
Q_20	26.645	51.885	22.890	15.101	39.925	56.767	32.456	13.544	24.204	34.263
pvQ_20	0.146	0.000	0.294	0.771	0.005	0.000	0.039	0.853	0.234	0.024

obsv	251	253	258	256	251	250	253	253	257	188

M1SP	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	-0.164%	-0.216%	-0.104%	-0.069%	-0.123%	-0.258%	-0.303%	0.014%	-0.069%	-0.061%
Std_dev	0.013	0.011	0.018	0.007	0.009	0.019	0.028	0.012	0.017	0.020
Minimum	-0.104	-0.058	-0.085	-0.029	-0.039	-0.099	-0.133	-0.038	-0.076	-0.134
Maximum	0.041	0.043	0.098	0.030	0.020	0.070	0.162	0.034	0.124	0.084
Skewness	-1.795	-0.735	0.890	0.186	-0.522	-0.040	0.159	-0.348	1.053	-0.972
Kurtosis	17.979	7.374	11.386	5.562	3.982	6.880	11.820	4.382	14.449	15.684
Quantile 1	-0.036	-0.040	-0.049	-0.019	-0.024	-0.054	-0.099	-0.037	-0.040	-0.057
Quantile 5	-0.022	-0.023	-0.033	-0.011	-0.017	-0.029	-0.050	-0.021	-0.029	-0.032
Quantile 95	0.016	0.015	0.022	0.010	0.013	0.027	0.031	0.019	0.021	0.028
Quantile 99	0.035	0.027	0.075	0.019	0.017	0.056	0.070	0.030	0.046	0.066
JB_Test	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001
Q_10	9.767	6.690	34.383	28.902	10.441	23.123	20.303	49.379	18.990	15.726
pvQ_10	0.461	0.754	0.000	0.001	0.403	0.010	0.027	0.000	0.040	0.108
Q_20	29.238	18.538	57.192	48.949	17.662	26.792	48.782	81.400	26.493	27.633
pvQ_20	0.083	0.552	0.000	0.000	0.610	0.141	0.000	0.000	0.150	0.118
obsv	246	250	250	252	254	255	255	256	257	188

Y1SP	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Mean (%)	-0.020%	-0.127%	0.006%	0.027%	-0.001%	-0.060%	-0.050%	-0.007%	0.013%	0.032%
Std_dev	0.011	0.013	0.009	0.006	0.005	0.007	0.004	0.003	0.007	0.005
Minimum	-0.046	-0.050	-0.026	-0.021	-0.014	-0.034	-0.017	-0.018	-0.030	-0.021
Maximum	0.033	0.055	0.032	0.025	0.026	0.035	0.014	0.011	0.027	0.014
Skewness	-0.831	-0.060	0.613	0.358	1.317	-0.171	-0.518	-0.694	-0.123	-0.859
Kurtosis	6.668	6.631	4.753	6.017	9.309	8.873	5.881	7.116	5.766	6.278
Quantile 1	-0.041	-0.044	-0.019	-0.014	-0.011	-0.021	-0.014	-0.012	-0.021	-0.018
Quantile 5	-0.020	-0.021	-0.015	-0.009	-0.007	-0.012	-0.007	-0.005	-0.010	-0.008
Quantile 95	0.016	0.017	0.015	0.010	0.007	0.010	0.005	0.005	0.011	0.009
Quantile 99	0.029	0.034	0.030	0.018	0.020	0.018	0.010	0.009	0.020	0.011
JB_Test	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	14.365	12.617	23.404	3.757	8.739	9.653	5.870	33.986	18.056	21.591
pvQ_10	0.157	0.246	0.009	0.958	0.557	0.471	0.826	0.000	0.054	0.017
Q_20	22.676	29.550	36.936	16.487	17.413	15.545	13.627	44.012	28.575	31.059
pvQ_20	0.305	0.077	0.012	0.686	0.626	0.744	0.849	0.001	0.096	0.054
obsv	246	250	250	252	254	255	255	256	257	188

M1NP	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Mean (%)	-0.321%	0.029%	0.310%	-0.510%	-0.178%	-0.079%	-0.136%	-0.262%	0.249%	0.139%
Std_dev	0.038	0.023	0.029	0.029	0.034	0.020	0.021	0.039	0.026	0.021
Minimum	-0.121	-0.067	-0.106	-0.128	-0.167	-0.078	-0.088	-0.146	-0.118	-0.103
Maximum	0.127	0.069	0.106	0.095	0.122	0.068	0.075	0.215	0.087	0.068
Skewness	0.297	0.062	-0.095	-0.101	-0.268	-0.296	-0.091	1.250	-0.366	-0.809
Kurtosis	3.988	3.482	5.257	5.802	5.712	4.860	4.622	9.495	5.377	6.358
Quantile 1	-0.095	-0.049	-0.088	-0.079	-0.088	-0.063	-0.047	-0.095	-0.066	-0.060
Quantile 5	-0.056	-0.040	-0.039	-0.054	-0.060	-0.032	-0.035	-0.061	-0.042	-0.037
Quantile 95	0.064	0.039	0.055	0.036	0.046	0.031	0.031	0.051	0.044	0.030
Quantile 99	0.115	0.061	0.082	0.079	0.089	0.050	0.055	0.137	0.068	0.054
JB_Test	0.006	0.229	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Q_10	10.114	5.535	27.878	14.785	9.060	12.828	2.261	14.333	13.669	6.678
pvQ_10	0.431	0.853	0.002	0.140	0.526	0.233	0.994	0.158	0.189	0.755
Q_20	18.202	11.786	38.546	27.265	19.914	19.048	6.620	22.165	29.132	13.595
pvQ_20	0.574	0.923	0.008	0.128	0.463	0.519	0.998	0.332	0.085	0.850
obsv	251	251	251	253	251	249	250	251	253	178

Y1NP	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Mean (%)	-0.093%	0.044%	0.098%	-0.087%	-0.020%	-0.066%	-0.057%	-0.137%	0.080%	0.108%
Std_dev	0.022	0.022	0.016	0.012	0.009	0.009	0.009	0.013	0.019	0.014
Minimum	-0.090	-0.068	-0.054	-0.035	-0.029	-0.032	-0.050	-0.055	-0.063	-0.051
Maximum	0.067	0.092	0.051	0.055	0.025	0.029	0.020	0.099	0.052	0.054
Skewness	-0.630	0.302	-0.059	0.295	-0.030	-0.066	-0.653	1.448	-0.169	-0.021
Kurtosis	5.104	4.679	3.786	4.504	2.875	3.792	6.129	17.824	3.734	5.529
Quantile 1	-0.066	-0.054	-0.036	-0.029	-0.022	-0.024	-0.020	-0.039	-0.050	-0.040
Quantile 5	-0.038	-0.036	-0.028	-0.021	-0.015	-0.016	-0.015	-0.021	-0.031	-0.019
Quantile 95	0.032	0.043	0.027	0.018	0.016	0.015	0.013	0.015	0.033	0.021
Quantile 99	0.054	0.071	0.039	0.032	0.021	0.023	0.019	0.024	0.047	0.042
JB_Test	0.001	0.001	0.037	0.001	0.500	0.036	0.001	0.001	0.034	0.001
Q_10	5.411	4.655	19.956	7.156	11.692	14.951	12.501	7.194	18.754	10.333
pvQ_10	0.862	0.913	0.030	0.711	0.306	0.134	0.253	0.707	0.043	0.412
Q_20	16.772	30.087	34.274	16.320	19.535	28.228	14.381	12.237	36.690	25.346
pvQ_20	0.668	0.068	0.024	0.697	0.487	0.104	0.811	0.908	0.013	0.189
obsv	251	251	251	253	251	249	250	251	253	184

Table 1B: Parameter estimates (in-sample)

Panel A : M1
NordPool

	GARCH(1,1)		EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	-0.001	-1.866	-0.001	-1.666	-0.001	-1.624
AR(1)	0.099	3.906	0.099	3.977	0.099	3.923
DoF	7.417	5.648	7.472	5.476	7.451	5.614
Constant	0.000	3.227	-0.208	-3.279	0.000	3.247
GARCH	0.858	40.219	0.971	111.817	0.858	40.696
ARCH	0.122	6.025	0.245	7.941	0.139	5.130
Leverage			0.020	1.169	-0.032	-1.108
BIC	-7916.176		-7911.274		-7916.176	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	-0.006	0.000	-0.011	0.000	-0.012
Max	0.131	5.768	0.131	5.401	0.131	5.782
Min	-0.170	-4.070	-0.171	-4.030	-0.171	-3.970
STD	0.028	0.996	0.028	0.996	0.028	0.996
Skewness	-0.051	-0.003	-0.051	-0.041	-0.051	-0.009
Kurtosis	5.874	4.347	5.874	4.223	5.874	4.334
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel B : Y1
NordPool

	GARCH(1,1)		EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	0.000	-0.702	0.000	-0.608	0.000	-0.552
AR(1)	0.027	1.106	0.031	1.287	0.031	1.265
DoF	9.313	6.681	7.951	6.468	8.302	6.554
Constant	0.000	1.979	-0.063	-2.052	0.000	1.657
GARCH	0.924	72.162	0.993	279.432	0.929	75.005
ARCH	0.065	5.529	0.137	6.116	0.069	4.575
Leverage			0.008	0.623	-0.010	-0.530
BIC	-10309.242		-10291.677		-10309.242	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	-0.003	0.000	-0.006	0.000	-0.006
Max	0.092	5.486	0.092	5.174	0.092	5.427
Min	-0.090	-6.469	-0.090	-6.086	-0.090	-6.248
STD	0.015	1.017	0.015	1.004	0.015	1.004
Skewness	-0.117	-0.192	-0.118	-0.181	-0.118	-0.190
Kurtosis	7.265	5.173	7.258	5.012	7.257	5.109
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel C: M1

Germany

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	-0.001	-3.663	-0.001	-3.501	-0.001	-3.570
AR(1)	0.114	4.961	0.107	4.769	0.114	4.912
DoF	4.166	10.577	4.239	10.745	4.177	10.513
Constant	0.000	3.449	-0.318	-2.848	0.000	3.480
GARCH	0.856	30.230	0.962	72.674	0.848	28.567
ARCH	0.105	4.605	0.191	5.786	0.123	4.238
Leverage			0.023	1.227	-0.025	-0.769
BIC	-10042.140		-10052.881		-10042.140	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	0.004	0.000	0.000	0.000	0.001
Max	0.158	7.284	0.158	8.042	0.158	6.885
Min	-0.122	-9.137	-0.122	-9.765	-0.122	-9.246
STD	0.016	1.012	0.016	1.018	0.016	1.011
Skewness	0.269	-0.245	0.274	-0.165	0.269	-0.316
Kurtosis	12.681	13.205	12.720	14.188	12.682	13.082
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel D : Y1
Germany

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	-0.001	-3.452	-0.001	-3.549	-0.001	-3.412
AR(1)	0.064	2.610	0.064	2.646	0.064	2.614
DoF	5.806	6.424	5.804	6.557	5.803	6.426
Constant	0.000	1.177	-0.101	-2.277	0.000	1.168
GARCH	0.904	65.582	0.989	216.408	0.904	64.741
ARCH	0.094	6.366	0.210	7.542	0.095	5.592
Leverage			0.004	0.314	-0.001	-0.064
BIC	-12128.136		-12116.546		-12128.136	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	0.016	0.000	0.017	0.000	0.016
Max	0.065	4.695	0.065	4.526	0.065	4.693
Min	-0.058	-4.266	-0.058	-4.231	-0.058	-4.266
STD	0.010	0.992	0.010	0.992	0.010	0.992
Skewness	0.162	0.190	0.162	0.208	0.162	0.189
Kurtosis	8.631	4.583	8.632	4.606	8.631	4.582
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel E: M1 Spain

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	-0.001	-4.196	-0.001	-4.186	-0.001	-4.108
AR(1)	0.127	5.852	0.122	5.656	0.127	5.826
DoF	3.447	10.063	3.170	9.759	3.451	10.094
Constant	0.000	2.678	-0.168	-3.196	0.000	2.721
GARCH	0.874	53.100	0.980	160.097	0.872	52.299
ARCH	0.126	5.804	0.267	7.139	0.140	4.586
Leverage			0.014	0.714	-0.023	-0.778
BIC	-10686		-10690		-10687	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	-0.001	-0.034	-0.001	-0.036	-0.001	-0.036
Max	0.166	4.530	0.166	4.570	0.166	4.581
Min	-0.136	-6.949	-0.136	-6.406	-0.136	-6.917
STD	0.016	0.969	0.016	0.918	0.016	0.971
Skewness	-0.047	-0.318	-0.044	-0.288	-0.047	-0.321
Kurtosis	19.843	6.867	19.832	6.824	19.842	6.893
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel F: Y1 Spain

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	0.000	-1.485	0.000	-1.695	0.000	-1.591
AR(1)	0.066	2.908	0.063	2.847	0.065	2.884
DoF	3.306	11.420	2.490	11.589	3.313	11.395
Constant	0.000	2.709	-0.287	-3.410	0.000	2.652
GARCH	0.791	37.040	0.969	115.034	0.795	37.748
ARCH	0.209	6.422	0.537	5.497	0.177	5.082
Leverage			-0.058	-1.748	0.056	1.340
BIC	-13048		-13049		-13048	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	-0.009	0.000	-0.004	0.000	-0.006
Max	0.053	7.018	0.053	5.832	0.053	7.094
Min	-0.049	-5.510	-0.049	-4.624	-0.049	-5.467
STD	0.008	1.003	0.008	0.778	0.008	1.003
Skewness	-0.255	0.324	-0.253	0.507	-0.254	0.378
Kurtosis	9.931	7.842	9.943	9.265	9.934	7.917
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel G: M1
France

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	-0.001	-1.322	-0.001	-1.639	-0.001	-1.576
AR(1)	0.090	3.875	0.087	3.897	0.090	3.900
DoF	3.389	10.308	3.357	10.541	3.380	10.398
Constant	0.000	3.495	-0.721	-3.294	0.000	3.491
GARCH	0.738	13.640	0.904	31.148	0.743	14.072
ARCH	0.144	4.082	0.227	5.335	0.097	3.034
Leverage			-0.045	-1.724	0.094	1.856
BIC	-8742.492		-8739.972		-8742.492	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	-0.006	0.000	0.001	0.000	0.000
Max	0.202	11.008	0.202	11.588	0.202	11.058
Min	-0.131	-6.770	-0.131	-6.559	-0.131	-6.774
STD	0.023	0.963	0.023	0.967	0.023	0.964
Skewness	0.434	0.777	0.434	0.997	0.434	0.842
Kurtosis	10.022	15.448	10.024	17.492	10.022	15.711
JB	1.000	1.000	1.000	1.000	1.000	1.000

Panel H: Y1
France

GARCH(1,1)			EGARCH(1,1)		GJR	
	Coef,	t-Stat	Coef,	t-Stat,	Coef,	t-Stat,
Constant	0.000	-1.333	0.000	-0.710	0.000	-1.061
AR(1)	0.010	0.431	0.014	0.604	0.009	0.384
DoF	7.819	5.208	7.540	5.192	7.788	5.145
Constant	0.000	0.720	-0.058	-1.962	0.000	0.648
GARCH	0.912	80.509	0.994	326.798	0.919	85.164
ARCH	0.088	6.683	0.187	7.547	0.096	6.124
Leverage			0.020	1.544	-0.030	-1.704
BIC	-12157.460		-12144.677		-12157.460	
	Residuals	Stand Residuals	Residuals	Stand Residuals	Residuals	Stand Residuals
Mean	0.000	0.003	0.000	-0.008	0.000	-0.003
Max	0.060	4.845	0.060	4.571	0.060	4.634
Min	-0.055	-3.843	-0.055	-3.901	-0.055	-3.799
STD	0.010	1.006	0.010	0.996	0.010	1.005
Skewness	-0.005	0.195	-0.005	0.178	-0.005	0.185
Kurtosis	7.907	4.118	7.905	4.089	7.907	4.082
JB	1.000	1.000	1.000	1.000	1.000	1.000

Table 2: VaR and ES Backtesting results for M1 and NordPool

Panel A: M1 and NordPool

	Alpha	**Pvalue Bin**	**Pvalue POF**	**Pvalue CCI**	**Pvalue DQ**	**F**	**Pvalue**	**Pvalue UN-N**	**P-value UN-t**
HS									
	0.01	0.006	0.016	0.285	0.014	29.710	0.000	0.004	0.015
	0.05	0.493	0.501	0.004	0.002	26.768	0.001	0.100	0.139
	0.95	0.874	0.875	0.001	0.000	35.242	0.000	0.102	0.141
	0.99	0.221	0.252	0.006	0.045	22.159	0.005	0.245	0.251
AR(1)-GARCH(1,1)									
	0.01	0.401	0.424	0.623	0.819	4.886	0.770	0.200	0.213
	0.05	0.712	0.709	0.648	0.538	3.473	0.901	0.488	0.474
	0.95	0.986	0.986	0.337	0.364	4.253	0.834	0.231	0.246
	0.99	0.650	0.658	0.663	0.595	3.560	0.894	0.051	0.076
AR(1)-EGARCH(1,1)									
	0.01	0.221	0.252	0.585	0.773	7.359	0.498	0.132	0.156
	0.05	0.874	0.875	0.384	0.397	4.297	0.829	0.346	0.352
	0.95	0.874	0.875	0.384	0.234	5.353	0.719	0.198	0.219
	0.99	0.650	0.658	0.077	0.639	7.732	0.460	0.083	0.102
AR(1)-GJR									
	0.01	0.650	0.658	0.663	0.516	3.844	0.871	0.326	0.326
	0.05	0.471	0.462	0.761	0.364	5.614	0.690	0.500	0.500
	0.95	0.471	0.462	0.184	0.402	8.258	0.409	0.495	0.481
	0.99	0.945	0.945	0.703	0.516	2.255	0.972	0.326	0.326
EWQR									
	0.01	0.108	0.140	0.548	0.049	15.615	0.048	0.115	0.141
	0.05	0.847	0.846	0.748	0.488	2.685	0.953	0.500	0.500
	0.95	0.493	0.501	0.018	0.011	19.883	0.011	0.158	0.187
	0.99	0.221	0.252	0.006	0.004	27.125	0.001	0.078	0.097
QR-COM									
	0.01	0.650	0.658	0.663	0.686	3.275	0.916	0.123	0.148
	0.05	0.712	0.709	0.253	0.465	5.645	0.687	0.280	0.295
	0.95	0.000	0.000	0.822	0.004	61.962	0.000	0.000	0.000
	0.99	0.000	0.000	0.323	0.002	52.264	0.000	0.000	0.000

Panel B: Y1 and NordPool

	Alpha	**Pvalue Bin**	**Pvalue POF**	**Pvalue CCI**	**Pvalue DQ**	**F**	**Pvalue**	**Pvalue UN-N**	**P-value UN-t**
HS									
	0.01	0.006	0.017	0.282	0.319	23.109	0.003	0.019	0.037
	0.05	0.064	0.076	0.002	0.001	36.861	0.000	0.025	0.049
	0.95	0.017	0.024	0.017	0.000	62.379	0.000	0.000	0.001
	0.99	0.006	0.017	0.282	0.000	42.286	0.000	0.000	0.001
AR(1)-GARCH(1,1)									
	0.01	0.232	0.263	0.129	0.248	12.472	0.131	0.144	0.166
	0.05	0.552	0.546	0.212	0.459	7.056	0.531	0.500	0.500
	0.95	0.327	0.339	0.100	0.304	11.376	0.181	0.422	0.417
	0.99	0.963	0.963	0.704	0.248	3.638	0.888	0.144	0.166
AR(1)-EGARCH(1,1)									
	0.01	0.668	0.676	0.076	0.190	10.074	0.260	0.312	0.314
	0.05	0.916	0.917	0.377	0.649	3.163	0.924	0.401	0.399
	0.95	0.327	0.339	0.100	0.385	10.902	0.207	0.311	0.322
	0.99	0.963	0.963	0.704	0.250	3.620	0.890	0.156	0.176
AR(1)-GJR									
	0.01	0.736	0.730	0.038	0.089	12.639	0.125	0.500	0.500
	0.05	0.263	0.248	0.125	0.298	12.036	0.150	0.500	0.500
	0.95	0.649	0.653	0.180	0.356	7.056	0.053	0.500	0.500
	0.99	0.471	0.449	0.787	0.102	8.149	0.419	0.469	0.454
EWQR									
	0.01	0.417	0.438	0.101	0.031	14.945	0.060	0.161	0.180
	0.05	0.327	0.339	0.007	0.010	23.489	0.003	0.097	0.134
	0.95	0.132	0.147	0.173	0.000	31.090	0.000	0.000	0.004
	0.99	0.114	0.146	0.550	0.002	21.847	0.005	0.000	0.004
QR-COM									
	0.01	0.000	0.000	0.069	0.140	85.775	0.000	0.000	0.000
	0.05	0.421	0.430	0.877	0.548	4.881	0.770	0.000	0.003
	0.95	0.000	0.000	0.986	0.000	145.103	0.000	0.000	0.000
	0.99	0.232	0.263	0.587	0.000	31.445	0.000	0.000	0.000

Panel C: M1 and Germany

	Alpha	Pvalue Bin	Pvalue POF	Pvalue CCI	Pvalue DQ	F	Pvalue	Pvalue UN-N	P-value UN-t
HS									
	0.01	0.442	0.462	0.627	0.857	4.416	0.818	0.181	0.197
	0.05	0.848	0.849	0.040	0.007	17.112	0.029	0.365	0.369
	0.95	0.218	0.231	0.011	0.007	24.877	0.002	0.300	0.313
	0.99	0.002	0.008	0.417	0.810	23.961	0.002	0.054	0.078
AR(1)-GARCH(1,1)									
	0.01	0.058	0.025	0.915	0.556	14.389	0.072	0.500	0.500
	0.05	0.231	0.215	0.126	0.076	15.318	0.053	0.500	0.500
	0.95	0.036	0.045	0.037	0.844	19.780	0.011	0.500	0.500
	0.99	0.698	0.705	0.666	0.684	2.990	0.935	0.500	0.500
AR(1)-EGARCH(1,1)									
	0.01	0.058	0.025	0.915	0.559	14.375	0.072	0.500	0.500
	0.05	0.395	0.384	0.100	0.123	12.563	0.128	0.500	0.500
	0.95	0.079	0.092	0.227	0.786	13.274	0.103	0.500	0.500
	0.99	0.698	0.705	0.666	0.673	5.356	0.719	0.500	0.500
AR(1)-GJR									
	0.01	0.058	0.025	0.915	0.546	14.422	0.071	0.500	0.500
	0.05	0.122	0.106	0.156	0.109	16.837	0.032	0.500	0.500
	0.95	0.218	0.231	0.360	0.827	8.400	0.395	0.500	0.500
	0.99	0.698	0.705	0.666	0.546	3.440	0.904	0.500	0.500
EWQR									
	0.01	0.709	0.702	0.747	0.266	4.625	0.797	0.500	0.500
	0.05	0.615	0.610	0.065	0.173	10.923	0.206	0.500	0.500
	0.95	0.218	0.231	0.044	0.375	14.199	0.077	0.500	0.500
	0.99	0.002	0.008	0.324	0.908	24.233	0.002	0.500	0.500
QR-COM									
	0.01	0.698	0.705	0.666	0.476	3.714	0.882	0.153	0.173
	0.05	0.741	0.739	0.278	0.389	5.648	0.687	0.500	0.500
	0.95	0.036	0.045	0.042	0.007	29.235	0.000	0.000	0.001
	0.99	0.000	0.000	0.051	0.204	84.726	0.000	0.000	0.000

Panel D: Y1 and Germany

	Alpha	Pvalue Bin	Pvalue POF	Pvalue CCI	Pvalue DQ	F	Pvalue	Pvalue UN-N	P-value UN-t
HS									
	0.01	0.022	0.041	0.482	0.402	17.307	0.027	0.015	0.031
	0.05	0.002	0.003	0.001	0.001	51.331	0.000	0.001	0.007
	0.95	0.002	0.003	0.612	0.000	60.003	0.000	0.000	0.000
	0.99	0.002	0.008	0.324	0.000	58.430	0.000	0.000	0.001
AR(1)-GARCH(1,1)									
	0.01	0.451	0.428	0.788	0.221	6.789	0.560	0.500	0.500
	0.05	0.498	0.490	0.010	0.022	19.568	0.012	0.500	0.500
	0.95	0.476	0.484	0.348	0.047	11.147	0.193	0.347	0.353
	0.99	0.451	0.428	0.788	0.007	13.751	0.088	0.405	0.397
AR(1)-EGARCH(1,1)									
	0.01	0.994	0.994	0.054	0.037	12.449	0.132	0.382	0.376
	0.05	0.498	0.490	0.010	0.024	19.399	0.013	0.500	0.500
	0.95	0.715	0.718	0.978	0.046	7.545	0.479	0.310	0.321
	0.99	0.130	0.088	0.872	0.023	16.763	0.033	0.284	0.289
AR(1)-GJR									
	0.01	0.451	0.428	0.788	0.220	6.799	0.558	0.500	0.500
	0.05	0.395	0.384	0.008	0.019	21.519	0.006	0.500	0.500
	0.95	0.476	0.484	0.348	0.047	11.149	0.193	0.354	0.359
	0.99	0.451	0.428	0.788	0.007	13.770	0.088	0.407	0.399
EWQR									
	0.01	0.126	0.158	0.159	0.050	17.475	0.026	0.034	0.053
	0.05	0.114	0.128	0.068	0.039	20.324	0.009	0.021	0.044
	0.95	0.054	0.065	0.982	0.000	43.708	0.000	0.000	0.001
	0.99	0.008	0.019	0.278	0.000	52.786	0.000	0.000	0.001
QR-COM									
	0.01	0.251	0.281	0.589	0.022	14.024	0.081	0.017	0.033
	0.05	0.023	0.031	0.347	0.102	21.179	0.007	0.000	0.002
	0.95	0.000	0.000	0.076	0.000	231.569	0.000	0.000	0.000
	0.99	0.000	0.000	0.244	0.000	316.955	0.000	0.000	0.000

Panel E: M1 and Spain

	Alpha	Pvalue Bin	Pvalue POF	Pvalue CCI	Pvalue DQ	F	Pvalue	Pvalue UN-N	P-value UN-t
HS									
	0.01	0.225	0.469	0.099	0.020	16.915	0.031	0.076	0.095
	0.05	0.435	0.870	0.000	0.000	55.160	0.000	0.260	0.278
	0.95	0.361	0.720	0.018	0.000	46.830	0.000	0.003	0.012
	0.99	0.225	0.469	0.628	0.000	22.814	0.004	0.002	0.009
AR(1)-GARCH(1,1)									
	0.01	0.351	0.694	0.747	0.907	3.603	0.891	0.500	0.500
	0.05	0.058	0.101	0.334	0.407	14.257	0.075	0.500	0.500
	0.95	0.000	0.000	0.002	0.624	50.562	0.000	0.221	0.238
	0.99	0.354	0.713	0.667	0.886	3.808	0.874	0.480	0.464
AR(1)-EGARCH(1,1)									
	0.01	0.223	0.421	0.789	0.964	5.280	0.727	0.500	0.500
	0.05	0.028	0.043	0.050	0.071	24.753	0.002	0.500	0.500
	0.95	0.001	0.002	0.007	0.218	40.370	0.000	0.453	0.445
	0.99	0.354	0.713	0.667	0.938	3.693	0.884	0.500	0.500
AR(1)-GJR									
	0.01	0.351	0.694	0.747	0.908	3.600	0.891	0.500	0.500
	0.05	0.028	0.043	0.250	0.398	18.086	0.021	0.500	0.500
	0.95	0.001	0.002	0.007	0.373	39.293	0.000	0.457	0.448
	0.99	0.354	0.713	0.667	0.929	3.711	0.882	0.500	0.500
EWQR									
	0.01	0.225	0.469	0.099	0.051	15.071	0.058	0.321	0.322
	0.05	0.361	0.720	0.000	0.000	40.922	0.000	0.500	0.500
	0.95	0.497	0.993	0.119	0.000	27.057	0.001	0.197	0.218
	0.99	0.128	0.286	0.590	0.000	38.138	0.000	0.079	0.098
QR-COM									
	0.01	0.351	0.694	0.747	0.740	4.011	0.856	0.231	0.240
	0.05	0.041	0.067	0.908	0.961	12.078	0.148	0.500	0.500
	0.95	0.003	0.009	0.680	0.074	27.021	0.001	0.002	0.009
	0.99	0.000	0.000	0.540	0.307	77.484	0.000	0.000	0.000

Panel F: Y1 and Spain

	Alpha	**Pvalue Bin**	**Pvalue POF**	**Pvalue CCI**	**Pvalue DQ**	**F**	**Pvalue**	**Pvalue UN-N**	**P-value UN-t**
HS									
	0.01	0.029	0.085	0.194	0.000	38.633	0.000	0.021	0.040
	0.05	0.247	0.501	0.004	0.000	30.742	0.000	0.118	0.154
	0.95	0.247	0.501	0.572	0.018	13.314	0.102	0.003	0.014
	0.99	0.128	0.286	0.590	0.013	16.304	0.038	0.003	0.012
AR(1)-GARCH(1,1)									
	0.01	0.351	0.694	0.747	0.689	4.154	0.843	0.500	0.500
	0.05	0.428	0.855	0.098	0.111	11.051	0.199	0.500	0.500
	0.95	0.114	0.242	0.252	0.384	11.845	0.158	0.405	0.403
	0.99	0.064	0.086	0.872	0.825	11.067	0.198	0.500	0.500
AR(1)-EGARCH(1,1)									
	0.01	0.127	0.214	0.830	0.707	8.284	0.406	0.500	0.500
	0.05	0.191	0.370	0.172	0.139	12.779	0.120	0.500	0.500
	0.95	0.195	0.401	0.838	0.049	11.473	0.176	0.500	0.500
	0.99	0.029	0.025	0.915	0.846	15.016	0.059	0.500	0.500
AR(1)-GJR									
	0.01	0.351	0.694	0.747	0.681	4.175	0.841	0.500	0.500
	0.05	0.195	0.401	0.271	0.537	8.946	0.347	0.370	0.373
	0.95	0.003	0.009	0.680	0.260	24.512	0.002	0.138	0.170
	0.99	0.064	0.086	0.872	0.820	11.078	0.197	0.500	0.500
EWQR									
	0.01	0.225	0.469	0.099	0.004	20.434	0.009	0.196	0.209
	0.05	0.195	0.401	0.631	0.076	11.156	0.193	0.372	0.375
	0.95	0.195	0.401	0.271	0.044	13.962	0.083	0.044	0.074
	0.99	0.065	0.162	0.159	0.034	19.577	0.012	0.062	0.085
QR-COM									
	0.01	0.128	0.286	0.127	0.249	13.525	0.095	0.117	0.144
	0.05	0.000	0.000	0.551	0.000	88.494	0.000	0.000	0.000
	0.95	0.000	0.001	0.159	0.000	98.103	0.000	0.000	0.000
	0.99	0.064	0.086	0.872	0.000	42.997	0.000	0.004	0.015

Panel G: M1 and France

	Alpha	Pvalue Bin	Pvalue POF	Pvalue CCI	Pvalue DQ	F	Pvalue	Pvalue UN-N	P-value UN-t
HS									
	0.01	0.251	0.281	0.127	0.052	15.356	0.053	0.027	0.047
	0.05	0.498	0.490	0.000	0.000	35.369	0.000	0.386	0.387
	0.95	0.376	0.386	0.001	0.000	34.651	0.000	0.500	0.500
	0.99	0.056	0.083	0.001	0.005	36.142	0.000	0.154	0.174
AR(1)-GARCH(1,1)									
	0.01	0.451	0.428	0.024	0.064	16.275	0.039	0.500	0.500
	0.05	0.170	0.154	0.384	0.041	15.581	0.049	0.500	0.500
	0.95	0.003	0.005	0.117	0.223	29.335	0.000	0.500	0.500
	0.99	0.451	0.428	0.788	0.064	9.251	0.322	0.500	0.500
AR(1)-EGARCH(1,1)									
	0.01	0.709	0.702	0.037	0.037	14.595	0.068	0.500	0.500
	0.05	0.498	0.490	0.205	0.014	14.541	0.069	0.500	0.500
	0.95	0.005	0.009	0.034	0.017	34.974	0.000	0.500	0.500
	0.99	0.251	0.281	0.127	0.037	16.038	0.042	0.500	0.500
AR(1)-GJR									
	0.01	0.709	0.702	0.037	0.030	15.023	0.059	0.500	0.500
	0.05	0.160	0.174	0.165	0.095	15.478	0.050	0.182	0.206
	0.95	0.000	0.000	0.047	0.081	44.698	0.000	0.043	0.072
	0.99	0.002	0.008	0.037	0.036	35.040	0.000	0.395	0.389
EWQR									
	0.01	0.251	0.281	0.127	0.157	13.139	0.107	0.120	0.146
	0.05	0.395	0.384	0.008	0.008	23.118	0.003	0.408	0.405
	0.95	0.218	0.231	0.011	0.027	22.143	0.005	0.500	0.500
	0.99	0.126	0.158	0.009	0.244	20.023	0.010	0.159	0.179
QR-COM									
	0.01	0.002	0.008	0.324	0.025	31.422	0.000	0.003	0.010
	0.05	0.000	0.000	0.007	0.000	202.055	0.000	0.000	0.000
	0.95	0.000	0.001	0.026	0.000	56.017	0.000	0.500	0.500
	0.99	0.000	0.000	0.642	0.000	155.884	0.000	0.000	0.000

Panel H: Y1 and France

	Alpha	**Pvalue Bin**	**Pvalue POF**	**Pvalue CCI**	**Pvalue DQ**	**F**	**Pvalue**	**Pvalue UN-N**	**P-value UN-t**
HS									
	0.01	0.001	0.003	0.004	0.001	50.663	0.000	0.000	0.003
	0.05	0.054	0.065	0.000	0.000	50.626	0.000	0.000	0.005
	0.95	0.000	0.000	0.024	0.000	83.263	0.000	0.000	0.000
	0.99	0.002	0.008	0.417	0.000	43.003	0.000	0.000	0.001
AR(1)-GARCH(1,1)									
	0.01	0.442	0.462	0.004	0.011	23.441	0.003	0.186	0.201
	0.05	0.848	0.849	0.009	0.009	19.623	0.012	0.294	0.307
	0.95	0.590	0.595	0.014	0.033	17.472	0.026	0.103	0.142
	0.99	0.056	0.083	0.195	0.011	23.002	0.003	0.186	0.201
AR(1)-EGARCH(1,1)									
	0.01	0.251	0.281	0.000	0.001	37.499	0.000	0.089	0.112
	0.05	0.590	0.595	0.003	0.008	23.090	0.003	0.179	0.204
	0.95	0.376	0.386	0.024	0.021	19.042	0.015	0.081	0.111
	0.99	0.126	0.158	0.553	0.001	22.281	0.004	0.055	0.079
AR(1)-GJR									
	0.01	0.709	0.702	0.000	0.002	29.042	0.000	0.500	0.500
	0.05	0.395	0.384	0.001	0.001	30.922	0.000	0.500	0.500
	0.95	0.741	0.739	0.003	0.003	24.513	0.002	0.500	0.500
	0.99	0.442	0.462	0.627	0.004	15.088	0.057	0.420	0.410
EWQR									
	0.01	0.002	0.008	0.037	0.008	37.973	0.000	0.001	0.006
	0.05	0.014	0.021	0.006	0.007	36.593	0.000	0.001	0.008
	0.95	0.023	0.031	0.134	0.000	49.235	0.000	0.000	0.000
	0.99	0.008	0.019	0.449	0.000	61.441	0.000	0.000	0.000
QR-COM									
	0.01	0.000	0.000	0.081	0.194	44.639	0.000	0.000	0.002
	0.05	0.476	0.484	0.005	0.012	22.523	0.004	0.028	0.052
	0.95	0.000	0.000	0.665	0.000	193.705	0.000	0.000	0.000
	0.99	0.000	0.000	0.384	0.000	118.907	0.000	0.000	0.000

Table 3: Correlation matrix of the variables in Quantile Regression. RTOS is the return of the dependent variable.

		RTOS	MK	CARBON	COAL	GAS	OIL	VOLD	VOLW	VOLM
M1NP	RTOS	1.00	0.02	-0.01	-0.02	-0.04	-0.03	-0.01	0.01	-0.01
	MK	0.02	1.00	-0.17	0.12	0.13	0.18	-0.01	0.00	0.00
	CARBON	-0.01	-0.17	1.00	0.72	0.09	0.24	0.13	0.23	0.28
	COAL	-0.02	0.12	0.72	1.00	0.57	0.64	0.11	0.19	0.23
	GAS	-0.04	0.13	0.09	0.57	1.00	0.68	0.06	0.08	0.09
	OIL	-0.03	0.18	0.24	0.64	0.68	1.00	0.02	0.03	0.04
	VOLD	-0.01	-0.01	0.13	0.11	0.06	0.02	1.00	0.56	0.41
	VOLW	0.01	0.00	0.23	0.19	0.08	0.03	0.56	1.00	0.75
	VOLM	-0.01	0.00	0.28	0.23	0.09	0.04	0.41	0.75	1.00
M1FR	RTOS	1.00	0.04	0.00	-0.01	0.00	0.01	-0.03	-0.07	-0.07
	MK	0.04	1.00	-0.16	-0.12	-0.16	-0.30	0.03	0.06	0.09
	CARBON	0.00	-0.16	1.00	0.72	0.09	0.25	-0.04	-0.07	-0.10
	COAL	-0.01	-0.12	0.72	1.00	0.57	0.64	-0.02	-0.03	-0.03
	GAS	0.00	-0.16	0.09	0.57	1.00	0.68	0.00	0.01	0.00
	OIL	0.01	-0.30	0.25	0.64	0.68	1.00	-0.09	-0.13	-0.14
	VOLD	-0.03	0.03	-0.04	-0.02	0.00	-0.09	1.00	0.56	0.41
	VOLW	-0.07	0.06	-0.07	-0.03	0.01	-0.13	0.56	1.00	0.74
	VOLM	-0.07	0.09	-0.10	-0.03	0.00	-0.14	0.41	0.74	1.00
M1GE	RTOS	1.00	0.06	0.01	-0.01	-0.03	-0.02	0.00	-0.03	-0.05
	MK	0.06	1.00	-0.60	-0.41	-0.16	-0.38	-0.03	-0.05	-0.07
	CARBON	0.01	-0.60	1.00	0.72	0.09	0.25	0.05	0.08	0.10
	COAL	-0.01	-0.41	0.72	1.00	0.57	0.64	0.07	0.11	0.14
	GAS	-0.03	-0.16	0.09	0.57	1.00	0.68	0.06	0.10	0.13
	OIL	-0.02	-0.38	0.25	0.64	0.68	1.00	-0.05	-0.09	-0.11
	VOLD	0.00	-0.03	0.05	0.07	0.06	-0.05	1.00	0.52	0.36
	VOLW	-0.03	-0.05	0.08	0.11	0.10	-0.09	0.52	1.00	0.68
	VOLM	-0.05	-0.07	0.10	0.14	0.13	-0.11	0.36	0.68	1.00
M1SP	RTOS	1.00	0.02	0.01	0.01	-0.03	-0.01	-0.12	-0.09	-0.10
	MK	0.02	1.00	0.53	0.29	-0.17	0.01	-0.01	0.00	0.03
	CARBON	0.01	0.53	1.00	0.72	0.09	0.24	-0.15	-0.21	-0.24
	COAL	0.01	0.29	0.72	1.00	0.57	0.64	-0.11	-0.15	-0.19
	GAS	-0.03	-0.17	0.09	0.57	1.00	0.68	0.05	0.06	0.04
	OIL	-0.01	0.01	0.24	0.64	0.68	1.00	-0.01	-0.03	-0.05
	VOLD	-0.12	-0.01	-0.15	-0.11	0.05	-0.01	1.00	0.60	0.47
	VOLW	-0.09	0.00	-0.21	-0.15	0.06	-0.03	0.60	1.00	0.78
	VOLM	-0.10	0.03	-0.24	-0.19	0.04	-0.05	0.47	0.78	1.00

Y1NP		RTOS	MK	CARBON	COAL	GAS	OIL	VOLD	VOLW	VOLM

	RTOS	1.00	0.06	0.02	0.01	-0.02	0.01	-0.02	-0.01	-0.01
	MK	0.06	1.00	-0.17	0.12	0.13	0.18	-0.24	-0.39	-0.47
	CARBON	0.02	-0.17	1.00	0.72	0.09	0.24	0.17	0.29	0.33
	COAL	0.01	0.12	0.72	1.00	0.57	0.64	0.06	0.10	0.11
	GAS	-0.02	0.13	0.09	0.57	1.00	0.68	-0.06	-0.09	-0.12
	OIL	0.01	0.18	0.24	0.64	0.68	1.00	-0.19	-0.31	-0.38
	VOLD	-0.02	-0.24	0.17	0.06	-0.06	-0.19	1.00	0.61	0.49
	VOLW	-0.01	-0.39	0.29	0.10	-0.09	-0.31	0.61	1.00	0.83
	VOLM	-0.01	-0.47	0.33	0.11	-0.12	-0.38	0.49	0.83	1.00
Y1 FR	RTOS	1.00	0.06	0.02	0.02	0.00	0.03	-0.05	-0.05	-0.02
	MK	0.06	1.00	-0.16	-0.12	-0.16	-0.30	-0.08	-0.13	-0.14
	CARBON	0.02	-0.16	1.00	0.72	0.09	0.25	0.16	0.24	0.25
	COAL	0.02	-0.12	0.72	1.00	0.57	0.64	0.08	0.12	0.13
	GAS	0.00	-0.16	0.09	0.57	1.00	0.68	-0.07	-0.10	-0.13
	OIL	0.03	-0.30	0.25	0.64	0.68	1.00	-0.18	-0.29	-0.36
	VOLD	-0.05	-0.08	0.16	0.08	-0.07	-0.18	1.00	0.62	0.49
	VOLW	-0.05	-0.13	0.24	0.12	-0.10	-0.29	0.62	1.00	0.80
	VOLM	-0.02	-0.14	0.25	0.13	-0.13	-0.36	0.49	0.80	1.00
Y1 GE	RTOS	1.00	0.05	0.02	0.02	-0.01	0.02	0.02	0.00	0.00
	MK	0.05	1.00	-0.60	-0.41	-0.16	-0.38	-0.06	-0.11	-0.13
	CARBON	0.02	-0.60	1.00	0.72	0.09	0.25	0.13	0.20	0.23
	COAL	0.02	-0.41	0.72	1.00	0.57	0.64	0.06	0.09	0.10
	GAS	-0.01	-0.16	0.09	0.57	1.00	0.68	-0.08	-0.12	-0.14
	OIL	0.02	-0.38	0.25	0.64	0.68	1.00	-0.22	-0.35	-0.41
	VOLD	0.02	-0.06	0.13	0.06	-0.08	-0.22	1.00	0.63	0.53
	VOLW	0.00	-0.11	0.20	0.09	-0.12	-0.35	0.63	1.00	0.85
	VOLM	0.00	-0.13	0.23	0.10	-0.14	-0.41	0.53	0.85	1.00
Y1SP	RTOS	1.00	0.05	0.02	0.02	-0.01	0.02	-0.04	0.00	-0.01
	MK	0.05	1.00	-0.60	-0.41	-0.15	-0.38	-0.24	-0.38	-0.48
	CARBON	0.02	-0.60	1.00	0.72	0.09	0.24	0.18	0.30	0.35
	COAL	0.02	-0.41	0.72	1.00	0.57	0.64	0.07	0.12	0.14
	GAS	-0.01	-0.15	0.09	0.57	1.00	0.68	-0.01	-0.01	-0.01
	OIL	0.02	-0.38	0.24	0.64	0.68	1.00	-0.08	-0.11	-0.14
	VOLD	-0.04	-0.24	0.18	0.07	-0.01	-0.08	1.00	0.64	0.49
	VOLW	0.00	-0.38	0.30	0.12	-0.01	-0.11	0.64	1.00	0.79
	VOLM	-0.01	-0.48	0.35	0.14	-0.01	-0.14	0.49	0.79	1.00

Table 4: Tail Index GARCH and Empirical

Tail Index k	FR	GE	SP	NP	Average

	M1	Y1	M1	Y1	M1	Y1	M1	Y1	
k* (Quantile 95%)	1.1	1.13	1.3	1.4	1.04	1.11	1.21	1.17	1.18
k* (Quantile 5%)	1.45	1.09	1.6	1.07	1.07	1.29	1.38	1.31	1.28
GARCH(1,1) Student-t ***k***	1.61	1.01	1.55	1.13	1.01	1.03	1.76	2.62	1.47
log(***k/k****) (5%)	4.55%	-3.31%	-1.38%	2.37%	-2.51%	-9.78%	10.56%	30.10%	3.83%
log(***k/k****) (95%)	16.54%	-4.88%	7.64%	-9.30%	-1.27%	-3.25%	16.27%	35.01%	7.10%