THE DETERMINANTS OF EU ELECTRICITY PRICES: WHOLESALE AND RETAIL

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The Determinants of EU Electricity prices: Wholesale and Retail

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This paper studies the determinants of wholesale and retail electricity prices for ten EU countries in the period 2008-2016. Demand, fuel prices, renewable-based production, weather variables and net balance between exports and imports explain monthly wholesale prices. But the economic impact of each fundamental factor varies across countries. Wholesale prices and changes in public deficit explain the behaviour of household retail prices. Monte Carlo simulations suggest that the probabilities of achieving EU's Climate and Energy Package target of reductions in energy consumption for horizons 2020 and 2030 are lower than 1% in all countries. CEP's target of 20-27% generation by renewables by France and Finland present non-compliance probabilities of 80% (above 99%) and 40% (80%) respectively in horizons 2020 (2030). Empirical results cast doubts on the mutual consistency of CEP's targets of reduction in consumption and increase in support to renewables.

Keywords: Wholesale electricity prices; Retail electricity prices; Climate and Energy Package (CEP); Renewables production

JEL Codes: C51; G13; L94; Q40

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1. Introduction

The 20-20-20 Climate and Energy Package (CEP) adopted in late 2008 require the EU's Member States to cut greenhouse gas emissions by 20%, to produce 20% of energy from renewable sources, and to cut gross primary energy consumption by 20%. In October 2014, Member States agreed to set targets for 2030: cut greenhouse gas emissions by 40%, produce 27% of energy from renewables and cut energy consumption by 27%. Understanding the impact of these measures on electricity prices, and so on utilities and consumers, is of paramount importance to market agents, investors and regulators.

In this paper we aim to shed light on the impact of these measures by studying the determinants of wholesale prices[1], and retail (households) prices[2] in ten EU countries in the period 2008-2016. Our goals are (i) model the impact of relevant variables on the behavior of monthly wholesale electricity prices in ten EU countries (Austria, Denmark, Finland, France, Germany, Greece, Italy, Portugal, Spain and Sweden) from 2008 to 2016, (ii) explain the behavior of annual retail electricity prices as a function of wholesale market prices and country-specific factors and, (iii) based on those models, carry out simulations for the 2020 and 2030 horizons to study possible price implications (both wholesale and retail) of the targets set out in 2009 and 2014.

[1] Wholesale prices are set in competitive markets and may be affected by several factors (load, temperature, fuel prices, renewables share, and carbon prices). Market prices for fossil fuels decreased since oil prices peaked in 2008. Due to the sharp decline in the carbon price (CO2 emission allowances) production of energy from high carbon emitting power plants has not been discouraged. So, fuel switching decisions for existing plants are influenced by demand, the relative costs of energy input (coal, gas) and the relative production from renewable energy sources.

[2] Retail prices contain two elements: cost of energy (based on wholesale prices and including distribution and transmission costs) and the "government wedge" (taxes, subsidies, public policies). In the EU, since 2008 the first part decreased, but, in most countries, the second part increased by more. With the increasing production of renewable electricity, the support to this was financed by consumers through levies on retail electricity prices. As a result, retail prices increased for households and, to a certain extent, industries.

Empirical analysis suggests that consumption (load), fuel prices, renewable-based production, weather variables and net balance between exports and imports explain monthly wholesale prices. But the economic impact of each fundamental factor varies across countries. Fuel prices are the most influential price driver in Austria, Denmark, France and Germany, but have little explanatory power in Finland, Greece and Spain; part of generation by renewables is a significant element in all countries, particularly in Portugal and Spain, but the size of its impact in Finland is four times higher than in Germany. Demand is the key ingredient in Finland and Italy, but its impact is modest in Austria, France or Greece. Temperature is a key factor in Sweden and Denmark but marginal in Austria, Portugal or Spain. Net balance between exports and imports is relevant in the Nordic countries and Greece but largely irrelevant France, Germany or Italy. These results stress the fact that the modelling of electricity prices is best done at the individual country level. Imposing common responses to the impact of fundamental variables on electricity prices, as most panel data models do, may produce misleading interpretations and conclusions.

Second, wholesale prices and changes in public deficit explain household retail prices. Household prices are significantly and negatively correlated with wholesale prices in seven countries (Austria, Denmark, Finland, France, Germany, Greece and Italy) and changes in public deficit have positive and significant explanatory power in six countries (Austria, Denmark, Finland, France, Germany and Spain). In Spain, the change from CESUR auctions to the new tariff setting system based on the PVPC (Voluntary Price for the Small Consumer) does not change retail price dynamics in any significant way.

Third, Monte Carlo simulations suggest that the probability of achieving CEP's target of reductions in energy consumption for horizons 2020 and 2030 are lower than 1% in all countries. France and Finland present non-compliance probabilities of 80% (above 99%) and 40% (80%) respectively in horizons 2020 (2030) about CEP's target of part of generation by renewables. Spain and Italy may face also challenges if corrective policy actions are not taken.

The analysis shows an important point about the mutual consistency of CEP's targets. Increase in generation from renewables decreases wholesale prices. Therefore, the energy part of retail prices, based on wholesale prices, declines accordingly. Declines in retail prices encourage consumption. A conflict between CEP's target of cut in amount used and CEP's target of increased production from renewables appears.

The rest of this paper is organized as follows. Section 2 reviews the literature. After describing the data in Section 3, we report results of empirical analysis in Section 4. Section 5 discusses Monte Carlo simulation and scenario analysis Section 6 contains conclusions and policy recommendations.

2. Literature review

Electricity price may be explained by several fundamental factors. The price responses to demand, fuel prices, temperature, precipitation and wind are studied in Nogales, Contreras, Conejo and Espinola(2002), Vehvilainen and Pyykkonen (2004), Rambharat, Brockwell and Seppi (2005) and Knittel and Roberts (2005) among others. Weron and Misiorek (2005) include load as explanatory variable in AR-type models. Karakatsani and Bunn (2008), compare three models: linear regression, time-varying regression and Markov regime-switching regression. They find fourteen fundamental price drivers, (e.g. demand, seasonality, learning processes, and price volatility among others). By comparing different models with or without external explanatory variables, models including market fundamentals and time-varying effects have a better performance for predicting day-ahead electricity prices. Jonsson et al. (2013) suggest that wind power generation should be accounted for in Western Danish price area of Nord Pool where renewable resources (wind) are used for generation. Wind has a strong influence on power prices because of fundamental differences from other energy sources. Also, the low marginal cost, nearly zero, of wind power can shift the supply function to the left. The results support the idea of including wind power generation as an influential factor on electricity price. Huurman, Ravazzolo, and Zhou (2012) show that including explanatory variables such weather proxies, e.g. daily average temperatures, total daily precipitation, daily average wind power, helps in forecasting electricity spot prices. Actual observations and weather forecasts are included to account for weather influence. Coulon and Howison (2009) develop a fundamental model based on a stochastic process for underlying factors, such as fuel prices, power demand, generation capacity availability, and a parametric form for the bid stack function which allows these price drivers being mapped into the power price. Worthington, Kay-Spratley and Higgs (2005) show that price volatility may help in forecasting spot prices. In summary, electricity prices markets are depending on many shocks in fuel prices, demand, supply, and institutional involvement, including, carbon dioxide prices. Therefore, literature shows that the following fundamental variables have been proven useful for explaining electricity prices

1. Fuel prices (crude oil, natural gas, coal)
2. Weather variables (e.g. temperature, wind speed)
3. Demand as measured by consumption (load)
4. Emission certificate prices (carbon prices)
5. Proportion of generation by renewables

6. Difference between electricity exports and imports (net balance)

In summary, fundamental factors play an important role in explaining electricity prices and how to model these factors' influence spot price behavior is a challenging task. Also, and depending on data frequency, other micro, and macro factors should be considered into modeling electricity prices. The shorter the time interval, transitory effects (e.g. plant outages, unplanned plant maintenance, cuts in distribution networks) and microstructural factors (market design and structure) become dominant. These factors may cloud the measuring of the impact of fundamental factors. The reason is that some of them evolve with high inertia. For instance, studies show fuel costs may not influence high-frequency electricity prices (Guirguis and Felder, 2004). The longer the time interval the more important fundamental (e.g. demand, fuel prices) factors become. In this paper we focus on a medium to long-term perspective and so use monthly, semi-annual and annual data. Monthly data provides a long sample size and smooths out the high volatility and spikes intra-day or daily data presents. Semi-annual and yearly data allows taking into account the impact of macro factors (e.g. government budget deficit) which cannot be observed at shorter frequencies.

3. Data

Monthly electricity spot price (wholesale price) data are computed as averages of daily prices from ten EU countries: Austria, Denmark, Finland, France, Germany, Greece, Italy, Portugal, Spain, and Sweden, which amount for 95% of total electricity amount used in the EU. Monthly data for explanatory variables is computed in the same way. Table 1 has data definitions and sources. Sample size is 108 data points from January, 2008 to December, 2016. The source of data for each country is shown in Table 1. Wholesale prices are shown in Figure 1.

[INSERT TABLE 1 HERE]

[INSERT FIGURE 1 HERE]

In Figure 1, we may see a drop in prices in all countries around 2008, coincident with the financial crisis period. However, the recovery process is different for each country. Denmark, Finland, and Sweden experienced price spikes around 2010-2011. In Austria and Germany, recovered until 2011 and declined since then. In France, Greece, and Italy, electricity prices recover around 2011-2012 but also declined since then. Spain and Portugal prices recovered around 2011 and look stationary since then. Electricity demand is seasonal. Therefore, electricity prices may have seasonal components. Figure 2 shows monthly price averages.

[INSERT FIGURE 2 HERE]

In April or May, electricity price is lower than in other seasons. In winter, most countries have higher electricity prices. Despite this similarity, seasonal effects are different across regions in EU. We may notice regional seasonal patterns: France-Italy-Greece present peaks in December and lows in May, Germany-Austria peak in October and are low in May, Sweden-Finland peak in February and are low in July, and Spain-Portugal peak in September and are low in April. This similarity between countries may be due to similar weather, similarity in heating or cooling systems, and similar structure of generation assets. Denmark exhibits a unique behavior, peaks in February and September and lows in March and July; one possible reason is location and its dependence on wind turbines to generate electricity.

3.1 Summary Statistics

Preliminary data analysis shows that the wholesale price series display the typical spot electricity price features of pronounced volatility, and, sometimes, positive skewness, excess kurtosis, seasonality and jumps. Table 2 provides information on basic statistics for monthly price series.

[INSERT TABLE 2 HERE]

Italy presents highest average prices (63.69€/MWh) and Sweden presents lowest average prices (39.48€/MWh). Price volatility, as measured by the coefficient of variation, is lowest in France (0.20) and highest in Sweden (0.37). In Austria, Denmark, Finland, Germany, and Sweden, Jarque-Bera tests reject the null hypotheses of normality. The reason is right skewness and high kurtosis caused by price spikes.

4. Empirical Analysis

4.1 Wholesale prices: univariate analysis

To understand the basic features of monthly electricity prices we apply the following univariate models to price series: ARMA, ARMA-GARCH, ARMA-TARCH-M, Markov regime-switching (MRS), Smooth transition AR (STAR) and Jump-Diffusion (JD). To save space, results are in Appendix A. We summarize main findings here. Univariate models' results suggest that EU electricity prices are characterized by some common features across countries but there are also significant differences. A common feature in the stochastic part of prices is mean reversion with an average half-life between four and two months. Price volatility's structure varies substantially across markets. For instance, the volatility feedback channel is important in Germany, Austria and Finland but not in other countries. Negative leverage effects appear in Denmark and Austria, but Finland presents positive leverage. We do an out-of-sample forecasting exercise. Results suggest that best models in-sample present similar forecasting accuracy than best out-of-sample models (except for Greece and Finland). All these facts suggest that specific univariate model should be used in each market to take account of its specific characteristics.

4.2 Wholesale prices: Multivariate models

As we are interested in the impact of fundamental variables on wholesale prices, we use linear regression based on the fundamental market factors defined in Section 2, which captures the average price formation over the sample period

$$p_{t,j} = \beta_0 + \sum_{j=1}^{K} \beta_j X_{t,j} + \eta_t \quad (1)$$

Where the dependent variable $p_{j,t}$ is the wholesale electricity price in country j at time t, and $X_{t,j}$ are explanatory variables either stochastic (e.g. demand) or deterministic (e.g. dummy seasonal variables). The noise process η_t follows

$$\phi(B)\eta_t = \theta(B)\sigma_t\varepsilon_t \qquad (2)$$

$$\phi(B) = 1 - \sum_{l=1}^{\phi} \phi_l B^l ; \;\; \theta(B) = 1 - \sum_{l=1}^{\theta} \theta_l B^l \qquad (3)$$

Functions $\phi(B)$ and $\theta(B)$ are polynomial functions of the backshift operator B, σ_t is the volatility and the innovation ε_t is N(0, σ_t). Volatility follows and EGARCH(1,1) process

$$\mathrm{Log}(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \varphi_1 \log(\sigma_{t-1}^2) \quad (4)$$

This model allows for exponential leverage effects in variance. Furthermore, forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis $\gamma_1 \neq 0$. As explained in section 2, stochastic explanatory variables *Xt,j* are Load, Brent Oil, Coal, Gas, Carbon, Temp, Renew, Netbal, and Seasonal Variables whose characteristics are in Table 1. Variables discussed in this section are motivated by theoretical considerations and make up public information available to market participants in a prompt way. We talk about expected effects of those variables on wholesale prices.

- *Load.* A proper specification of the effect of demand is essential as a chief influence on prices. Our demand variable is defined as the monthly average of daily final electricity consumption. We expect increases in load to be associated with increases in prices.
- *Brent Oil, Coal and Gas Prices.* Spot fuel prices stand for the relevant operational and opportunity costs. Depending on the structure of the generation assets the size of the influence of other fuel prices may be different across countries. But we expect the impact to be positive for all fuels.
- *Carbon Prices.* Increases (decreases) in the carbon price (CO2 emission allowances) discourages (encourages) production of energy from high carbon emitting power plants. This alters the production merit order of electricity suppliers, with corresponding effects on spot prices.
- *Temp.* Many studies (e.g. Knittel and Roberts, 2005) document that weather variables have explanatory power for electricity prices and so we include Daily average temperatures in degrees Celsius as a representative variable. In countries with low average temperatures, the expected sign is negative (decrease in demand and prices due to high temperatures) and is positive in the opposite case.
- *Renew*. The part of renewables over gross generation is our measure of the impact of renewables on spot prices. Several studies (e.g. Würzburg, Labandeira and

Linares, 2013) documents that increasing generation from renewables are associated with decreases in wholesale prices and may increase price volatility.

- *Netbal.* We define net balance (*Netbal*) as the difference between exports and imports of electricity. If domestic prices are below (above) prices in connected neighbour countries, is profitable to export (import) power from other countries. Therefore, the impact of Netbal may be dependent on two different situations. If in the domestic market there is high (low) demand and net balance is positive, we should see a positive (negative) correlation between domestic wholesale prices and Netbal, because less (more) net electricity available in the domestic market. But, if in the domestic market there is high (low) demand and net balance is negative, we should see a negative (positive) correlation between domestic wholesale prices and Netbal because net (exports) imports (increase) decrease domestic prices.
- *Seasonality*. A seasonal part is important, not least as a proxy for the yearly pattern of fuel prices. Monthly dummy variables and seasonal autoregressive coefficients were the most adequate representation.

Table 3 shows results of fitting a linear regression, based on the fundamental market factors. Estimation is by Maximum likelihood with Newey-West covariance matrix, robust to autocorrelation and heteroscedasticity.

[INSERT TABLE 3 HERE]

Load is significant in three cases (DK, FI and IT) with expected positive sign. Fuel prices (oil, coal, gas) are significant in seven cases, Brent oil in three cases (FR, IT, SE), coal in three cases (AT, DK, GE) and natural gas in one case (SE), always with the expected positive sign. The size of impact is associated with the composition of the generation assets in each country. Renewables presents significant and negative effect in all countries as expected. Carbon prices explain significantly electricity prices in five cases (AT, GE, GR, PT and SE) although in Sweden the coefficient is negative. Temperature has a negative and significant impact in two cases (DK, SE) corresponding to countries with low average temperatures, as expected. Netbalance presents positive impact in in three cases (DK, FI, GR) and negative impact in two cases (PT, SE). The reasons for these differing signs should be related to relative price issues, as discussed. Deterministic seasonality effects are captured by dummy variables, significant in five cases (AT, GE, IT, PT, SE). Stochastic seasonality effects appear in all cases as significant seasonal AR coefficients suggest.

EGARCH volatility is significant in all cases but leverage effects are significant in three cases only. In two cases (FR, GR) the effect is positive, meaning that positive shocks (unexpected increases in prices) increase price volatility, but in one case (PT) the effect is negative. Fit of models varies from 77% (SP) to 92% (DK). Conventional tests for multicollinearity, residual serial correlation, squared residuals, outliers' influence, endogeneity, normality and over-fitting all showed that there were no salient mis-specification problems.

Table 4 presents measures of Economic Impact[3] (EI) for explanatory variables. The higher (in absolute terms) the EI, stronger the explanatory power of the associated fundamental factor.

[INSERT TABLE 4 HERE]

[3] $EI(X) = \beta_x \sigma(X)/Mean(Y)$

Fuel prices show the highest EI in four countries; coal in Austria, Denmark and Germany and Brent Oil in France. Renewables show salient EI in Portugal and Spain but demand (load) has the highest EI in Finland and Italy. Temperature in Sweden and Netbal in Greece finish the list.

4.3 Retail prices: households

An important reason leading liberalization efforts in electricity markets across the EU was the expectation of achieving lower average EU prices and price convergence through wholesale and retail competition. Wholesale prices have decreased in all countries, see Figure 3,

[INSERT FIGURE 3 HERE]

However, electricity prices for households (and industrial) users have exploded in the sample period[4], see Figure 4. In 2017, average EU wholesale electricity prices are at their lowest for 12 years, gas prices have fallen by 50% since 2013 and oil prices by 60% since 2014. However, retail electricity prices have risen by 3% a year since 2008. The key factors are rising network costs and government taxes and levies.

[INSERT FIGURE 4 HERE]

In a recent paper Pereira da Silva and Cerqueira (2017) study the determinants of EU

[4] In fact, retail prices have increased in many EU countries almost constantly since the starting of the liberalization process in 1998. Between 1994 and 2014, average electricity prices for consumers in the EU - 15 countries have increased from 0.1020€ / kWh to 0.1429€ kWh, an increase of 40.1%. (http://ec.europa.eu/eurostat/data/database). See Florio (2014) for a review of the effects of liberalization of electricity markets in the EU.

electricity retail prices with annual data from 2000 to 2014 by a dynamic panel data model of lagged levels of the dependent variables and several explanatory variables (e.g. load per capita, real GDP per capita, gas prices, share of renewables, and carbon prices). Load, gas prices and renewable share are positively and significantly correlated with household prices apart from taxes and levies.

In this paper we adopt a different approach. Retail prices contain two elements, namely the cost of energy (based on wholesale prices and including distribution and transmission costs) and the "government wedge" (taxes and levies). Results in section 4.2 suggest that different variables explain wholesale prices in different countries. For instance, coal prices are the main price driver in Austria, Denmark and Germany, but are irrelevant in Portugal. So, we run a regression of household prices on direct measures of those two components, i.e. wholesale prices and (change in) government deficit. We hypothesize wholesale prices should explain the part of retail price due to the cost of energy. The size of the government wedge part is related to the current situation of public finances, as reflected in the public deficit, a macroeconomic indicator. Presumably, the higher the financial cost of subsidies funded out of the government budget, the higher the deficit and the higher the taxes and levies included in the "government wedge". High retail prices reflect rising taxes and the costs of supporting public policies levies, collected through electricity retail sales, Robinson (2015).

We model yearly household prices (ph_{it}) in the period 2008-2016 by a using model which includes two explanatory variables, wholesale prices (pw_{it}) and change in public deficit (ΔD_{it}). The model is

$$ph_{it} = \beta_1 pw_{it} + \beta_2 \Delta D_{it} + \epsilon_t \quad (5)$$

Parameters are estimated by maximum likelihood and the estimator of the covariance matrix is Newey-West (HAC). Results are in Table 5.

[INSERT TABLE 5 HERE]

A fact we find over and over again is that there are noticeable differences across countries. Wholesale prices are significantly and negatively correlated with household prices in seven countries (AT, DK, FI, FR, GE, GR and IT) whereas in the remaining three (PT, SP, SE) parameters are not statistically different from zero. The negative correlation may, at first sight, look surprising. But as Figures 3 and 4 make clear, both prices followed divergent trends in the sample. Therefore, the importance of the energy component in wholesale prices decreased, which explains the negative sign. Changes in public deficit have positive and significant explanatory power in six countries (AT, DK, FI, FR, GE and SP) suggesting that the government wedge component is explained to some extent by changes in the fiscal situation of a given country. We should stress the preliminary nature of these findings, given the size of the sample. However, we find the positive correlation between the taxes and levies included in the "government wedge" and the change in the budgetary situation to be economically appealing. The reason is that higher the subsidies, the higher the deficit and the higher the taxes and levies included in the "government wedge". This would imply high retail prices, as the empirical evidence suggests.

4.3 Retail prices: the changes in tariff setting methods in Spain

In this section we test the impact on retail prices of the change occurred in the method of setting regulated prices for small consumers in Spain. From July 2007 to March 2014 the tariff energy term (roughly 50% of the final invoice amount) was fixed by the CESUR auctions (last resort tariff, TUR). However, from April 2014 to the present, the Government implemented a new tariff setting system based on the PVPC (Voluntary Price for the Small Consumer).

To analyse the possible impact of these changes, we use two EUROSTAT series[5] which reports electricity prices for small consumers including and apart from all taxes and levies. Data are semi-annual and the sample is from the second semester of 2007 to the second semester of 2016, totalling nineteen observations. We fit a GARCH-AR(1) model to the natural logarithm of both series and include a dummy variable taking values equal to one from the first semester[6] of 2014 to the second semester of to December 2016 and zero elsewhere[7]. The coefficient of the dummy variable in both series is not different from zero neither in the mean equation nor in the variance equation. This suggests that the new tariff setting system does not impact significantly retail prices (including or excluding taxes and levies).

5. Simulations

This section presents the results of two Monte Carlo simulations. First, we study the expected distribution of electricity consumption by 2020 and 2030 and, based on the empirical distribution of simulated paths, compute the probabilities of compliance of the first target set by CEP in terms of cuts in consumption. Second, we analyze the expected

[5] 6000,4161903,KWH,I_TAX,EUR,ES Band DC 2500-5000kWh including taxes and 6000,4161903,KWH,E_TAX,EUR,ES Band DC 2500-5000kWh excluding taxes
[6] Results do not change if the dummy variable takes values equal to one from the second semester of 2014.
[7] To save space we summarize main results. Details are available on request.

distribution of generation by renewables as proportion over gross generation by 2020 and 2030 and, based on the empirical distribution of simulated paths, compute the probabilities of compliance of the second target set by CEP in terms of generation by renewables.

5.1 Electricity consumption

The first target set by CEP is cut by 20% in energy consumption by 2020 and by 27% by 2030 in comparison with average figures for 2008. In the case of electricity market we use load as the measure of energy consumption. We model yearly consumption in all countries by using an AR(2) model which allows for stochastic volatility, trends and cycles[8]. The model is

$$(1 - \rho_1 B - \rho_2 B^2) load_t = \mu + \sigma_t \epsilon_t \quad (6)$$

Based on this univariate model we do a Monte Carlo Analysis of 10,000 trajectories and compute 1% quantiles of empirical distribution of terminal values for horizons 2020 and 2030. We compare these quantiles against total amount used in 2008 and reductions of this amount by 20% and 27% respectively. Simulation results are summarized in Table 6.

[INSERT TABLE 6 HERE]

Results suggest the probability of achieving CEP's targets for horizons 2020 and 2030 are lower than 1% in all countries. We emphasize those results depend on the assumption of no significant policy changes on this matter appearing within the time horizons 2020 and 2030.

[8] Estimation results are not included to save space and are available on request. Conventional tests for residual serial correlation, non-constant variance, normality and over-fitting all indicated that there were no salient mis-specification problems.

5.2 Production from renewables

The second target set by CEP is production by renewables should amount at least to 20% of total gross energy production by 2020 and by 27% by 2030. We model yearly production by renewables divided by gross generation by using an AR(2) model which allows for stochastic volatility, trends and cycles[9]. The model is

$$(1 - \rho_1 B - \rho_2 B^2) renew_t = \mu + \sigma_t \epsilon_t \quad (7)$$

Based on this univariate model we do a Monte Carlo Analysis of 10,000 trajectories and compute 1%, 50% and 99% quantiles of empirical distribution of terminal values for horizons 2020 and 2030. Next, we compare these quantiles against CEP targets of 20% and 27% respectively. Simulation results are summarized in Table 5.2.

[INSERT TABLE 5.2 HERE]

Results suggest the probability of achieving CEP's targets for horizons 2020 and 2030 differs across countries. Austria, Denmark, Portugal and Sweden present probabilities of non-compliance below 1% for both horizons. Germany presents a 2% probability of non-compliance by 2020. In Greece (1%), Spain (5%) and Italy (10%) risk of non-compliance for 2030 appears. For horizon 2020 (2030), France and Finland present non-compliance probabilities of 80% (above 99%) and 40% (80%) respectively. So, as results suggest, if prompt action is not taken, at least two countries (Finland and specially France) will face large challenges in achieving CEP targets. Three other countries (Italy, Spain and Greece)

[9] Estimation results are not included to save space and are available on request. Conventional tests for residual serial correlation, heteroscedasticity, normality and over-fitting all indicated that there were no particular mis-specification problems.

may face the risks towards horizon 2030. Again, we stress results follow from the assumption of no significant policy changes on this matter will appear within the time horizons 2020 and 2030.

6. Conclusions and Policy Implications

In this paper, we study whether fundamental variables have explanatory power for monthly wholesale electricity prices for ten EU countries in the period 2008-2016. Variables such as demand, fuel prices, renewable-based production, weather variables and net balance between exports and imports help to explain monthly wholesale prices. But the significance and size of their impact varies markedly across countries

We also report evidence suggesting that household retail prices are explained by wholesale prices and changes in public deficit. Although we stress the preliminary nature of this result, we find the positive correlation between the taxes and levies included in the "government wedge" and the change in the budgetary situation to be economically meaningful. Higher government deficits hint at higher electricity retail prices.

Monte Carlo simulations indicate that the probability of achieving CEP's target of reductions in energy consumption for horizons 2020 and 2030 are lower than 1% in all countries. This result has profound policy implications. Simulations are based on the assumption of stable prices. If retail prices decrease due to the impact of renewables and to improvements in fiscal balances energy consumption will be still higher. To achieve substantive reductions in amount used, definite policy actions should be taken.

Another point of concern is that France and Finland present non-compliance probabilities of 80% (above 99%) and 40% (80%) respectively in horizons 2020 (2030) on CEP's target of part of generation by renewables. These results emerge from the natures of their generation assets. For instance in France generation is based on nuclear sources to a considerable extent. The change from these generation assets to other with greener and sustainable characteristics presents major challenges to policymakers. If steps are not taken in this direction, is easy to expected growing opposition from these two countries to EU's intents of enforcement of CEP's target on renewables.

Also, the results bring out an important issue about the mutual consistency of two of the EU's Climate and Energy Package targets. Empirical evidence suggests that increase in generation from renewables decreases significantly wholesale prices in all countries. Therefore, the energy part of retail prices, based on wholesale prices, also declines. Declines in retail prices encourage consumption. The consequence is a clash between CEP's target of cut in consumption and CEP's target of increased production from renewables. If governments put more weight in the target of cut in consumption and increase the non-energy part of retail prices, the discontent of consumers with liberalized electricity market will increase. If governments support increases in renewable generation, the downward pressure on prices will increase, making the cut in consumption still more problematic. Furthermore, in 2017 the European Commission has proposed binding targets for 2030 in conflict with the agreement at European Council in 2014 that there would be no binding targets for energy efficiency.

In summary, results are relevant for testing liberalized electricity markets in Europe and point out that ambitious policy goals of integrating European electricity markets face large challenges, including mutually inconsistent CEP’s targets.

References

Barndorff-Nielsen, Ole E. 1997. "Normal Inverse Gaussian Distributions and Stochastic Volatility Modelling." *Scandinavian Journal of Statistics* 24 (1): 1-13.

Benth, Fred Espen and Steen Koekebakker. 2008. "Stochastic Modeling of Financial Electricity Contracts." *Energy Economics* 30 (3): 1116-1157.

Benth, Fred Espen and Jurate Saltyte-Benth. 2004. "The Normal Inverse Gaussian Distribution and Spot Price Modelling in Energy Markets." *International Journal of Theoretical and Applied Finance* 7 (2): 177-192.

Berkowitz, Jeremy. 2001. "Testing Density Forecasts, with Applications to Risk Management." *Journal of Business & Economic Statistics* 19 (4): 465-474.

Bublitz, Andreas, Dogan Keles, and Wolf Fichtner. 2017. "An Analysis of the Decline of Electricity Spot Prices in Europe: Who is to Blame?" *Energy Policy* 107: 323-336.

Cartea, Álvaro and Marcelo G. Figueroa. 2005. "Pricing in Electricity Markets : A Mean Reverting Jump Diffusion Model with Seasonality." . *Applied Mathematical Finance*, 25, 123-134.

Conejo, A. J., M. A. Plazas, R. Espinola, and A. B. Molina. 2005. "Day-Ahead Electricity Price Forecasting using the Wavelet Transform and ARIMA Models." *IEEE Transactions on Power Systems* 20 (2): 1035-1042.

Contreras, J., R. Espinola, F. J. Nogales, and A. J. Conejo. 2003. "ARIMA Models to Predict Next-Day Electricity Prices." *IEEE Transactions on Power Systems* 18 (3): 1014-1020. Coulon, Michael and Sam Howison. 2009. "Stochastic Behavior of the Electricity Bid Stack: From Fundamental Drivers to Power Prices." *Journal of Energy Markets* 2 (1): 29-69.

Diebold, Francis X., Joon-Haeng Lee, and Gretchen C. Weinbach. 1994. "Regime Switching with Time-Varying Transition Probabilities." *Business Cycles: Durations, Dynamics, and Forecasting*: 144-165.

Escribano, A., J. I. Peña, and P. Villaplana. 2011. "Modelling Electricity Prices: International Evidence." *Oxford Bulletin of Economics and Statistics* 73 (5): 622-650.

Florio M. 2014. “Energy reforms and Consumer prices in the EU over twenty years”. *Economics of Energy and Environmental Policy*, 3:37–52.

Forsberg, Lars and Tim Bollerslev. 2002. "Bridging the Gap between the Distribution of Realized (ECU) Volatility and ARCH Modelling (of the Euro): The GARCH-NIG Model." *Journal of Applied Econometrics* 17 (5): 535-548.

Gao, Feng, Xiaohong Guan, Xi-Ren Cao, and Alex Papalexopoulos. 2000. "Forecasting Power Market Clearing Price and Quantity using a Neural Network Method." *IEEE Transactions on Power Systems* 20 (2): 867-874.

Garcia, R. C., J. Contreras, M. van Akkeren, and J. B. C. Garcia. 2005. "A GARCH Forecasting Model to Predict Day-Ahead Electricity Prices." *IEEE Transactions on Power Systems* 20 (2): 867-874.

Garcia-Martos, C., J. Rodriguez, and M. J. Sanchez. 2007. "Mixed Models for Short-Run Forecasting of Electricity Prices: Application for the Spanish Market." *IEEE Transactions on Power Systems* 22 (2): 544-552.

Gareta, Raquel, Luis M. Romeo, and Antonia Gil. 2006. "Forecasting of Electricity Prices with Neural Networks." *Energy Conversion and Management* 47 (13): 1770-1778.

Geman, Hélyette and Andrea Roncoroni. 2006. "Understanding the Fine Structure of Electricity Prices." *The Journal of Business* 79 (3): 1225-1261.

Guirguis, H., and Felder, F. 2004. “Further Advances in Forecasting Day-Ahead Electricity Prices Using Time Series Models”. *KIEE International Transactions on Power Engineering*, 4, 159−166.

Granger, Clive W. J., Timo Teräsvirta, and Heather M. Anderson. 1993. "Modeling Nonlinearity Over the Business Cycle." In *Business Cycles, Indicators and Forecasting*, 311-326: National Bureau of Economic Research, Inc.

Hansen, Peter R., Asger Lunde, and James M. Nason. 2011. "The Model Confidence Set." *Econometrica* 79 (2): 453-497.

Huurman, Christian, Francesco Ravazzolo, and Chen Zhou. 2012. "The Power of Weather." *Computational Statistics & Data Analysis* 56 (11): 3793-3807.

Janczura, Joanna and Rafal Weron. 2009. "Regime-Switching Models for Electricity Spot Prices: Introducing Heteroskedastic Base Regime Dynamics and Shifted Spike Distributions.".

Janczura, Joanna and Rafał Weron. 2012. "Efficient Estimation of Markov Regime-Switching Models: An Application to Electricity Spot Prices." *AStA Advances in Statistical Analysis* 96 (3): 385-407.

Jonsson, T., P. Pinson, H. A. Nielsen, H. Madsen, and T. S. Nielsen. 2013. "Forecasting Electricity Spot Prices Accounting for Wind Power Predictions." *IEEE Transactions on Sustainable Energy* 4 (1): 210-218.

Karakatsani, Nektaria V. and Derek W. Bunn. 2008. "Forecasting Electricity Prices: The Impact of Fundamentals and Time-Varying Coefficients." *International Journal of Forecasting* 24 (4): 764-785..

Karlis, Dimitris. 2002. "An EM Type Algorithm for Maximum Likelihood Estimation of the Normal–inverse Gaussian Distribution." *Statistics and Probability Letters* 57 (1): 43-52.

Kass, R.E., Raftery, A.E., 1995. “Bayes factors”. *Journal of the American Statistical Association*. 90 (430), 773–795.

Knittel, Christopher R. and Michael R. Roberts. 2005. "An Empirical Examination of Restructured Electricity Prices." *Energy Economics* 27 (5): 791-817.

Li, Lingfei, Rafael Mendoza-Arriaga, Zhiyu Mo, and Daniel Mitchell. 2016. "Modelling Electricity Prices: A Time Change Approach." *Quantitative Finance* 16 (7): 1089-1109.

Li, W. K., and T. K. Mak. "On the Squared Residuals Autocorrelations In Non-Linear Time Series With Conditional Heteroskedasticity." Journal of Time Series Analysis 15, no. 6 (1994): 627-636.

Misiorek, Adam, Stefan Trueck, and Rafal Weron. 2006. "Point and Interval Forecasting of Spot Electricity Prices: Linear Vs. Non-Linear Time Series Models." *Studies in Nonlinear Dynamics & Econometrics* 10 (3): 2.

Mugele, Christian, Svetlozar T. Rachev, and Stefan Truck. 2005. "Stable Modeling of Different European Power Markets." *Investment Management and Financial Innovations* 2 (3): 65-85.

Nogales, F. J., J. Contreras, A. J. Conejo, and R. Espinola. 2002. "Forecasting Next-Day Electricity Prices by Time Series Models." *IEEE Transactions on Power Systems* 17 (2): 342-348.

Peña, J. I. and R. Rodriguez. 2016 “Time-Zero Efficiency of European Power Derivatives Markets”. *Energy Policy, 9*5, 253-268.

Pereira da Silva, P. and P.A. Cerqueira. 2017. “Assessing the determinants of household electricity prices in the EU: a system-GMM panel data approach”. *Renewable and Sustainable Energy Reviews* 73 (2017) 1131–1137.

Rambharat, B. R., Brockwell, A. E., and Seppi, D. J. 2005. “A threshold autoregressive model for wholesale electricity prices”. *Journal of the Royal Statistical Society*, Series C, 54, 287−299.

Robinson, D. 2015. “The Scissors Effect”. *Oxford Institute for Energy Studies, paper El 14.*

Rosenblatt, Murray. 1952. "Remarks on a Multivariate Transformation." *The Annals of Mathematical Statistics* 23 (3): 470-472.

Schwarz, Gideon. 1978. "Estimating the Dimension of a Model." *The Annals of Statistics* 6 (2): 461-464.

Shafie-khah, M., M. Parsa Moghaddam, and M. K. Sheikh-El-Eslami. 2011. "Price Forecasting of Day-Ahead Electricity Markets using a Hybrid Forecast Method." *Energy Conversion and Management* 52 (5): 2165-2169.

Vehvilainen, I., and Pyykkonen, T. 2004. Stochastic factor model for electricity spot price – the case of the Nordic market. *Energy Economics*, 27, 351−367.

Weron, Rafal. 2014. "Electricity Price Forecasting: A Review of the State-of-the-Art with a Look into the Future." *International Journal of Forecasting* 30 (4): 1030-1081.

Weron, Rafał and Adam Misiorek. 2008. "Forecasting Spot Electricity Prices: A Comparison of Parametric and Semiparametric Time Series Models." *International Journal of Forecasting* 24 (4): 744-763.

Weron, Rafał, Ingve Simonsen, and Piotr Wilman. 2004. "Modeling Highly Volatile and Seasonal Markets: Evidence from the Nord Pool Electricity Market." In *The Application of Econophysics*, 182-191: Springer.

Wolak, Frank A. 2000. "Market Design and Price Behavior in Restructured Electricity Markets: An International Comparison." In *Deregulation and Interdependence in the Asia-Pacific Region, NBER-EASE Volume 8*, 79-137: National Bureau of Economic Research, Inc

Würzburg, K. X. Labandeira and P. Linares. 2013. “Renewable generation and electricity prices: Taking stock and new evidence for Germany and Austria”. *Energy Economics* 40, Supplement 1, S159-S171.

Worthington, Andrew, Adam Kay-Spratley, and Helen Higgs. 2005. "Transmission of Prices and Price Volatility in Australian Electricity Spot Markets: A Multivariate GARCH Analysis." *Energy Economics* 27 (2): 337-350.

Table 1: Wholesale Electricity Prices and Explanatory Variables

This table contains definitions and sources of wholesale electricity prices and explanatory variables for models in section 4.

Country	Source Name	Web Page
Austria	EXAA	http://www.exaa.at/en/marketdata/historical-data
Denmark	ENERGINET	https://en.energinet.dk/Electricity/Energy-data
Finland	NORDPOOL	http://www.nordpoolspot.com/Market-data1/Elspot/Area-Prices/FI/Monthly/?view=table
Germany	ENERGINET	https://en.energinet.dk/Electricity/Energy-data
Greece	GME	http://www.mercatoelettrico.org/En/Download/DatiStorici.aspx
France	GME	http://www.mercatoelettrico.org/En/Download/DatiStorici.aspx
Italy	GME	http://www.mercatoelettrico.org/En/Download/DatiStorici.aspx
Portugal	OMIP	http://www.omip.pt/Downloads/tabid/104/language/en-GB/Default.aspx
Spain	OMIP	http://www.omip.pt/Downloads/tabid/104/language/en-GB/Default.aspx
Sweden	ENERGINET	https://en.energinet.dk/Electricity/Energy-data

Explanatory V.	
BRENT OIL	Brent Oil Crude Oil (petroleum), Dated Brent, light blend 38 API, fob U.K., Euro per Barrel
COAL	Coal Coal, Australian thermal coal, 12000- btu/pound, less than 1% sulfur, 14% ash, FOB Newcastle/Port Kembla, Euro per Metric Ton
GAS	Natural gas Natural Gas, Natural Gas spot price at the Henry Hub terminal in Louisiana, Euro per Million Metric British Thermal Unit
RENEW	Proportion of renewables: Generation by Renewables/Gross Generation
LOAD	Consumption (load) in GWh
CARBON	Carbon prices ECX EUA Futures, Continuous Contract #1 (C1) (Front Month)
TEMP	Average Daily temperatures in degrees Celsius
NETBAL_DIV	(Exports of electricity - Imports of electricity)/1000
Sources	***ENTSOE, EnergyNet, Eurostat, IEA, IndexMundi, Quandl, World Bank***

Table 2: Descriptive Statistics of Monthly Electricity Prices

The table shows descriptive statistics of monthly electricity prices. The time span is from 01/2008 to 12/2016 for Austria (AT), Denmark (DK), Spain (ES), Finland (FI), Germany (GE), Italy (IT), Portugal (PT), Sweden (SE), France (FR) and Greece (GR). Units in €/MWh.

	AT	DK	FI	FR	GE	GR	IT	PT	SP	SE
Mean	41.76	39.39	41.13	60.39	41.58	58.22	63.62	46.50	45.73	38.64
Median	38.83	37.68	38.11	61.13	39.11	57.12	63.71	47.13	46.56	35.37
Maximum	89.19	77.67	93.70	91.70	88.30	90.80	99.07	76.55	73.03	93.99
Minimum	22.58	13.72	13.67	30.83	21.99	32.15	31.99	15.39	17.12	9.10
Std. Dev.	12.45	12.31	12.53	12.36	12.30	13.39	14.43	12.92	11.69	14.36
Skewness	1.29	0.73	1.64	-0.03	1.25	0.20	0.16	0.08	-0.11	1.25
Kurtosis	5.35	3.64	7.11	3.11	5.20	2.55	2.75	3.20	3.01	5.61
JB Pval	0.00	0.00	0.00	0.96	0.00	0.44	0.68	0.87	0.89	0.00
Sample	108	108	108	108	108	108	108	108	108	108
CV=SD/M	0.30	0.31	0.30	0.20	0.30	0.23	0.23	0.28	0.26	0.37

Table 3: Determinants of Wholesale Electricity Prices

This table present results of $p_{t,j} = \beta_0 + \sum_{j=1}^{K} \beta_j X_{t,j} + \eta_t$ where the dependent variable $p_{j,t}$ is the wholesale electricity price in country j at time t, and $X_{t,j}$ are explanatory variables and $\phi(B)\eta_t = \theta(B)\sigma_t \varepsilon_t$. σ_t is the volatility and the innovation ε_t is N(0, σ_t). Volatility follows and EGARCH(1,1) process $\text{Log}(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \varphi_1 \log(\sigma_{t-1}^2)$.The presence of leverage effects can be tested by the hypothesis $\gamma_1 \neq 0$ Parameters are estimated by maximum likelihood and the estimator of the covariance matrix is Newey-West (HAC) robust to autocorrelation and heteroscedasticity. Parameters in **boldface** (*cursive*) are significant at 1% (5%) level.

	AT	DK	FI	FR	GE	GR	IT	PT	SP	SW
BRENTOIL	*0.053*	-0.011	0.016	**0.326**	-0.028	*0.134*	**0.265**	-0.058	-0.039	**0.039**
COAL	**0.197**	**0.238**	0.075	*0.171*	**0.283**	0.095	0.079	-0.007	0.096	0.209
GAS	0.731	-0.333	0.527	*-2.703*	-1.124	-0.198	1.083	-1.311	-1.463	**0.457**
RENEW	**-34.078**	**-25.203**	**-76.823**	**-104.875**	**-25.840**	*-23.271*	**-52.390**	**-29.071**	**-37.476**	**-47.187**
LOAD	0.002	**0.000**	**0.015**	0.000	-0.001	0.002	**0.005**	**-0.017**	0.002	-0.002
CARBON	**0.472**	-0.107	0.010	*0.536*	**0.458**	**0.530**	0.081	**0.284**	-0.131	**-0.065**
TEMP	-0.345	**-0.971**	-0.421	0.588	-0.423	-0.009	-0.307	-1.112	0.598	**-1.505**
NETBAL_DIV	-0.307	**8.658**	**11.213**	-0.873	-0.174	**14.739**	0.606	**-9.580**	-0.643	**-5.939**
@MONTH=1	*21.055*	-9.602	*-68.942*	49.761	**46.903**	*40.896*	**-84.478**	**154.663**	15.543	**69.707**
@MONTH=2	*22.727*	-4.480	*-54.637*	47.017	**48.346**	*39.108*	**-79.754**	**148.671**	16.406	**72.578**
@MONTH=3	*23.181*	-5.040	*-61.888*	43.145	**47.229**	34.627	**-85.950**	**144.712**	8.566	**73.677**
@MONTH=4	**27.448**	4.436	-46.449	40.969	**46.376**	32.154	**-73.097**	**138.759**	10.769	**74.004**
@MONTH=5	**31.700**	13.246	-27.907	39.518	**45.901**	33.208	**-75.589**	**148.617**	12.855	**81.346**
@MONTH=6	**33.659**	19.437	-17.987	40.107	**48.043**	33.504	**-77.771**	**152.086**	12.166	**83.430**
@MONTH=7	**34.870**	19.776	-20.403	41.580	**51.133**	37.992	**-89.501**	**158.512**	6.195	**81.914**
@MONTH=8	**33.919**	22.198	-16.565	37.478	**48.384**	37.936	**-64.812**	**153.983**	7.412	**87.561**
@MONTH=9	**35.052**	19.826	-23.248	39.779	**50.694**	36.164	**-75.207**	**154.238**	13.591	**83.631**
@MONTH=10	**31.217**	9.258	-44.642	38.808	**52.332**	*36.909*	**-76.410**	**156.158**	17.113	**74.994**
@MONTH=11	**26.948**	2.592	*-51.450*	43.119	**49.401**	*37.888*	**-77.123**	**151.669**	17.914	**71.186**
@MONTH=12	*20.476*	-4.528	-58.595	46.770	**45.875**	*37.899*	**-76.732**	**154.867**	20.344	**69.047**
AR(1)	**0.271**	*0.173*	**0.382**	**0.673**	0.271	**0.382**	**0.650**	**0.492**	**0.713**	**0.396**
AR(2)	0.089	-0.102	-0.062	**0.003**	-0.065	*0.205*	0.023	*0.151*	0.081	-0.018
AR(6)	0.019	*-0.090*	**-0.053**	**-0.118**	-0.039	-0.056	0.018	0.014	0.044	-0.069
AR(12)	**-0.232**	**-0.550**	**-0.575**	**-0.313**	-0.119	-0.045	-0.058	**-0.448**	**-0.205**	**-0.187**
AR(24)	**-0.116**	**-0.498**	**-0.609**	**-0.347**	**-0.176**	-0.145	**-0.282**	**-0.277**	-0.107	0.033
AR(36)	*-0.113*	**-0.590**	**-0.485**	0.046	0.011	**0.368**	0.123	-0.016	0.057	-0.005
ω	1.049	**1.057**	2.749	**5.660**	**0.100**	**3.163**	3.321	**2.650**	1.751	0.491
α_1	**1.734**	**-0.645**	*0.625*	-0.076	**0.872**	-0.529	0.094	**-1.077**	0.515	**2.810**
γ_1	0.064	-0.223	0.146	*0.357*	0.005	*0.525*	-0.100	**-1.152**	-0.286	-0.063
φ_1	-0.297	**0.742**	-0.127	**-0.725**	**0.662**	-0.041	-0.256	**0.370**	0.272	-0.016
Adjusted R-squared	0.882	0.918	0.766	0.825	0.847	0.883	0.895	0.801	0.771	0.806
Q(24)(r)	23.550	28.141	23.442	21.801	29.925	21.294	**37.653**	16.873	17.361	21.664
Q(24)(r^2)	37.036	15.745	17.009	20.255	20.396	15.150	17.814	15.224	25.252	25.111
JB	1.453	2.365	7.948	2.680	0.471	2.762	0.391	0.408	1.407	2.727
Sample size	108	108	108	108	108	108	108	108	108	108

Table 4: Economic Impact of Determinants of Wholesale Electricity Prices

This table presents the EI from regression results in Table 3. EI(X) = $\beta_x \sigma$ (X)/Mean(Y). The coefficient of the variable with strongest impact is in boldface.

	AU	DK	FI	FR	GE	GR	IT	PO	SP	SW
BRENTOIL	0.023	-0.005	0.007	**0.099**	-0.012	0.042	0.077	-0.023	-0.016	0.019
COAL	**0.147**	**0.189**	0.057	0.088	**0.212**	0.051	0.039	-0.004	0.066	0.169
GAS	0.021	-0.010	0.016	-0.054	-0.033	-0.004	0.021	-0.034	-0.039	0.014
RENEW	-0.101	-0.086	-0.116	-0.059	-0.032	-0.036	-0.068	**-0.095**	**-0.085**	-0.075
LOAD	0.018	0.061	**0.364**	-0.010	-0.039	0.020	**0.133**	-0.101	0.044	-0.130
CARBON	0.077	-0.019	0.002	0.060	0.075	0.062	0.009	0.042	-0.020	-0.011
TEMP	-0.057	-0.150	-0.093	0.048	-0.066	-0.001	-0.031	-0.120	0.081	**-0.321**
NETBAL_DI	-0.005	0.113	0.101	-0.026	-0.009	**0.077**	0.003	-0.092	-0.008	-0.170

Table 5: Determinants of Household Electricity Prices

We model yearly household prices (ph_{it}) in the period 2008-2016 by a using model which includes two explanatory variables, wholesale prices (pw_{it}) and change in public deficit *(DD_{it})*. Parameters are estimated by maximum likelihood and the estimator of the covariance matrix is Newey-West (HAC). Parameters in boldface are significant at 1% level.

	AT	DK	FI	FR	GE	GR	IT	PT	SP	SE
Wholesale	**-0.421**	**-1.323**	**-0.641**	**-1.251**	**-3.179**	**-1.770**	**-1.102**	-0.971	1.275	0.250
D(Public Defict)	**1.638**	**3.760**	**2.885**	**6.201**	**9.588**	0.471	2.220	5.990	**4.984**	4.335
Adjusted R-squared	0.389	0.742	0.493	0.690	0.811	0.374	0.348	0.153	0.322	-0.020
Q(7)(r)	7.565	9.771	14.134	4.263	3.399	10.290	7.461	15.795	8.428	12.343
Q(7)(r^2)	5.551	3.354	13.740	12.040	8.565	6.160	1.972	13.434	17.593	4.117
JB	1.453	2.365	7.948	2.680	0.471	2.762	0.391	0.408	1.407	2.727
Sample size	8	8	8	8	8	8	8	8	8	8

Table 6: Electricity consumption in 2020 and 2030

The table shows results of a Monte Carlo Analysis of 10000 trajectories We model yearly consumption in all countries by using an AR(2) model $(1 - \rho_1 B - \rho_2 B^2) load_t = \mu +$

$\sigma_t \epsilon_t$. Based on this model we compute the 1% quantile of the empirical distribution of load terminal values for horizons 2020 and 2030 and compare these quantiles against total consumption in 2008 and CEP targets (reductions of 20% and 27% respectively). Units are GWh

	AT	DK	FI	FR	GE	GR	IT	PT	SP	SE
Load 2008	68378	85199	87267	494499	557162	56310	339481	50592	263995	158170
Target 2020	54702	68159	69814	395599	445730	45048	271585	40474	211196	126536
Q(1%,2020)	**69923**	**71952**	**81169**	**449278**	**497433**	**47553**	**282410**	**46697**	**252348**	**131285**
Target 2030	49916	62195	63705	360984	406728	41106	247821	36932	192716	115464
Q(1%,2030)	**71572**	**70818**	**81098**	**449227**	**498818**	**47461**	**279686**	**46726**	**252333**	**130764**
Observations	10000	10000	10000	10000	10000	10000	10000	10000	10000	10000

Table 7: Production by renewables in 2020 and 2030

The table shows results of a Monte Carlo Analysis of 10000 trajectories We model yearly production by renewables in all countries by using an AR(2) model $(1-\rho_1 B -$ $\rho 2B2renewt= \mu+\sigma t\epsilon t$. Based on this model we compute 1%, 50% and 99% quantiles of the empirical distribution of renew terminal values for horizons 2020 and 2030 and compare these quantiles against CEP targets (20% and 27% respectively). Units are percentage of generation by renewables divided by gross generation.

	AT	DK	FI	FR	GE	GR	IT	PT	SP	SE
Target 2020	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
Q(1%,2020)	49%	32%	**11%**	**11%**	**19%**	24%	21%	34%	25%	41%
Q(50%,2020)	69%	56%	24%	**17%**	32%	36%	34%	48%	36%	50%
Q(99%,2020)	89%	81%	37%	23%	46%	47%	47%	61%	48%	59%
Target 2030	27%	27%	27%	27%	27%	27%	27%	27%	27%	27%
Q(1%,2030)	48%	36%	**11%**	**10%**	32%	**27%**	**21%**	33%	**24%**	40%
Q(50%,2030)	69%	64%	**24%**	**17%**	64%	40%	34%	48%	36%	53%
Q(99%,2030)	89%	92%	37%	**23%**	98%	53%	48%	62%	48%	66%
Observations	10000	10000	10000	10000	10000	10000	10000	10000	10000	10000

Figure 1: Monthly Electricity Wholesale Spot Prices

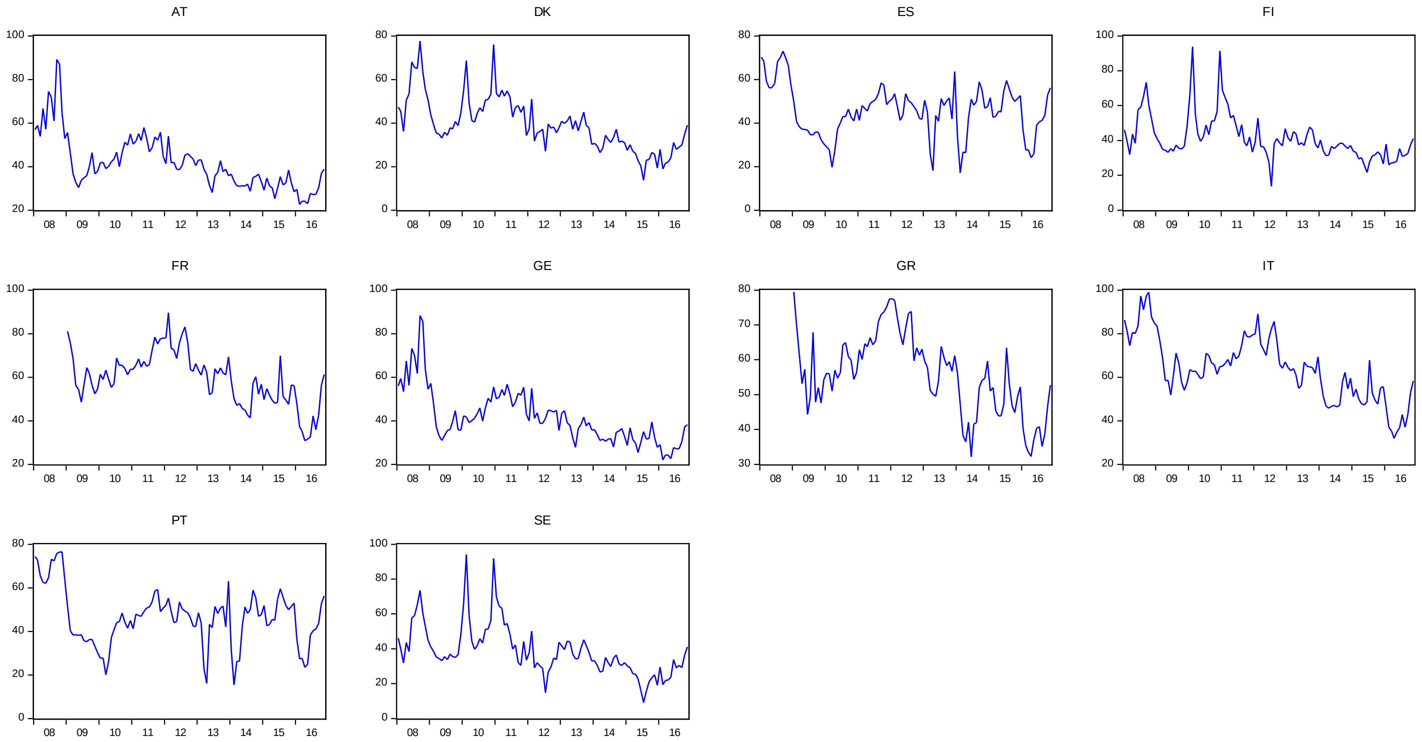


Figure 2: Monthly Averages

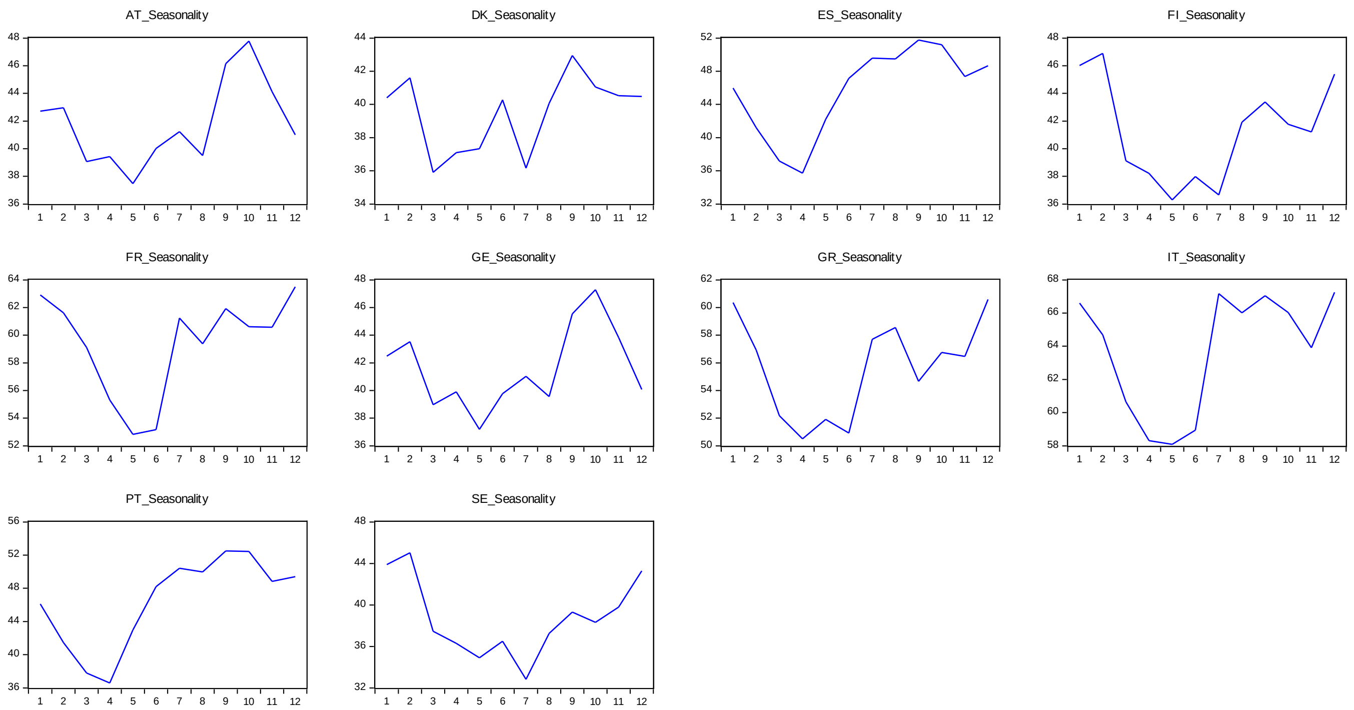


Figure 3. Yearly Wholesale prices €/MWh.

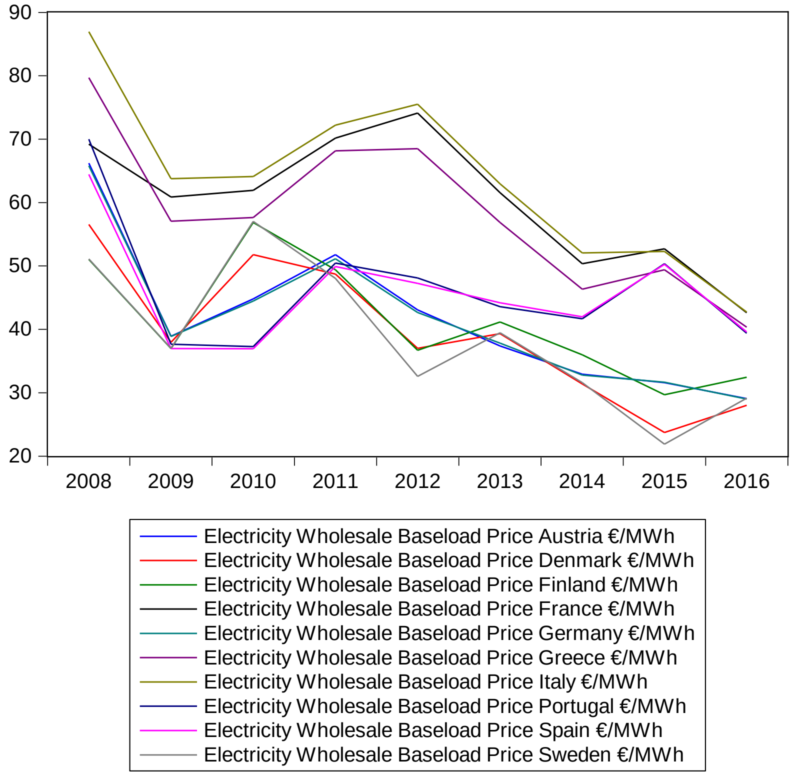
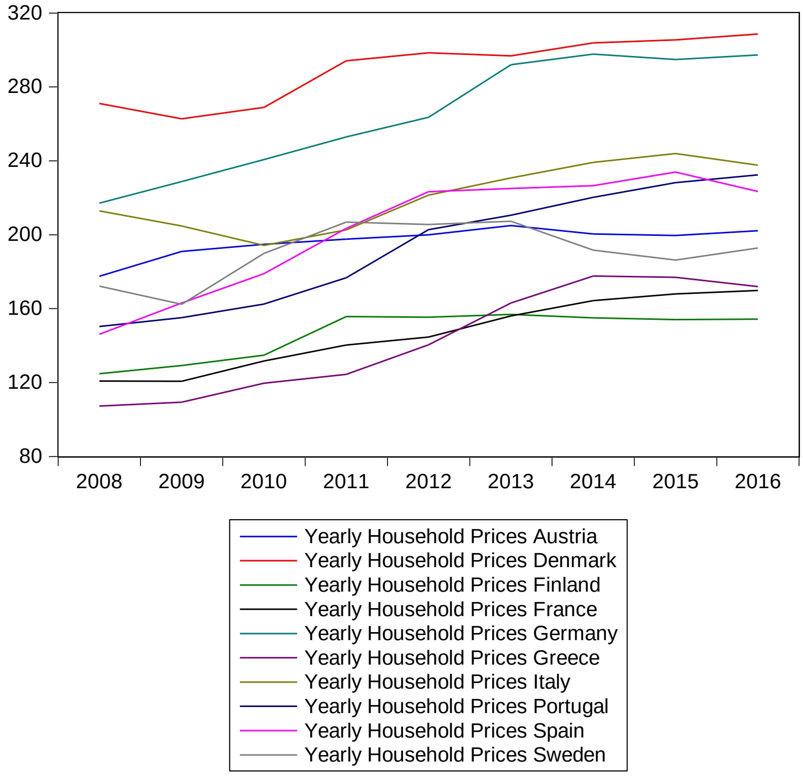


Figure 4. Yearly Household prices c€/MWh. Prices include all taxes and levies.



The Determinants of EU Electricity prices: Wholesale and Retail

APPENDIX A

I. Univariate Models for Spot price

(I) Literature Review

Electricity spot (day-ahead) prices present specific characteristics, different to other energy commodities. Knittel and Roberts (2005) study the behavior of California's restructured hourly electricity prices from 1998 to 2000 and point out the following characteristics: (a), stationarity in both the price level and squared prices; (b), intraday, weekly and seasonal cycles; (c), extreme price swings in short time; (d), censoring from above; (e), existence of negative prices; (f), positive skew that is larger (smaller) during periods of high (low) demand variability; (g), volatility is higher (lower) during periods of high (low) demand; (h) inverse leverage effect, which means that electricity price's volatility tends to rise more with positive shocks than with negative shocks. In the book from Ito et al.. (2000), Wolak conducts an international comparison of the behavior of spot electricity prices. He chooses the half-hourly (hourly in the case of Nord Pool) prices from England & Wales market (1990-1997), Nord Pool (Norway and Sweden, 1992-1997), Victoria (1994-1997) and New Zealand (1996-1997). First, he finds "tremendous volatility" in days and weeks. It is also interesting about how generation technology can affect the market prices both in mean and in standard deviation. He reports that prices in markets dominated by fossil fuel (England & Wales and Victoria) tend to be much more volatile than prices in markets dominated by hydroelectric capacity (Nord Pool and New Zealand). And this is also confirmed by the fact that even in an integrated system like New Zealand, the region with electricity produced principally from fossil fuel experiences higher spot price volatility. However, the effect of generation technology on the average of electricity spot price is the other way around. Wolak points out that average price in the fossil fuel-dominated markets tends to be more stable across years than prices in the hydroelectric-dominated system. In a comprehensive study, Escribano, Peña, and Villaplana (2011) study electricity spot prices of several markets around the world including European countries, North American countries and other countries like Argentina and Australia. They summarize four main characteristics of electricity spot prices that should be included simultaneously: Seasonality (monthly and weekly), mean-reverting, jumps (the price jump does not stay in the new level but reverts to the previous level rapidly), and volatility (high volatility and volatility clustering). From these three studies, we may gather that a specific model should be used to take into account a specific price behavior in a given market. Literature e.g Cartea and Figueroa (2005), suggest that the electricity prices should be decomposed into two components: deterministic component and stochastic component. The deterministic part will account for time trend, seasonality, or other fixed effects of price series, while the stochastic part will consider the mean-reversion, non-constant volatility or jumps exhibited in the price series. The general format of univariate models we will estimate in this paper is the following:

$$\ln(p_t) = s_t + x_t \tag{A1}$$

1.1 Deterministic seasonality

There are many ways of estimating the deterministic part, see Weron (2014) for a review of literature. Specific formulations of deterministic components depend on the time interval of data. For instance, the following specification has been used in many papers to capture the trend and seasonal cycles with daily data (assuming 365 trading days in the year):

$$s(t) = \alpha_1 + \alpha_2 \frac{t}{365} + \alpha_3 \cos\left(\alpha_4 + 2\pi \frac{t}{365}\right) + \alpha_5 \cos\left(\alpha_6 + 4\pi \frac{t}{365}\right) \tag{A2}$$

Where t takes values from 1 to N, where N is the number of daily observations in the sample. Alternatively, dummy variables taking into account daily effects (week-of-day), monthly effects or quarterly effects (season effects) may also be used. Unless indicated otherwise, in what follows, we discuss models for the stochastic factor of spot prices x_t.

1.2 Autoregressive Models

Considering price as a time series with autocorrelation across time both in prices and errors, the Autoregressive Integrated Moving Average (ARIMA) model is the most widely used model to deal with this problem. Contreras et al. (2003) apply this model to predict the electricity spot price in the Spanish market and Californian market. Instead of using the general ARIMA model, the authors proposed an ARIMA model with special forms:

$$\phi(B)p_t = \theta(B)\varepsilon_t$$

$$\phi(B) = 1 - \sum_{l=1}^{\phi} \phi_l B^l\,;\;\; \theta(B) = 1 - \sum_{l=1}^{\theta} \theta_l B^l$$

Functions $\phi(B)$ and $\theta(B)$ are polynomial functions of the backshift operator B. Thus, some of the coefficients ϕ_l and θ_l can be set to 0. Then, by choosing the lag l, hourly, weekly, or other seasonal effects can be accounted for. Because the Spanish market shows more volatility, they find that the Spanish model needs more lagged prices in order to predict future spot price than Californian market does. Similar to the ARMA model, ARIMA model also performs better when price volatility is low. To the authors' opinion, the mean weekly error, which is an average of the seven-daily mean error, around 10% may be acceptable, but this view is open to question. However, later, Weron and Misiorek (2008) conduct a comparison between AR model and ARIMA model applied in the literature focus on Californian market as well. In order to cope with weekly seasonality, their best model structure for AR model is to include lags for month and weekend. Somewhat surprisingly, they report that, in their sample, AR model performs better than ARIMA model. This result shows proof for the mean-reverting behavior in electricity price, but it seems including MA terms do not help forecast.

Despite the performance of the AR-type model, there is one fact about spot electricity prices that cannot be neglected, heteroscedasticity both in unconditional and conditional variance. In this case, Generalized AutoRegressive Conditional Heteroskedastic models (GARCH) are commonly used for control heteroscedasticity. Garcia et al. (2005) study the Spanish market and Californian market around 1999 to 2000. They find support for the generalized heteroskedastic error specification. Additionally, they conclude that GARCH model outperforms ARIMA model when there are high volatility and price spikes. But, when comparing GARCH model's performance in high-volatility periods against its performance in low volatility periods, the results still seems to show that GARCH model does a better job when there is less volatility in the price; when there is high volatility, GARCH model captures the general trend, but it usually fails to predict dramatic price fluctuations. Mugele et al. (2005) propose a GARCH model with stable innovations to capture heavy tails, high kurtosis, and asymmetries in electricity spot prices, as they are not in agreement with the usual assumption of normally distributed error term. In their study on three European markets (German, Nordic and Polish markets), they find striking differences among them. For the Nordic and German market, the prices show heavy tails, spikes, high volatility, and heteroscedasticity. On the other hand, in the case of the Polish market, prices present a less extreme behavior. But this may be caused by fewer data being available for the Polish market or for differences in the structure of the generation assets. Meanwhile, according to Blanco, Peña and Rodriguez (2016, SSRN), there is evidence suggesting that the Normal Inverse Gaussian (NIG) distribution, which was first used for modelling speculative returns in Barndorff-Nielsen (1997), fits also heavy-tailed and skewed financial data well and is, at the same time, analytically tractable, see, for instance, Forsberg and Bollerslev (2002) who introduced the GARCH-NIG model, see also Karlis (2002) among others. Empirical experience suggests a good fit of the NIG law to financial data. In addition, the NIG distribution has attractive features such as it is closed-form under convolution. Therefore, the NIG distribution is particularly useful for modelling energy prices. Applications to energy prices are in Benth and Šaltyte-Benth (2004) and Benth et al. (2008).

Knittel and Roberts (2005) propose EGARCH model to account for volatility clustering and innovations' asymmetric impact on price volatility. They argue that positive price shocks increase volatility more than negative shocks because the positive shocks usually are positive demand shock and due to the convex marginal cost. The intuition is that a positive demand surprise has a larger impact on price changes. To compare EGARCH model with other models (e.g ARCH), the authors find that during the crisis period in the Californian market, EGARCH model performs better. However, EGARCH model doesn't do better in the pre-crisis period.

Overall, time series regression with ARMA-GARCH type model performs well in capturing the general trend. However, when the price series exhibits ill-behavior characteristics, to account for innovation distribution, it is possible to use the stable Paretian distribution or NIG to define the error term distribution. Or, if the price series reacts with more volatility in the case of positive shocks, using EGARCH or similar models like Threshold ARCH (TARCH) would a reasonable choice.

1.3 Reduced-form models: continuous time and regime-switching

Weron (2014) classifies two models into the Reduced-form model family: jump-diffusion models and Markov regime-switching models. Both types of models focusing on replicating the stochastic process of the electricity spot price, and in many cases, they are used together with models mentioned in the previous section.

The motivation of using jump-diffusion model is the behavior of the electricity price, that exhibits jumps and mean-reverting characteristics. First introduced by Merton, the only difference between the Brownian Motion and the Jump-diffusion model is a Poisson jump process. The basic equation of Jump-diffusion is as follows:

$$dx_t = u(x,t)\,dt + \sigma(x,t)\,dw_t + dq(x_t,t)$$

$u(x,t)\,dt + \sigma(x,t)\,dw_t$ is a Brownian motion with drift process allowing mean reversion to a stochastic or deterministic long-term mean at a constant rate; $dq(x_t,t)$ is the increments of a pure jump process. This compound Poisson jump process has two sources of randomness: one is intensity λ causing the price to jump randomly; the other one is the jump size that is also modeled randomly, Merton assumes the log stock price jump size follows a normal distribution which defined by two parameters μ and δ (variance). Therefore, by introducing three parameters λ, μ and δ, the skewness and excess kurtosis can be captured. Knittel and Roberts (2005) also use a time-dependent jump intensity model to allow the jump intensity parameter to vary over time. To the authors' opinion, the jumps are more likely to occur when there is congestion, which indicates that high demand periods should be accounted for. In the paper by Geman and Roncoroni (2006), in order to control the variation of the price shifted away from the trend, the authors add another term to equation (22), $\theta_1[u(t) - E(t^-)]\,dt$, where θ_1 represents the average variation and $[u(t) - E(t^-)]$ controls the speed of mean reversion. This is necessary, argued by the authors, because the previous jump-diffusion model does not explain the significant deviations from normality in terms of high-order moments. Weron, Simonsen et al. (2004) discuss the electricity spot price in Nord Pool and mention that electricity prices tend to revert rapidly to their normal level after a jump, but many models use the mean reversion to force the price back may not be fast enough. Therefore, in their model, they assume that a negative jump always follows a positive jump with the same magnitude.

While improving fit in comparison with simple Brownian motions, jump-processes mantain the assumption of constant volatility, which is not realistic since many empirical works suggest heteroscedasticity. Cartea and Figueroa (2005) posit a mean-reverting jump diffusion model with time-varying volatility. In their case, a yearly averaged rolling historical volatility with a window of 30 days is used. The output of the model shows that the simulated price path resembles accurately the evolution of electricity spot prices as observed in the market of England and Wales. Another paper by Escribano, Peña and Villaplana (2011) propose a model with time-varying jump-process but including GARCH structure of volatility. In their model, in order to tackle the problem that high rate of mean reversion would lead to a highly-overestimated value of the parameter outside the 'spike regime' (Weron, 2014), they define three cases of jumps. Specifically, the first case indicates a constant probability, the second case indicates the probability depends on the time of the year, and the third case suggests the intensity process depends on variables related to demand or supply conditions. In the results, a model that incorporates AR, GARCH and time-varying jump process under Case 3 performs best.

As mentioned by Weron (2014), one of the major weaknesses of jump-diffusion models is that the frequency of consecutive spikes in real data cannot be accounted for. An attempt to solve this shortcoming is presented in Li et al. (2016) by time changing the Jump Cox-Ingersoll-Ross (JCIR) process with a random clock that is a composite of a Gamma subordinator and a deterministic clock with seasonal activity rate. The time-changed JCIR process is a time-inhomogeneous Markov semi-martingale which can be either a jump-diffusion or a pure-jump process, and it has a mean-reverting jump component that leads to mean reversion in the prices in addition to the smooth mean-reversion force. Furthermore, they argue "the characteristics of the time-changed JCIR process are seasonal, allowing spikes to occur in a seasonal pattern".

An alternative to jump-diffusion models is Markov regime-switching models. The simple idea of Markov regime-switching model is that the price series will have different underlying stochastic processes depending on the state or regimes, and switching mechanism is Markovian controlled by an unobservable variable. Karakatsani and Bunn (2008) compare time-varying regressions and linear regression with first-order Markov regime-switching process. The results indicate similar performance between these two models. Misiorek et al. (2006) calibrate a TAR-Markov regime-switching model to California Power Exchange system spot prices. The difference between these models with models before is that an observable variable determines the regime. The Threshold Autoregressive model (TAR) can be used here as it assumes a threshold value to define each regime regression, like the following equation used in the paper:

$$P_t = \begin{cases} \phi_1(B)p_t = \Psi_{1,1}z_t + d_{1,1}D_{mon} + d_{1,2}D_{sat} + d_{1,3}D_{sun} + \varepsilon_t & v_t \geq T \\ \phi_1(B)p_t = \Psi_{2,1}z_t + d_{2,1}D_{mon} + d_{2,2}D_{sat} + d_{2,3}D_{sun} + \varepsilon_t & v_t < T \end{cases}$$

v_t is an observable variable and T being the threshold; The v_t used in the paper includes combinations of past prices and load. By comparing this model to other linear models, the authors conclude that non-linear, threshold regime-switching model outperform other linear models. However, they suggest that an additional GARCH component would decrease the point forecasting efficiency.

Janczura and Weron (2009) propose a shifted spike distribution regime-switching model. The reason for introducing this distribution is that in the case of defining the 'expected spike size' as the difference between the expected value in the spike and base regime, the figure could turn out to be negative, even though using different price models can alleviate the problem, still some of these low values may be classified to be in the spike regime. As a result, the authors introduce a distribution which assigns zero probability to prices below a certain quantile. The 'shifted lognormal' of price distribution is defined as follows:

$$log(x_t - m) \sim N(\alpha, \sigma^2)$$

Where m is the median value of x_t; 'shifted Pareto' law they defined as below:

$$X_t \sim F_{pareto}(\alpha, \lambda) = 1 - \left[\frac{\lambda}{x}\right]^{\alpha}$$

In the end, they conclude that using shifted spike regime distributions will lead to more realistic descriptions of electricity spot prices. However, no forecast is done in the paper then we don't know the performance of the model out-of-sample.

In the paper by Janczura and Weron (2010), they calibrate and test several Markov-regime models with different distribution and different base regime dynamics. In the class of two-regime models, they report that a regime-switching model with median-shifted lognormal spikes distribution and heteroscedastic base regime fits the data better than the ones with heteroscedastic base regime dynamics. For three-regime models, another regime reversing regime is included: the initial spike regime is followed by the reversing regime and then move back to the base regime. The authors also compare three-regime models with two-regime models, and they conclude that three-regime models with median-shifted lognormal spikes distribution and heteroscedastic base regime dynamic is even better than the two-regime model.

In the previous works, the process in the spike regime is assumed to belong to a parametric model class, such as log-normal or compound Poisson distributions. Eichler and Turk (2013) propose a semiparametric distribution which means that no assumptions are made about the form of the distribution, excepting the assumption that the extreme prices modeled by the spike regime must exceed a given threshold. They show that this model can compete with the existing methods but requires less computation time and distributional assumptions. With no specific assumption of the process in spike regime, this model may also help when the distribution is unknown.

Reduced-form models are generally more focused on recovering the main characteristics of electricity spot prices instead of forecasting accurately. Opposite to the statistical models, reduced-form models are reported to perform well in modeling volatility or spikes. For jump-diffusion model, the main focus is how to model the jump-size and intensity. While for regime-model, it is important to understand the mechanism of switching among regimes. In summary, Markov regime-switching model seems to do better as it also takes frequency of spikes into consideration. But, it remains an open question to what extent including external variables helps the model's performance.

(II) The Models

The basic assumption is :

$$\ln(p_t) = s_t + x_t \tag{A3}$$

Where s_t is the deterministic component similar to the one defined in (A2), it is as follows:

$$s_t = Constant + C_1 \frac{t}{12} + C_2 \cos\left(C_3 + \frac{2\pi t}{12}\right) + C_4 \cos\left(C_5 + \frac{4\pi t}{12}\right) \tag{1a}$$

$Constant\ and\ C_1$ consist of a linear trend component. According to the general feature of seasonality of monthly electricity price, we use two sinusoidal functions to capture the possible two peaks in the price series over one year.

In the following section, we describe the specifications we have chosen to model the stochastic component x_t.

(i) Benchmark model

The benchmark model is a simple random walk with drift, defined as follows:

$$x_t = a + x_{t-1} + \varepsilon_t \tag{1b}$$

Where a is the mean; x_t is the stochastic process of price series at time *t* which depends on its lagged value at *t-1*, σ is the volatility (assumed to be constant) and the innovation ε_t is Niid(0, σ) or, in other words, a white noise process. This benchmark model will be used as a yardstick in comparisons with other models.

(ii) Mean-reverting model with constant volatility

Electricity price oscillates around its long-run mean. This mean depends on production costs that may change slowly over time. To account for this characteristic, mean-reverting model is commonly used by the literature. A mean-reverting model is defined as

$$(1 - B)x_t = \beta(\mu - x_{t-1}) + \varepsilon_t \tag{1c}$$

Where μ is the long run mean and $|\beta| \leq 1$ is the mean reverting coefficient; the higher β, the quicker the mean reversion is. Model (1c) can also be written as an AR(1) model:

$$x_t = \beta\mu + (1 - \beta)x_{t-1} + \varepsilon_t \tag{1c'}$$

Thus, in this case, $\beta\mu$ will be the constant estimated by the regression, and the innovation ε_t is Niid(0, σ). Notice that when $\beta = 0$ we obtain the benchmark model without drift.

(iii) AR-GARCH model

One of the drawbacks of AR-type models is the assumption of constant variance, while most financial time series exhibit time-dependent volatility. Therefore, the second model we use is AR-GARCH(1,1) model, in which the mean equation of x_t is the same as (1c') but the residual is defined as:

$$\varepsilon_t = \sqrt{\sigma_t^2} \cdot v_t \tag{1d}$$

$$\sigma_t^2 = \kappa + \gamma\varepsilon_{t-1}^2 + \rho\sigma_{t-1}^2 \tag{1e}$$

This is a GARCH (1,1) model where κ is a constant term; v_t is assumed to be normally distributed Niid(0, 1); ε_{t-1} is the previous error term from equation (1c') and σ_{t-1} is the variance of last period.

(iv) TARCH model

As mentioned in literature, it is convenient to allow for asymmetric effects (leverage effect) between positive and negative shocks on volatility. Therefore, TARCH model is proposed here to deal with this asymmetry. More specifically, the variance regression in this case will be:

$$\sigma_t^2 = \kappa + \gamma\varepsilon_{t-1}^2 + \varphi\varepsilon_{t-1}^2 I_{t-1}(\varepsilon_{t-1} < 0) + \rho\sigma_{t-1}^2 \tag{1f}$$

Where I_t=1, if $\varepsilon_{t-1} < 0$ (negative shocks) and zero otherwise. Thus, the impact of positive shocks is γ while for negative shocks is $\gamma + \varphi$. $\varphi \neq 0$ implies asymmetry. Positive leverage effect (downward shocks cause higher volatility than upward shocks) exists if $\varphi > 0$. The inverse leverage effect (positive shocks increase volatility more than negative shocks) appears when $\varphi < 0$.

(v) TARCH-M model

The next model we propose to use is TARCH-M model to account for mean-reversion effect, non-constant volatility, asymmetry effect and the effect of standard deviation on the price series. asymmetry effect and the effect of standard deviation on the price series. The equation is:

$$x_t = \beta(\mu) + (1-\beta)x_{t-1} + \phi \ln\left(ó^2\right) + \varepsilon_t \tag{1g}$$

Where ϕ is the risk premium parameter which measure the impact of variance on the mean of x_t; We include monthly dummies in the variance regression to study possible monthly effects on volatility.

(vi) Markov-regime switching model (MRS)

Another model we include in the analysis is Markov-regime switching model to account for nonlinear patterns such as asymmetry or volatility clustering. Hamilton first shows an example of a Markov switching model with constant transition probability specification. Alternatively, Diebold et al. (1994) adopt two state models that employ time-varying logistic parameterized probabilities. Regimes depend on the value of an unobserved discrete state variable s_t. There are M possible regimes, and the variable of interest x_t is in regime m in period t when $s_t = m$, for m=1,…M. We define a Markov regime switching model as follows:

$$x_t = Constant_m + \beta_m x_{t-1} + \varepsilon_t \tag{1h}$$

The constant and the coefficient of lagged value may change across regimes, represented by m = 1, …., M. ε_t is assumed to be normally distributed. The variance σ^2 may be also regime dependent, $\varepsilon_t = \sqrt{\sigma_m^2} \cdot v_t$. In this Markov framework, the probability of being in regime j at time t depends on the regime i at time t-1

$$P(s_t = j | s_{t-1} = i) = p_{ij}(t)$$

The transition matrix contains these probabilities

$$p(t) = \begin{bmatrix} p_{11}(t) & \dots & p_{1M}(t) \\ & \dots & \\ p_{M1}(t) & \dots & p_{MM}(t) \end{bmatrix} \tag{1i}$$

Where i=1, …., M and j=1, …., M; and the ij-th element denotes for the probability of transitioning from regime i in period t-1 to regime j in period t. For the probabilities in each row i, we define p_{ij} in terms of a multinomial logit:

$$p_{ij}(G_{t-1}, \delta_i) = \frac{\exp\left(G_{t-1}^{'}\delta_{ij}\right)}{\sum_{s=1}^{M} \exp\left(G_{t-1}^{'}\delta_{is}\right)} \tag{1j}$$

G_{t-1} contains economic variables that may affect the state transition probabilities. Thus, it is apparent that the probabilities are time-varying, evolving as logistic function of $G_{t-1}^{'}\delta_{ij}$. The special case of constant probability is handled by choosing G_{t-1} to be identically equal to 1.

(i) Smooth transition autoregressive model (STAR)

Granger and Terasvirta (1993) propose a class of model known as smooth transition regressions, they consider multivariate models but focus on single-equation nonlinear relations. Depending on the transition function, the model can be seen as a smooth transition between linear models and the alternative one. On the one hand, the STAR model can be thought of as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, 0 and 1, where the transition from one regime to the other is smooth. On the other hand, the STAR model can be said to allow for a `continuum' of regimes, each associated with a different value of the transition function between zero and one. Specifically, considering the following smooth transition autoregressive model:

$$x_t = c(1) + \beta \;\; x_{t-1} + \left(c(2) + \theta \;\; x_{t-1}\right) F\left(\alpha^{'} z_t\right) + \varepsilon_t \tag{1k}$$

Where $\varepsilon_t \sim N\ iid\ (0, \sigma^2)$, z_t is the "indicator variable" which may be a linear combination of the components of x_t or just a single lagged component of x_t, plus a constant. In this paper, we adopt an exponential STR (ESTAR) model in which the transition function F, bounded between zero and one, takes the form as:

$$F(\alpha' z_t) = 1 - exp[-r(x_{t-1} - C)^2\ ], r > 0 \tag{1l}$$

Notice that specification (1*l*) imply a transition function such that the regimes are associated with small and large absolute values of x_{t-1}. If $x_{t-1} = C$ then F(.) = 0 and $c(1)$ and β are the relevant parameters. But if x_{t-1} goes to ±∞ then F(.) = 1 and the relevant parameters are $c(1)$ + $c(2)$ and β+θ.

(ii) Jump-diffusion process

Following Cartea and Figueroa (2005), we define the stochastic process as a zero-level mean-reverting jump diffusion process:

$$dx_t = constant + \alpha x_{t-1} dt + \sigma dZ_t + lnJ\ dq_t \tag{1m}$$

Where α is the speed of mean reversion, σ is the time-invariant volatility, dZ is the increment of the standard Brownian motion, J is the random jump size follows log-Normal distribution under which $lnJ \sim N\ \left(-\frac{\sigma_J^2}{2}, \sigma_J^2\right)$ and dq_t is a Poisson process which is defined as:

$$dq_t = \begin{cases} 1 & with\ probability \quad \lambda dt \\ 0 & with\ probability\ (1 - \lambda dt) \end{cases} \tag{1n}$$

and parameter λ is the intensity of the process. Thus, the mean equation can be written as:

$$dx_t = \begin{cases} constant + \alpha x_{t-1} dt + \sigma dZ_t + lnJ & prob. = \lambda dt \\ constant + \alpha x_{t-1} dt + \sigma dZ_t & prob. = 1 - \lambda dt \end{cases} \tag{1o}$$

Therefore, with probability of λdt, the price will experience jumps following the distribution of lnJ.

(III) Model selection methods

(i) In-sample fit

Maximum likelihood estimation method is commonly used to estimate the parameters of a model. Usually instead of maximizing the likelihood function, it is more convenient to work with the negative log-likelihood where we seek to minimize the negative log-likelihood value. We use the negative log-likelihood value to choose between models. To take into account sample size, we use the Schwarz criterion (Schwarz, 1978), also known as the Bayesian information criterion:

$$BIC = -2\log(L) + plog(n) \qquad (A4)$$

Where $-\log(L)$ is the negative value of log-likelihood of the fitted model, p is the number of parameters to be estimated, and n is the sample size. Thus, lower BIC means better fit. Additionally, for a given sample size *n*, BIC favors simpler models with smaller number of parameters p. The BIC is one consistent model selection criteria because it will asymptotically select the candidate model having the correct structure with probability one. On the other hand, the commonly-used Akaike information criterion (AIC) is not consistent; see Kass and Raftery (1995).

(ii) Out-of-sample evaluation

To compare out-of-sample forecasts accuracy, the more common way is to calculate the forecast error of model i at time *t*, being the difference between the forecast value $\hat{x}_{it}$ and the observed value x_t . However, using directly forecast errors may overlook the significance of each forecast error as there are both negative and positive values. Therefore, a loss function is defined to fit different purposes for evaluating forecast errors. Typically, the loss function is the square or the absolute value of forecast errors which are symmetric functions. In this paper, we use the squared loss function, as is common in the literature. It may be argued that over-prediction or under-prediction is more costly in practice; however, this requires the clarification on the model's usage. The loss function is as follows:

$$g(e_{it}) = (\hat{x}_{it} - x_t)^2$$

Where e_{it} is the one-step-ahead forecasting error obtained using model i for period t. Besides checking the forecast error, it is also very important to evaluate the probability density function forecasted by models. Rosenblatt (1952), argues that under the null hypothesis of the chosen model being correct, the distribution of the probability integral transformation follows i.i.d. U(0,1):

$$y_t = \int_{-\infty}^{p_t} \hat{f}(u)\, du = \hat{F}_t(p_t) \qquad (A5)$$

Where p_t is the one-step-ahead forecasting error, and $\hat{f}(\cdot)$ is the forecasted density, and $\hat{F}(\cdot)$ is the distribution function. This density is gauged by analyzing the empirical distribution of model's residuals. If the model is correct and there is no structural change, the distribution of out-of-sample one-step-ahead forecasting errors and the distribution of in-sample residuals should be the same. According to the equation (5), the forecast density should coincide with the true density of residuals in order to decide the model's forecast performance. For the convenience to test, Berkowitz (2001) proposed a transformation of the probability transform:

$$z_t = N^{-1}(y_t) \qquad (A6)$$

Where N^{-1} is the inverse of the standard normal distribution functions. If the sequence of y_t is i.i.d. U(0,1), then z_t should be i.i.d N(0,1). Therefore, it provides a way of using normality test to check density forecast performance of each model. Following Berkowitz (2001), we adopt the use of log-likelihood ratio test for the joint hypothesis of independent observations with zero mean and unit variance:

$$z_t - \mu = \rho(z_{t-1} - \mu) + \xi_t \qquad (A7)$$

$$LR = -2[L(0,1,0) - L(\hat{\mu}, \hat{\sigma}^2, \hat{\rho})] \quad \sim \chi^2(3) \qquad \text{(A8)}$$

Under the null, if z_t follows i.i.d N(0,1), the parameters $\mu, \rho, var(\xi_t)$ should be equal to 0, 0, 1 respectively. As a result, rejection to LR suggests autocorrelation among forecast errors and nonstandard Normal distribution. Additionally, normality tests (e.g. Jarque-Bera) should be applied to z_t.

The last method we use for comparing models is the Model Confidence Set (MCS) proposed by Hansen et al (2011). The MCS procedure is based on an equivalence test and an elimination rule, and its objective is to determine a set of models in which the significantly inferior models are eliminated. To be more specific, the objects (models in this paper) are evaluated in terms of a loss function, defined by $L_{it} = L(\hat{x}_{it}, x_t)$, and the relative performance variable is such:

$$u_{ij} = E\left(L_{i,t} - L_{j,t}\right) \quad for\ all\ i,j \in M^0 \tag{A9}$$

M^0 is the finite number of objects (models) that are indexed by i=1,…, m_0. Therefore, the objects can be ranked in terms of expected loss, and the alternative i is preferred to alternative j if $u_{ij} \leq 0$. By using MCS, we can obtain models which have better forecast ability among all proposed models at a significance level.

We consider the following two groups: countries which have regulated electricity price for certain types of consumers, and countries which do not have such regulations. The first group contains Denmark, Spain, France, Greece, Italy, and Portugal. Austria, Finland, Germany, and Sweden are in the second group. Within each group, we find that neighboring countries present similar price behavior. Figure 3 shows regional seasonal patterns: France-Italy-Greece, Germany-Austria, Sweden-Finland, and Spain-Portugal.

[INSERT FIGURE 3A HERE]

This similarity may be due to similar weather, similarity in heating or cooling systems, and similar structure of generation assets. Denmark exhibits a unique behavior; one possible reason is geographically location and its dependence on wind turbines to generate electricity.

II. Univariate models' analysis

Data span from January 2008 to November 2016 (see definitions in Table 1 in the main text). We fit models by using data from January 2008 to December 2014 (in-sample) and the remaining data (January 2015 to November 2016) is employed in the out-of-sample forecasting exercise. Table 11A presents results of the estimation of the deterministic component for each country.

[INSERT TABLE 11A HERE]

Figure 5 suggest a common declining trend in prices since 2008.

[INSERT FIGURE 5A HERE]

Trend coefficients are significant for all countries except Portugal and Spain. We see that Portugal and Spain experienced an increase after 2008, then fluctuated around 40€/MWh until 2016. According to Bublitz, Keles and Fitchner (2017) who analyze the German market, the drop in coal and carbon emission allowance prices was the main reason for the decline of electricity spot prices, whereas expansion of photovoltaics was not the main price driver. Meanwhile, the non-linear seasonal part is significant also for all countries. In Spain, Greece, Italy, Portugal, the significant coefficients in two cosine functions confirm two peaks per year in the price movement. The constants are significant for all countries as well, being around 4, which indicates the mean of electricity prices across all countries is around 54.6€/kwh.

Next, we analyze results of univariate models on stochastic component of price series for each country by classifying two groups: countries without regulated prices, and countries with regulated prices. Table 12 in the Appendix A shows results of normality test for series x_t. Three (Spain, Portugal and Finland) out ten series do not follow normal distributions. Table 13 in the Appendix A presents unit root tests. Results suggest that x_t series are stationary.

[INSERT TABLE 12A HERE]

[INSERT TABLE 13A HERE]

(I) Countries with regulated prices

Considering the similarity in electricity prices, we discuss first the results of Spain (Table14A,15A,16A) and Portugal (Table 17A,18A,19A).

[INSERT TABLE 14A HERE]

[INSERT TABLE 15A HERE]

[INSERT TABLE 16A HERE]

[INSERT TABLE 17A HERE]

[INSERT TABLE 18A HERE]

[INSERT TABLE 19A HERE]

For all models, the coefficient of lag-one value x_{t-1} is positive in the Spanish market and significant with values ranging from 0.71 (mean-reverting) to 0.88 (TARCH-M-Dummies) suggesting a mean-reverting process with a half-life between two and six months[1]. Results are similar in Portugal. The volatility feedback channel (influence of variance on price) is not significant for both countries. In the variance equation, no evidence of leverage effect appears. Significant and consistently negative coefficients of monthly dummies are found in the variance equations for April, August, and October in the case of Spain. Residual diagnostics suggest correlated residuals in the benchmark model but not in others. Squared residuals are correlated at 1% in the benchmark and mean-reverting model. Once we allow for GARCH/TARCH effects, these correlations are no longer significant. Residuals from all models are not normal, but they are at 1% level for GARCH model. NIG results confirm this. In summary, residual analyses suggest mis-specification in the benchmark and the mean-

[1] Half-life (H) of a mean reverting process X is the time for the value of X at time t=T to reach the middle level between the current value (t=0) and the long run mean. The half-life value is H=ln(2)/(1-b) where b is the estimator of the slope coefficient in AR(1) process x(t) = a + b*x(t-1) + e(t). In the example above, b=0.71, H=ln(2)/0.29=2.39 months.

reverting model, because significant autocorrelation in the conditional mean and conditional variance. Once we take these effects into account, no signs of mis-specification appear.

According to Markov-regime switching model, there are two states. The first state, Regime 1, is characterized by high volatility (variance is 0.28 for Spain and 0.33 for Portugal) and zero conditional mean, implying lack of inertia in the price process. On the other hand, in Regime 2, the variance is lower (0.09 for Spain and 0.11 for Portugal) and there is high inertia in the price process, as suggested by the coefficient in the one-lag price (0.92 for Spain and 0.90 for Portugal). The probability of switching from regime 1 to regime 1 is high for both countries (0.82 for Spain, 0.83 for Portugal). But it is much less likely for state 2 (low variance) switching to state 1 (high variance), the probability is around 0.06 for Spain and it is 0.03 for Portugal. This confirms volatility clustering in the price behavior. The expected duration in high variance state is around 5.5 months for both two countries, and in low variance state the number is around 18 months for Spain, 32 months for Portugal.

In ESTAR model, the slope parameter and the threshold are significant for Spain and for Portugal, suggesting non-linearity across time. The slope parameters in both cases are around 18 meaning the impact from the non-linear part is moderate. Also, the thresholds are negative, being around -0.55 for both cases. According to Jump-diffusion model, the estimated frequencies of jumps (parameter lambda (λ) in Tables 15 and 18) are almost 3 times per year for Portugal, and almost 4 times per year for Spain. Moreover, the estimated mean reversion rate (parameters $\alpha * dt$ which represents the speed of mean reversion) is around 1.57 months for Spain and 1.65 months for Portugal. Estimated mean of jump size is around 0.87 for Spain and 0.99 for Portugal, with variance to be 1.33 and 1.02 respectively. Residual analysis does not hint at misspecification of the jump-diffusion model. This is interesting because non-constant variance can be modelled as a series of (independent) jumps or as a stochastic process (GARCH/TARCH). Both methods seem to fit the data similarly in this sample. Next, we fit NIG distribution as the density forecasts as suggested by the literature that it is a good choice. There are two parameters in NIG distribution (NIG (χ, ξ)) showed in the table, the first one (χ) is for asymmetry and the second one (($|\xi|<1$) is for kurtosis. With normal distribution, both χ and ξ would be 0. And, ξ goes to 1 indicates heavy-tailed distribution. So, for Spain and for Portugal, the distributions are mostly quite heavy-tailed, with ξ being around 0.5 across models. As an additional test we perform Li-Mak test on residuals from GARCH-type model, see Li and Mak (1994) for reference. The null hypothesis is adequately fitted ARCH process, thus rejecting the null means model misspecification. According to Table 49A, we cannot reject the null hypothesis at 1% significance level.

[INSERT TABLE 49A HERE]

In the case of Spain, model selection methods' results in Table 16 suggest that, based on the BIC criterion, GARCH model produces best in-sample fit, (-0.71) followed by TARCH (-0.68), and the worst performing model in-sample is the benchmark (-0.39). Regarding out-of-sample forecasts, the best model is GARCH model (0.0137) followed by TARCH model (0.0142), and the worst-performing model is the jump-diffusion (0.13). The benchmark model presents the worst performance in-sample and residuals diagnostics point out several violations of the model's assumptions (normality, constant variance, uncorrelated residuals) but results from MCS procedure show that the benchmark's and other models' forecast abilities are similar and superior to ESTAR/Jump diffusion model. Among those, GARCH model produces consistently best in-sample fit and out-of-sample forecasts. The Jump-diffusion model does a particularly poor job in out-of-sample performance. LR tests are significant in ESTAR and jump-diffusion.

Regarding to Portugal, we may see in Table 19 that GARCH model (-0.65) gives the best in-sample fit, and then Markov regime switching model (-0.63). On the other hand, Markov regime switching model (0.0147) gives the best forecast performance, with benchmark model (0.0153) to be the second best. Regarding to MCS procedure, ESTAR model and Jump-diffusion model is eliminated at 1% significance level, indicating no significant difference among forecasts from the rest models.

So, the forecasting performance of the best in-sample model (GARCH) is undistinguishable from the forecasting performance of the best out-of-sample model (Markov regime switching model).

The next countries being analyzed together are France (Table 20A,21A,22A), Greece (Table 23A,24A,25A) and Italy (Table 26A,27A,28A).

[INSERT TABLE 20A HERE]

[INSERT TABLE 21A HERE]

[INSERT TABLE 22A HERE]

[INSERT TABLE 23A HERE]

[INSERT TABLE 24A HERE]

[INSERT TABLE 25A HERE]

[INSERT TABLE 26A HERE]

[INSERT TABLE 27A HERE]

[INSERT TABLE 28A HERE]

The explanatory power of lag-one value is quite high for three countries, (around 0.80) suggesting slow mean-reversion and similar half-life value of the processes. Second, asymmetry effects of news on variance are not significant for all three countries. Also, the variance´s impact on the mean of price is also not significant except in the case of France. The GARCH component has significantly negative effect (-0.13) on the mean of price process according to TARCH-M model for France. In the variance regression including monthly dummies as variables, we see that no consistently monthly effects for France and Italy across models. But in Greece, February, October, and December are found negatively related with variance in GARCH-Dummies models.

Markov-regime switching models for three countries indicate quite different stochastic process behavior: In the case of France, regime 1 (volatility around 0.09) is characterized by a slow mean-reverting rate (0.79), while in regime 2 (volatility around 0.01) the process is non-stationary (coefficient on x_{t-1} is around 1.34) and has a significantly negative mean (around -0.02). The probability of staying in regime 1 is around 0.84 if previous state is regime 1, but the probability is almost 1 for regime 2 switching back to regime 1, suggesting volatile behavior. And the expected durations are 6.17 months and 1 months for regime 1 and regime 2 respectively; In the case of Greece, the regime 1 (volatility around 0.12) has negative conditional mean (-0.3), implying lack of inertia in the price process, while the regime 2 (volatility around 0.07) has a mean-reverting rate (0.81) with zero conditional mean. The probability of switching from regime 2 to regime 1 is low (0.04), but it is more likely for the process to stay in regime 1 after being in regime 1 (0.79). Therefore, the expected duration in regime 2 is around 28.5 months, and it is 4.72 months in regime 1; In the case of Italy, both regime 1 (volatility around 0.08) and regime 2 (volatility around 0.002) have similar mean-reverting rate (around 0.85), but the expected mean value of regime 2 is 0.01. The transition probabilities show that it is less likely for the process to switch from regime 2 to regime 1 (around 0.1), while the probability of switching from regime 1 to regime 2 is around 0.85 (being the difference between 1 and Probability 1-1). Thus, the expected durations for the two regimes are similar, with the number being 1.17 and 9.88 for regime 1 and regime 2 individually.

Considering ESTAR model, we see that all coefficients for Italy are not significant at 90% confidence level, except the coefficient of lag-1 value in the linear part (being 1.73). But for France, all coefficients are significant. Among those, the slope parameter is quite large (2132), suggesting large influence from the non-linear part, and the threshold value is significantly negative (-0.25). In Greece, the coefficient of lag-1value is not significant, but the slope parameter is large (234.6) with a negative threshold (-0.1).

With respect to Jump-diffusion model, in the case of France, we find that the jump variance (1.09) and jump mean size (0.96) are not significant, so does the estimated number of jumps (1.87 times per year). But the estimated mean-reverting rate is around 1.7 months. And the standard deviation of the process is around 0.27. In the case of Greece, only the estimated mean-reverting rate is significant (1.92 months), while the estimated jump mean size is 0.92, the estimated jump variance is 1.18 and the number of jumps is 3.55 per year. However, for Italy, no significant coefficients are found, suggesting a poor fit of the model.

Residuals from all models for France and Italy are normally distributed and no autocorrelation or ARCH effect is found (except MRS for France). Residuals of models for Greece are negative skewed and heavy-tailed, according to the parameters of NIG distribution fitted. However, we see that all models (except Jump diffusion models) fail to pass the LR test for density forecast in the case of France and Italy. This suggests structural change in prices during the forecasting period. According to the annual report of electricity in France (RTE, 2016), it is documented that the power demand rose in 2015 after holding the same level for three years. One reason is the weather impact as 2015 was the third warmest year on record. Another reason is the whole economy recovering from the previous financial crisis, with power consumption increased by 0.5% excluding the energy sector. Therefore, by comparing the process for the forecasting period of the three countries, we see that the process of France and of Italy experienced high spikes at a higher frequency than they did before 2014 (Figure 8A).

[INSERT FIGURE 8A HERE]

In Greece, there is no structural change. Failure of LR tests of all univariate models in the case of France and Italy, remarks the importance of controlling for external factors which may change the structure of price behavior. In France the best in-sample fit is given by the mean-reverting model. The benchmark model produces the best forecast accuracy. But according to MCS procedure, there is no significant difference of forecast accuracy between the benchmark model and the mean-reverting model.

For model evaluation, for France, without considering LR test, the best in-sample fit is given by the mean-reverting model (-1.96), followed by ESTAR model (-1.95). While, the TARCH model produces the best forecast accuracy (0.0211), followed by mean-reverting model (0.02129). According to MCS procedure, there is no significant difference among forecast losses from the following three models: mean-reverting model, GARCH model and TARCH model.

For Greece, the Jump diffusion model has the best in-sample fit (-1.67), then is the Markov regime switching model being the second best (-1.64). When it comes to forecast accuracy, mean reverting model has the lowest MSE (Mean Squared Errors, 0.0116), followed by TARCH model (0.0119). The MCS procedure confirms no significant difference of forecast losses among models such as mean-reverting model, GARCH model, TARCH model, and Markov regime switching model.

For Italy, the benchmark model (-2.27) and the mean-reverting model (-2.28) are shown to be the first and second best in-sample fit. The ESTAR model (0.0154) and the GARCH model (0.0157) are the first and second best out-of-sample forecast performance. The MCS procedure eliminates the benchmark model, TARCH-M model, and Jump-diffusion model, leaving other models in the set.

The last country in this group is Denmark (Table 29A,30A,31A).

[INSERT TABLE 29A HERE]

[INSERT TABLE 30A HERE]

[INSERT TABLE 31A HERE]

Similar to results above, we find high explanatory power of lag-one value on price (around 0.7), indicating slowly mean-reverting process and similar half-life value. No significant effect of variance on the mean of process is found, according to TARCH-M model. Also, no significant monthly effect is found once we include monthly dummies into the variance regressions. No leverage effect appears.

In Markov regime switching model, regime 1 (volatility around 0.17) is characterized by zero conditional mean and mean-reverting rate around 0.37 which suggests a slower mean-reverting rate. Regime 2 (volatility around 0.08) has a mean-reverting rate around 0.92 which is higher than regime 1. According to the transition probability, the likelihood of switching from regime 2 to regime 1 is low (0.19) and the probability of staying in regime 1 when the previous state is in regime 1 is high (0.8). The results of expected durations in regime 1 and in regime 2 are 4.88 months and 5.31 months individually.

ESTAR model produces no significant coefficients except the threshold (-0.21), and the estimated slope parameter is large (around 103.3) indicating large influence of the non-linear part. Jump-diffusion model suggests that there is around 5.47 jump per year and that the jump size has an estimated mean around 0.93 with variance to be around 1.17. Residuals from models are normally distributed according the Jarque-Bera normality test. The LR tests confirm all models are well specified, except the benchmark model and TARCH-M model can be rejected at 10% significance level.

The best in-sample fit is mean reverting model (-0.969), followed by benchmark model (-0.844). The best out-of-sample forecast is ESTAR model (0.028), followed by Markov regime switching model (0.032). MCS procedure eliminates the Jump diffusion model, but no significant difference appears between forecasts from all other models.

We summarize our findings as follows:

- Best in-sample and out-of-sample models contain mean reversion
- Leverage effects are not significant
- Volatility feedback is significant in France only

- Significant deterministic seasonal effects on variance appear in Spain (April, August, October) and Greece (February, October, December);
- Spain, Portugal and Greece, present non-normal residuals with heavy tails and skewness. Significant ARCH effect is found in Spain and Portugal. According to Li-Mak test we don't find evidence of model misspecification;
- In France and Italy all models fail the LR tests, suggesting structural change in the process.

Table 2A summarizes main findings.

[INSERT TABLE 2A HERE]

The second column contains the best in-sample model, the third column the average half-life, the fourth column the best out-of-sample model and the fifth column informs whether MCS test finds differences in forecasting accuracy between models in columns (2) and (4). Greece is the only case in which this situation happens.

(II) Countries without regulated prices

For start, we will discuss the results for Austria (Table 32,A33A,34A and Germany (Table 35A,36A,37A9.

[INSERT TABLE 32A HERE]

[INSERT TABLE 33A HERE]

[INSERT TABLE 34A HERE]

[INSERT TABLE 35A HERE]

[INSERT TABLE 36A HERE]

[INSERT TABLE 37A HERE]

For both countries, the coefficients of lag-one value are around 0.7 suggesting a slowly mean-reverting process. While asymmetric effect between positive and negative shock is found in TARCH-M model for both cases with φ (in equation (1f)) being significantly negative (-0.28 in the case of Austria and -0.21 in the case of Germany), which means there is inverse leverage effect. Also for Germany, log of variance is found to has negative effect (-0.02) on the mean of process, but it is not significant in the case of Austria. Regarding to monthly dummies in the variance regression, July, October and December are discovered to have consistently negative influences on the volatility for Austria; Only October is found negatively related with volatility for Germany.

According to Markov regime switching model, the features of regime 1 (volatility around 0.1) and regime 2 (volatility around 0.04) are quite different for Germany: regime 1 has zero conditional mean and mean-reverting rate being 0.77, while regime 2 has positive conditional mean (0.28) and coefficient on lag-1 value around 1.18 suggesting non-stationary process. As to transition probability, it is more likely for the process to stay in regime 1 (0.92) and the probability of switching from regime 2 to regime 1 is almost 1, suggesting quite volatile process. As a result, the expected durations are 12.2 month and 1 months in regime 1 and in regime 2 individually. ESTAR model also suggests non-linear trend over time: the estimated slope parameter is around 405.9 and the estimated threshold value is 0.33. As to Jump diffusion model, the estimated mean-reverting rate is around 2.47 months. The frequency of jumps is estimated to be around 8.71 times per year, while the estimated jump size has a mean around 0.94 and variance to be 1.14. Residuals are all normally distributed. But, LR test of density forecast rejects the TARCH-M model.

For Austria, in Markov regime switching model, regime 1 has a mean-reverting rate around 0.79 and variance around 0.12, regime 2 (volatility around 0.0001) has an expected mean around 0.01 and mean reverting coefficient around 0.75. The probability of switching from regime 2 to regime 1 is almost 0.99, and it is unlikely to switch from regime 1 back to regime 2 (probability being the difference between 1 and Probability 1-1, 0.05). Thus, the expected durations in regime 1 is around

19.9 months, while it is 1 month in regime 2. In ESTAR model, the slope parameter is around 486.6 indicating great influence from the non-linear part with threshold value to be around 0.34. Jump diffusion model gives estimation of mean-reverting rate to be around 2.92 months, and the estimated jump size has a mean around 0.94 and a variance around 1.14. Residuals from all models are normally distributed. And, no model fails the LR test, which suggests well specifications of all models.

Considering BIC, we see that GARCH model (-1.56) fit the in-sample data best, followed by TARCH model (-1.45), in the case of Austria. According to MSE, GARCH model (0.0124) produces the best out-sample forecasts, and the second best is mean reverting model (0.012805). MCS procedure confirms that there is no significant difference among forecast losses from the mean-reverting model, GARCH model, TARCH model, TARCH-M model and Markov regime switching model.

As to Germany, GARCH model has the best in-sample fit (-1.37), followed by mean reverting model (-1.31). And, GARCH model produces best out-of-sample forecasts (MSE being 0.0152), followed by TARCH-M model (0.0153). MCS procedure shows that the forecast losses from GARCH model and TARCH model have no significant difference from each other.

Then we proceed to analyze Finland (Table 38A,39A,40A) and Sweden (Table 41A,42A,43A).

[INSERT TABLE 38A HERE]

[INSERT TABLE 39A HERE]

[INSERT TABLE 40A HERE]

[INSERT TABLE 41A HERE]

[INSERT TABLE 42A HERE]

[INSERT TABLE 43A HERE]

Though these two countries share some mutual points, they differ in several aspects. The one lagged value on stochastic process explains much of the process´s behavior, as the coefficients are around 0.7 for both cases. Asymmetric effects are found in TARCH-M model in the case of Finland, the $I_{(resid<0)}$ has coefficient positive (0.28), suggesting positive leverage effect between positive and negative shocks. While, in the case of Sweden, we find asymmetric effect in TARCH model and TARCH-M model. However, the two models suggest different results: positive leverage effect in TARCH model ($I_{(resid<0)}$ coefficient being 0.11), and negative leverage effect in TARCH-M model ($I_{(resid<0)}$ coefficient being -0.20). As to the impact of variance on the mean process, we only find significantly positive effect (0.11) for Finland, no effect is discovered for Sweden. Once we include monthly dummies into variance regressions, no consistently monthly effect across models in both cases.

According to Markov-regime switching model, the process of Finland has two states: regime 1 (volatility around 0.31) has a mean-reverting rate around 0.46 and zero conditional mean; regime 2 (volatility around 0.10) has a higher mean-reverting rate around 0.82 and zero conditional mean. The probability of staying in regime 1 is around 0.68 and the probability of switching from regime 2 to regime 1 is similar (0.12), therefore the expected durations in regime 1 is around 3.1 months and in regime 2 is around 8.766 months. ESTAR model suggests little influence from the non-linear part as the slope parameter is estimated to be 13.83, and the estimated threshold value is -0.61. Jump diffusion model estimates the mean reverting rate to be around 3.82 months and the general volatility of the process to be 0.43. Though not significant, the estimated jumps have a mean 0.82 and variance 1.48, and the frequency of jumps is around 1.65 times per year. Residuals from most models are mostly non-normally distributed, except Jump diffusion model, all positive skewed and heavy-tailed. According to LR test, only TARCH-M model fails at 1% significance level.

The process of Sweden, in Markov regime switching model, is characterized by two regimes: regime 1 (volatility around 0.25) has zero conditional mean and mean-reverting rate around 0.54;

regime 2 (volatility around 0.09) has a higher mean reverting rate (0.92) than regime 1 has. The probability of staying in regime 1 if previous state is regime 1 is around 0.72, and the probability of switching to regime 1 from regime 2 is around 0.21. Therefore, the expected durations in regime 1 is around 3.61 months, while it is around 4.67 months in regime 2. In ESTAR model, no significant coefficients are found. But, the estimated threshold parameter is 0.18, and the estimated slope parameter is small (1.59) indicating low influence of non-linear part on linear part. From Jump diffusion model, the estimated mean reverting rate is around 3.64 months and the general variance of the process is 0.45. Though not significant, the estimated jump frequency is around 1.33 times per year and the jump size has a mean around 0.09 and a variance around 1.33. Residuals from most models, except Jump diffusion model, are not normally distributed, with positive skewness and heavy tails. And, all models pass the LR test on density forecast, suggesting well-specification.

Considering model evaluation, in the case of Finland, we see that Jump diffusion model (-0.45) has the best in-sample fit, then is the GARCH model (-0.44). Regard to out-of-sample forecast, the mean reverting model produces the lowest MSE (0.01743), followed by TARCH model (0.01838). The MCS procedure eliminates all other models, leaving the mean reverting model, GARCH model, TARCH model and Markov-regime switching model in the set.

In the case of Sweden, mean reverting model (-0.42) has the lowest BIC, followed by the Jump diffusion model (-0.36). On the other hand, TARCH-M model has the lowest MSE (0.051), followed by Markov regime switching model (0.053). According to the MCS procedure, the forecast losses from the mean-reverting model, GARCH model, TARCH model, TARCH-M model, Markov regime switching model and ESTAR model have no significantly difference among each other.

As conclusions, we summarize our findings for this part as follows:

- Best in-sample and out-of-sample models contain mean reversion;

- Inverse leverage effect is found in the case of Austria and of Germany (TARCH-M model). Positive leverage effect is found in the case of Finland. In Sweden there are mixed results, with positive leverage effect in TARCH and inverse leverage effect in TARCH-M model;
- Volatility feedback effects are found, positive in Finland and in Germany;
- Regarding to monthly dummies in the variance regression, July, October and December are discovered to have consistently negative influences on the volatility for Austria. October is found negatively related with volatility for Germany.
- The residual distribution for Austria and Germany is normal. Residuals for Finland and Sweden are positive skewed and heavy-tailed.

Table 3A summarizes results

[INSERT TABLE 3A HERE]

The second column contains the best in-sample model, the third column the average half-life, the fourth column the best out-of-sample model and the fifth column informs whether MCS test finds differences in forecasting accuracy between models in columns (2) and (4). Finland is the only case in which this situation happens.

Above results suggest that each market has its own features. In Austria and Germany, inverse leverage effect is significant. But in Finland leverage effect is positive. Volatility feedback is important in France, Germany, and Finland. Structural change happens in France and Italy in 2015. In Greece and Finland, in contrast with the remaining eight countries, models with best in-sample performance give worse forecasts than best out-of-sample models. In summary, different models should be chosen to fit the price series for different countries.

Table 2A: Best models for countries with regulated prices

Countries included are Denmark, Spain, France, Greece, Italy, and Portugal. The table shows the best model being chosen under both in-sample criteria and out-of-sample criteria.

Country	Best model in-sample (Jan2008-Dec2014)	Half-Life (Months)	Best model out-of-sample (Jan2015-Nov2016)	MCS Test Significant difference in forecasting accuracy
DK	The mean-reverting model	2.17	ESTAR model	NO
ES	GARCH model	2.39	GARCH model	NO
PT	GARCH model	5.78	Markov regime switching model	NO
FR	The mean-reverting model	4.33	TARCH model	NO
GR	The Jump diffusion model	3.42	The mean-reverting model	YES
IT	The mean-reverting model	5.33	ESTAR model	NO

Table 3A: Best models for countries with non-regulated prices

Countries included are Austria, Finland, Germany, and Sweden. The table shows the best model being chosen under both in-sample criteria and out-of-sample criteria.

Country	Selected model in-sample (Jan2008-Dec2014)	Half-Life (Months)	Best model out-of-sample (Jan2015-Nov2016)	MCS Test Significant difference in forecasting accuracy
AT	GARCH model	2.67	GARCH model	NO
GE	GARCH model	2.57	GARCH model	NO
SE	The mean-reverting model	2.31	TARCH-M model	NO
FI	The Jump diffusion model	1.87	The mean-reverting model	YES

(I) Deterministic components of the price series

Table 11A: Deterministic Components of each price series for ten countries in EU

The table reports the results of coefficients from the deterministic components of price series for the chosen countries in EU. The model we fit is $\ln(p_t) = s_t + x_t$, where s_t is the deterministic component $s_t = Constant + C_1 \frac{t}{12} + C_2 \cos\left(C_3 + \frac{2\pi t}{12}\right) + C_4 \cos\left(C_5 + \frac{4\pi t}{12}\right)$.

Variables	AT	DK	ES	FI	FR	GE	GR	IT	PT	SE
C(1)	-0.08***	-0.09***	-0.02	-0.06***	-0.06***	-0.08***	-0.06***	-0.07***	-0.03	-0.09***
C(2)	0.10***	0.08**	-0.18***	0.10**	0.07**	0.10**	0.08**	0.09**	-0.19***	0.11**
C(3)	0.86**	0.96*	10.9***	0.29	0.57	0.86**	0.72	0.93**	-1.67***	0.02
C(4)	-0.03	-0.02	0.07**	-0.03	-0.03	-0.03	0.04	-0.03	0.07**	0.01
C(5)	-0.61	-1.1	-0.44	0.83	1.22	-0.45	-7.29***	1.61***	-0.30	-4.35
Constant	4.06***	4.04***	3.88***	3.94***	4.34***	4.06***	4.27***	4.43***	3.93***	3.99***

(II) Normality test and unit root test on stochastic process

Before starting to apply univariate models, we conduct normality test and unit root test on the stochastic component of price series for each country.

Table 12A: Description of stochastic components for ten countries in EU

The table gives basic information of the stochastic components for the chosen countries in EU, after controlling the deterministic components. The p-value of Jarque-Bera tests suggest that most series become normally distributed except Spain, Finland, Sweden, and Portugal (at 5% significance level). The stochastic components of these four countries exhibit left skewness and heavy tail.

	AT	DK	ES	FI	FR	GE	GR	IT	PT	SE
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.01	0.04	-0.01	0.02	0.00	0.02	0.02	0.03	-0.01
Maximum	0.39	0.53	0.50	0.68	0.36	0.39	0.31	0.35	0.54	0.70
Minimum	-0.44	-0.70	-0.76	-0.99	-0.35	-0.42	-0.40	-0.37	-0.84	-1.01
Std. Dev.	0.17	0.21	0.25	0.23	0.17	0.17	0.17	0.15	0.27	0.28
Skewness	-0.23	-0.27	-0.66	-0.30	-0.09	-0.26	-0.32	-0.22	-0.68	-0.35
Kurtosis	3.50	3.39	3.19	6.08	2.61	3.28	2.62	2.75	3.38	3.94
Jarque-Bera p-value	0.36	0.36	**0.02**	**0.00**	0.70	0.47	0.33	0.57	**0.01**	**0.04**
Observations	107	107	107	107	95	107	95	107	107	107

Table 13A: Unit Root Tests of stochastic components for ten countries in EU

The table reports the results of four unit-root tests on the stochastic components of the chosen countries. For Augmented Dickey-Fuller test and Elliot-Rothenberg-Stock point-optimal test, the null hypothesizes are that the series has unit root; For KPSS test, the null hypothesis is that the series is trend-stationary; For Ng-Perron tests, the null hypothesis is the series has unit root. *, **, *** represent significant level 1%, 5%, 10% respectively.

Countries	ADF	ERS	KPSS	Ng-Perron			
				MZa	MZt	MSB	MPT
AT	-3.76***	1.28**	0.07	-23.1***	-3.33***	0.14***	1.29***
DK	-3.21**	2.63**	0.1	-14.5***	-2.51***	0.17***	2.36**
ES	-4.13***	2.7**	0.08	-37.1***	-4.12***	0.11***	1.18***
FI	-4.98***	1.24***	0.07	-28.1***	-3.69***	0.13***	1.05***
FR	-3.22**	1.61***	0.22	-16.7***	-2.85***	0.17***	1.62***
GE	-4.09***	1.15***	0.07	-26.0***	-3.54***	0.14***	1.15***
GR	-3.37**	1.61**	0.2	-16.2***	-2.84***	0.18**	1.53***
IT	-3.15**	1.61***	0.14	-17.6***	-2.90***	0.17***	1.62***
PT	-4.05***	2.7***	0.08	-12.1**	-2.47**	0.20**	2.01**
SE	-4.14***	1.83**	0.07	-21.4***	-3.16***	0.15***	1.54***

(III) Univariate models

(i) Models' results for Spain

Table 14A: Univariate Models results for Spain (I)

The table reports results of univariate models in the case of Spain. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							0.02	-0.01
Constant	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01	0.08	-0.05
x_{t-1}		0.71***	0.87***	0.90***	0.86***	0.88***	0.88***	0.71***
				Variance Regression				
C			0.01**	0.02**	0.01**	0.03**	0.01**	0.03***
RESID(-1)^2			0.50**	0.19***	0.19	0.10	0.23	0.08
I(resid<0)					0.56	0.27	0.45	0.14
GARCH(-1)			0.24	0.59***	0.26	0.59***	0.24	0.59***
Feb				-0.01		-0.01		-0.01
Mar				-0.03		-0.04**		-0.05
Apr				-0.04***		-0.03**		-0.03**
May				-0.02**		-0.03		-0.03***
Jun				-0.02		-0.03		-0.03***
Jul				-0.02		-0.03		-0.03***
Aug				-0.03**		-0.03*		-0.03***
Sep				-0.02*		-0.02		-0.02***
Oct				-0.03***		-0.03**		-0.03***
Nov				-0.02		-0.02		-0.02
Dec				-0.01		-0.02		0.04
Q(12) p-value	0.04	0.32	0.20		0.29		0.30	
Q(12) squared p-value	0.00	0.00	0.01		0.02		0.01	
Jarque-Bera p-value	0	0	0.15		0.07		0.07	
Density forecast	NIG(0.2,0.8)	NIG(-0.02,0.54)	NIG(0.13,0.79)		NIG(0.13,0.78)		NIG(0.07,0.8)	

Table 15A: Univariate Models results for Spain (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	-0.21
Constant	-0.09	Constant	-1.57***	speed	1.57**
x_{t-1}	0.24	β (x_{t-1})	-2.36***	sigma	0.28**
variance	0.28***	Threshold Variables (nonlinear part)		Jump variance	1.33**
Regime 2		Constant	1.58***	lambda	3.94**
Constant	-0.01	$\theta(x_{t-1})$	3.03***	Jump mean	0.87**
x_{t-1}	0.92***	Slope ϒ	20.7***		
variance	0.09***	Threshold C	-0.56***		
Probability 1-1	0.82				
Probability 2-1	0.06				
Expected duration 1	5.43				
Expected duration 2	17.9				
Q(12) p-value	0.18		0.37		0.15
Q(12) squared p-value	0.00		0		0.33
Jarque-Bera p-value	0		0		0.70
Density forecast	NIG(0.02,0.57)		NIG(-0.03,0.47)		NIG(-0.01,0.04)

Table 16A: Evaluations of Univariate Models for Spain

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-0.39	-0.50	**-0.71**	**-0.68**	-0.63	-0.67	-0.56	-0.61
MSE (Out-of-sample)	0.0143	0.0142	**0.0137**	**0.0142**	0.0144	0.0143	0.0168	0.13
LR test	1.23	3.89	1.94	3.24	2.26	3.86	2.44	8.03**
MCS							Eliminated	Eliminated

(ii) Models' results for Portugal

Table 17A: Univariate Models results for Portugal (I)

The table reports results of univariate models in the case of Portugal. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							0.02	-0.01
Constant	-0.01	-0.01	-0.03**	0.00	-0.03	-0.02	0.05	-0.01
x_{t-1}		0.72***	0.88***	0.90***	0.88***	0.90***	0.88***	0.86***
				Variance Regression				
C			0.01**	0.03	0.01**	0.03	0.01**	0.03
RESID(-1)^2			0.75**	0.19**	0.49	0.01	0.48	0.01
I(resid<0)					0.37	0.33	0.27	0.26
GARCH(-1)			0.21	0.59***	0.23	0.58***	0.24	0.57***
Feb				-0.01		0.01		0.01
Mar				-0.03		-0.04		-0.03
Apr				-0.03		-0.04		-0.05**
May				-0.04		-0.03		-0.02
Jun				-0.03		-0.03		-0.03
Jul				-0.03		-0.03		-0.03
Aug				-0.04		-0.03		-0.03
Sep				-0.03		-0.02		-0.02
Oct				-0.04		-0.03		-0.03
Nov				-0.02		-0.02		-0.02
Dec				-0.03		-0.01		-0.02
Q(12) p-value	0.02	0.20	0.15		0.19		0.20	
Q(12) squared p-value	0	0	0.01		0.04		0.04	
Jarque-Bera p-value	0	0	0.05		0.006		0.003	
Density forecast	NIG(0.16,0.78)	NIG(-0.04,0.62)	NIG(0.1,0.77)		NIG(0.1,0.77)		NIG(0.05,0.78)	

Table 18A: Univariate Models results for Portugal (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	-0.15
Constant	-0.15	Constant	-1.90***	speed	1.66**
x_{t-1}	0.10	β (x_{t-1})	-2.69**	sigma	0.32**
variance	0.33***	Threshold Variables (nonlinear part)		Jump variance	1.02**
Regime 2		Constant	1.91***	lambda	2.99**
Constant	-0.01	$\theta(x_{t-1})$	3.41***	Jump mean	0.99**
x_{t-1}	0.90***	Slope ϒ	17.2**		
variance	0.11***	Threshold C	-0.63***		
Probability 1-1	0.83				
Probability 2-1	0.03				
Expected duration 1	5.86				
Expected duration 2	32.3				
Q(12) p-value	0.14		0.24		0.05
Q(12) squared p-value	0.01		0.001		0.52
Jarque-Bera p-value	0		0		0.71
Density forecast	NIG(-0.03,0.58)		NIG(-0.05,0.47)		NIG(-0.09,0.32)

Table 19A: Evaluations of Univariate Models for Portugal

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-0.26	-0.36	**-0.65**	-0.60	-0.55	**-0.63**	-0.49	-0.54
MSE (Out-of-sample)	**0.0153**	0.0154	0.016	0.016	0.016	**0.0147**	0.02	0.16
LR test	1.47	4.32	5.04	5.62	4.10	3.08	2.45	2.98
MCS							Eliminated	Eliminated

(iii) Models' results for France

Table 20A: Univariate Models results for France (I)

The table reports results of univariate models in the case of France. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.13**	-0.04***
Constant	-0.001	0.001	-0.0002	-0.01	0.002	-0.001	-0.67**	-0.26***
x_{t-1}		0.84***	0.85***	0.92***	0.82***	0.87***	0.88***	0.83***
				Variance Regression				
C			0.004	0.01***	0.01	0.01	0.004***	0.01***
RESID(-1)^2			-0.03	-0.14	-0.07	-0.04	0.36	0.05
I(resid<0)					0.28	-0.16	0.07	3.17
GARCH(-1)			0.55	-0.34	0.18	0.61	0.13	0.45***
Feb				0.004		-0.002		-0.01***
Mar				0.01		-0.003		-0.01***
Apr				0.0003		-0.01		-0.01***
May				-0.004**		-0.01		0.01
Jun				-0.004**		-0.0002		-0.01***
Jul				0.003		-0.001		-0.01***
Aug				0.003		-0.003397		0.002
Sep				0.01		0.002		-0.01**
Oct				0.01		-0.006		-0.004
Nov				0.0004		-0.004*		-0.01***
Dec				-0.003		-0.01		-0.01***
Q(12) p-value	0.74	0.90	0.90		0.95		0.38	
Q(12) squared p-value	0.69	0.60	0.62		0.54		1.000	
Jarque-Bera p-value	0.08	0.43	0.43		0.69		0.21	
Density forecast	NIG(0.02,0.06)	NIG(0.01,0.03)	NIG(0.01,0.03)		NIG(0.01,0.03)		NIG(0.10,0.13)	

Table 21A: Univariate Models results for France (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	-0.01
Constant	0.004	Constant	-56.0***	speed	1.70**
x_{t-1}	0.79***	β (x_{t-1})	-207.6***	sigma	0.27**
variance	0.09***	Threshold Variables (nonlinear part)		Jump variance	1.09
Regime 2		Constant	56.04***	lambda	1.87
Constant	-0.02***	$\theta(x_{t-1})$	208.4***	Jump mean	0.96
x_{t-1}	1.34***	Slope ϒ	2132***		
variance	0.01***	Threshold C	-0.25***		
Probability 1-1	0.84				
Probability 2-1	1.00				
Expected duration 1	6.17				
Expected duration 2	1.00				
Q(12) p-value	0.98		0.99		0.99
Q(12) squared p-value	0.01		0.49		0.03
Jarque-Bera p-value	0.62		0.96		0.97
Density forecast	NIG(0.01,0.03)		NIG(0.003,0.02)		NIG(-0.004,0.03)

Table 22A: Evaluations of Univariate Models for France

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-1.94	**-1.96**	-1.78	-1.74	-1.77	-1.73	**-1.95**	-1.78
MSE (Out-of-sample)	0.024	**0.02129**	0.02132	**0.0211**	0.026	0.022	0.027	0.04
LR test	22.7***	21.6***	22.1***	20.8***	95.3***	22.2***	44.9***	2.29
MCS	Eliminated				Eliminated	Eliminated	Eliminated	Eliminated

(iv) Models' results for Greece

Table 23A: Univariate Models results for Greece (I)

The table reports results of univariate models in the case of Greece. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.003	-0.003
Constant	-0.0007	0.002	0.008	0.03***	0.006	0.03**	0.01	0.01
x_{t-1}		0.80***	0.86***	0.90***	0.85***	0.93***	0.89***	0.86***
				Variance Regression				
C			0.001	0.01***	0.001	0.01***	0.001	0.01***
RESID(-1)^2			0.16*	0.09	-0.17	0.06	0.03	0.13
I(resid<0)					0.65	0.04	0.15	-0.03
GARCH(-1)			0.72***	0.59*	0.69***	0.58*	0.75***	0.60
Feb				-0.01*		-0.01*		-0.01*
Mar				-0.01		-0.01		-0.01
Apr				-0.01*		-0.01*		-0.01
May				-0.01*		-0.01**		-0.01
Jun				0.02		0.004		0.01
Jul				-0.02**		-0.01**		-0.01
Aug				-0.01		-0.01		-0.001
Sep				0.003		0.002		-0.01
Oct				-0.02**		-0.02*		-0.01***
Nov				-0.01		-0.01*		-0.01
Dec				-0.01***		-0.01***		-0.01***
Q(12) p-value	0.49	0.78	0.96		0.97		0.95	
Q(12) squared p-value	0.25	0.44	0.97		0.93		0.98	
Jarque-Bera p-value	0	0	0		0		0	
Density forecast	NIG(-0.09,0.59)	NIG(-0.17,0.41)	NIG(-0.19,0.50)		NIG(-0.19,0.48)		NIG(-0.18,0.54)	

Table 24A: Univariate Models results for Greece (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	0.16
Constant	-0.30***	Constant	-0.39*	speed	1.92**
x_{t-1}	-0.32	β (x_{t-1})	-2.45	sigma	0.18
variance	0.12***	Threshold Variables (nonlinear part)		Jump variance	1.18
Regime 2		Constant	0.41*	lambda	3.55
Constant	0.02	$\theta(x_{t-1})$	3.23*	Jump mean	0.92
x_{t-1}	0.81***	Slope ϒ	234.6*		
variance	0.07***	Threshold C	-0.10***		
Probability 1-1	0.79				
Probability 2-1	0.04				
Expected duration 1	4.72				
Expected duration 2	28.5				
Q(12) p-value	0.99		0.85		0.21
Q(12) squared p-value	0.99		0.39		0.22
Jarque-Bera p-value	0		0		0
Density forecast	NIG(-0.09,0.33)		NIG(-0.06,0.27)		NIG(0.11,0.35)

Table 25A: Evaluations of Univariate Models for Greece

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-1.55	-1.59	-1.51	-1.49	-1.50	**-1.64**	-1.58	**-1.67**
MSE (Out-of-sample)	0.013	**0.0116**	0.012	**0.0119**	0.013	0.012	0.014	0.06
LR test	1.17	1.49	2.37	2.15	5.94	1.20	4.17	2.13
MCS	Eliminated				Eliminated		Eliminated	Eliminated

(v) Models’ results for Italy

Table 26A:A Univariate Models results for Italy (I)

The table reports results of univariate models in the case of Italy. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.13*	0.0004
Constant	-0.0001	0.002	-0.001	0.004	-0.004	0.006	-0.69*	0.01
x_{t-1}		0.87***	0.87***	0.82***	0.88***	0.83***	0.82***	0.83***
				Variance Regression				
C			0.001	0.01	0.0004***	0.005	0.002*	0.01
RESID(-1)^2			-0.04	-0.11	-0.17***	-0.040	0.17	-0.03
I(resid<0)					0.05	-0.05	0.11	-0.05
GARCH(-1)			0.90***	0.62	1.10***	0.60	0.38	0.64
Feb				-0.002		-0.002		-0.003
Mar				-0.004		-0.01		-0.005
Apr				-0.002		-0.002		-0.002
May				-0.005		-0.01		-0.006
Jun				0.003		0.001		0.002
Jul				-0.004		-0.002		-0.004
Aug				-0.003		-0.002		-0.004
Sep				0.001		-0.002		0.002
Oct				-0.001		-0.001		-0.003
Nov				-0.003***		-0.003		-0.004***
Dec				-0.006		-0.006		-0.007
Q(12) p-value	0.67	0.84	0.81		0.91		0.72	
Q(12) squared p-value	0.40	0.67	0.72		0.55		0.90	
Jarque-Bera p-value	0.78	0.98	0.91		0.36		0.72	
Density forecast	NIG(0.004,0.02)	NIG(0,0.02)	NIG(0,0.02)		NIG(0,0.02)		NIG(0.31,0.44)	

Table 27A: Univariate Models results for Italy (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	0.02
Constant	0.001	Constant	0.01	speed	1.58
x_{t-1}	0.88***	β (x_{t-1})	1.73**	sigma	0.25
variance	0.08***	Threshold Variables (nonlinear part)		Jump variance	1.01
Regime 2		Constant	-0.02	lambda	4.75
Constant	0.01***	$\theta(x_{t-1})$	-0.89	Jump mean	1
x_{t-1}	0.83***	Slope ϒ	176		
variance	0.002***	Threshold C	-0.004		
Probability 1-1	0.15				
Probability 2-1	0.10				
Expected duration 1	1.17				
Expected duration 2	9.88				
Q(12) p-value	0.89		0.89		0.44
Q(12) squared p-value	0.64		0.69		0.34
Jarque-Bera p-value	0.97		0.91		0.99
Density forecast	NIG(0,0.02)		NIG(0.01,0.04)		NIG(0,0.02)

Table 28A: Evaluations of Univariate Models for Italy

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	**-2.27**	**-2.28**	-2.13	-2.17	-2.12	-2.14	-2.13	-2.13
MSE (Out-of-sample)	0.02	0.02	**0.0157**	0.0158	0.02	0.02	**0.0154**	0.02
LR test	21.9***	19.4***	19.4***	20.2***	22.5***	19.5***	19.8***	5.80
MCS	Eliminated				Eliminated			Eliminated

(vi) Models' results for Denmark

Table 29A: Univariate Models results for Denmark (I)

The table reports results of univariate models in the case of Denmark. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.01	-0.002
Constant	0.002	0.01	0.004	0.002	0.01	0.01	-0.03	-0.01
x_{t-1}		0.68***	0.73***	0.78***	0.77***	0.75***	0.81***	0.70***
				Variance Regression				
C			0.03***	0.02	0.02**	0.02	0.02***	0.02
RESID(-1)^2			0.11	0.22	0.32	-0.04	0.67	-0.06
I(resid<0)					-0.29	0.20	-0.58	0.21
GARCH(-1)			-0.81***	-0.07	-0.26	0.52	-0.13	0.59
Feb				0.01		-0.01		-0.01
Mar				0.01		0.02		0.01
Apr				-0.01		-0.03		-0.03
May				-0.01		-0.01		-0.01
Jun				-0.002		-0.01***		-0.01
Jul				0.01		0.001		-0.002
Aug				-0.01		-0.03**		-0.03
Sep				-0.01		-0.01		-0.01
Oct				-0.01		-0.01		-0.01
Nov				-0.01		-0.02		-0.02
Dec				0.04		0.02		0.02
Q(12) p-value	0.66	0.97	0.99		0.99		0.99	
Q(12) squared p-value	0.46	0.95	0.96		0.97		0.96	
Jarque-Bera p-value	0.33	0.31	0.11		0.32		0.32	
Density forecast	NIG(-0.02,0.41)	NIG(0.02,0.16)	NIG(0.02,0.19)		NIG(0.02,0.22)		NIG(0.02,0.24)	

Table 30A: Univariate Models results for Denmark (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	0.06
Constant	0.05	Constant	0.11	speed	3.43**
x_{t-1}	0.37**	β (x_{t-1})	1.78	sigma	0.33
variance	0.17***	Threshold Variables (nonlinear part)		Jump variance	1.17
Regime 2		Constant	-0.07	lambda	5.47
Constant	-0.01	$\theta(x_{t-1})$	-1.30	Jump mean	0.93
x_{t-1}	0.92***	Slope ϒ	103.3		
variance	0.08***	Threshold C	-0.21***		
Probability 1-1	0.80				
Probability 2-1	0.19				
Expected duration 1	4.88				
Expected duration 2	5.31				
Q(12) p-value	0.95		0.96		0.20
Q(12) squared p-value	0.77		0.97		0.02
Jarque-Bera p-value	0.13		0.14		0.18
Density forecast	NIG(0.03,0.20)		NIG(0.05,0.22)		NIG(0.05,0.09)

Table 31A: Evaluations of Univariate Models for Denmark

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	**-0.844**	**-0.969**	-0.842	-0.807	-0.841	-0.796	-0.842	-0.835
MSE (Out-of-sample)	0.041	0.035	0.035	0.036	0.036	**0.032**	**0.028**	0.08
LR test	6.49*	5.17	5.60	6.18	6.26*	4.83	1.89	4.91
MCS								Eliminated

(vii) Models' results for Austria

Table 32A: Univariate Models results for Austria (I)

The table reports results of univariate models in the case of Austria. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.003	0.001
Constant	0.0002	0.001	0.003	-0.01	0.01	-0.01	-0.01	-0.001
x_{t-1}		0.79***	0.74***	0.74***	0.78***	0.77***	0.83***	0.77***
				Variance Regression				
C			0.0001	0.03	0.0001	0.01***	0.001**	0.01**
RESID(-1)^2			-0.10**	0.30*	-0.01	0.22	0.14***	0.19
I(resid<0)					-0.14	0.08	-0.28***	0.08
GARCH(-1)			1.11***	0.61**	1.06***	0.60**	0.88***	0.61**
Feb				-0.03		-0.01		0.00
Mar				-0.03		-0.01		-0.01
Apr				-0.02		-0.01		-0.01
May				-0.02		-0.01		-0.01
Jun				-0.02		-0.01		-0.01
Jul				-0.03*		-0.01***		-0.01*
Aug				-0.01		0.003		0.003
Sep				-0.03		-0.02		-0.01*
Oct				-0.03*		-0.01**		-0.01*
Nov				-0.01		-0.001		-0.001
Dec				-0.03*		-0.02***		-0.01*
Q(12) p-value	0.17	0.46	0.58		0.37		0.25	
Q(12) squared p-value	0.34	0.57	0.81		0.61		0.49	
Jarque-Bera p-value	0.69	0.1	0.91		0.23		0.56	
Density forecast	NIG(0.01,0.14)	NIG(0,0.36)	NIG(-0.002,0.38)		NIG(0,0.36)		NIG(0.01,0.32)	

Table 33A: Univariate Models results for Austria (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	0.09
Constant	0.001	Constant	-1.92***	speed	2.92**
x_{t-1}	0.79***	β (x_{t-1})	5.80***	sigma	0.12
variance	0.12***	Threshold Variables (nonlinear part)		Jump variance	1.14**
Regime 2		Constant	1.95***	lambda	8.11
Constant	0.01***	$\theta(x_{t-1})$	-4.90**	Jump mean	0.94**
x_{t-1}	0.75***	Slope ϒ	486.6*		
variance	0.0001***	Threshold C	0.34***		
Probability 1-1	0.95				
Probability 2-1	0.99				
Expected duration 1	19.9				
Expected duration 2	1				
Q(12) p-value	0.48		0.64		0.81
Q(12) squared p-value	0.50		0.65		0.05
Jarque-Bera p-value	0.1		0.05		0.72
Density forecast	NIG(0,0.36)		NIG(0.02,0.38)		NIG(0.01,0.09)

Table 34A: Evaluations of Univariate Models for Austria

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-1.36	-1.42	**-1.56**	**-1.45**	-1.29	-1.35	-1.34	-1.38
MSE (Out-of-sample)	0.015	**0.012805**	**0.0124**	0.012809	0.013	0.013	0.014	0.03
LR test	2.69	2.05	1.71	2.46	2.19	2.04	3.61	3.52
MCS	Eliminated						Eliminated	Eliminated

(viii) Models' results for Germany

Table 35A: Univariate Models results for Germany (I)

The table reports results of univariate models in the case of Germany. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.02*	-0.03
Constant	0.0004	0.001	-0.002	-0.02	0.01	-0.02	-0.09	-0.13
x_{t-1}		0.76***	0.73***	0.67***	0.74***	0.75***	0.75***	0.89***
				Variance Regression				
C			0.00	0.01**	0.0004	0.01***	0.001**	0.01***
RESID(-1)^2			-0.10*	0.19	-0.05	0.18	0.02	0.16
I(resid<0)					-0.12	0.07	-0.21**	-0.29
GARCH(-1)			1.10***	0.62*	1.08***	0.62**	1.01***	0.69**
Feb				-0.01		-0.01		-0.003
Mar				-0.02		-0.02		-0.02
Apr				-0.01		-0.01		-0.01
May				-0.01		-0.02**		-0.01
Jun				-0.01		-0.02**		-0.02**
Jul				-0.02***		-0.02***		-0.01
Aug				0.001		-0.01		-0.01
Sep				-0.01		-0.02		-0.02**
Oct				-0.02***		-0.02***		-0.01***
Nov				-0.002		-0.001		-0.01
Dec				-0.01		-0.01		-0.01
Q(12) p-value	0.03	0.19	0.35		0.19		0.16	
Q(12) squared p-value	0.74	0.81	0.58		0.42		0.33	
Jarque-Bera p-value	0.5	0.11	0.83		0.33		0.06	
Density forecast	NIG(0.02,0.08)	NIG(0.04,0.2)	NIG(0.04,0.20)		NIG(0.04,0.20)		NIG(0.03,0.17)	

Table 36A: Univariate Models results for Germany (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
<u>Regime 1</u>		<u>Threshold Variables (linear part)</u>		constant	0.07
Constant	-0.02	Constant	-1.66**	speed	2.47
x_{t-1}	0.77***	β (x_{t-1})	5.25***	sigma	0.12
variance	0.1***	<u>Threshold Variables (nonlinear part)</u>		Jump variance	1.14**
<u>Regime 2</u>		Constant	1.68***	lambda	8.71**
Constant	0.28***	$\theta(x_{t-1})$	-4.39**	Jump mean	0.94**
x_{t-1}	1.18***	Slope ϒ	405.9		
variance	0.04***	Threshold C	0.33***		
Probability 1-1	0.92				
Probability 2-1	1				
Expected duration 1	12.2				
Expected duration 2	1				
Q(12) p-value	0.19		0.61		0.76
Q(12) squared p-value	0.98		0.79		0.83
Jarque-Bera p-value	0.16		0.08		0.06
Density forecast	NIG(0.04,0.19)		NIG(0.05,0.41)		NIG(0.01,0.06)

Table 37A: Evaluations of Univariate Models for Germany

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-1.23	**-1.31**	**-1.37**	-1.30	-1.25	-1.12	-1.19	-1.23
MSE (Out-of-sample)	0.019	0.0154	**0.0152**	**0.0153**	0.018	0.016	0.017	0.04
LR test	3.67	2.36	2.27	2.61	12.3***	2.41	4.29	1.33
MCS	Eliminated	Eliminated			Eliminated	Eliminated	Eliminated	Eliminated

(ix) Models' results for Finland

Table 38A: Univariate Models results for Finland (I)

The table reports results of univariate models in the case of Finland. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							0.11***	0.07***
Constant	0.002	0.01	0.0002	0.01	-0.01	0.01	0.41***	0.32***
x_{t-1}		0.63***	0.77***	0.73***	0.76***	0.74***	1.05***	0.90***
				Variance Regression				
C			0.02**	0.02	0.02**	0.03	0.01***	0.03***
RESID(-1)^2			0.88***	0.29	0.58	0.13	-0.16***	-0.20**
I(resid<0)					0.42	0.42	0.28***	0.47***
GARCH(-1)			-0.02	0.03	-0.04	0.55***	0.81***	0.35*
Feb				0.02		-0.04		-0.01
Mar				0.01		-0.03**		-0.028
Apr				-0.01		-0.05		-0.03*
May				-0.004		-0.02		-0.03***
Jun				0.01		-0.04		-0.003
Jul				0.07*		0.01		-0.02
Aug				-0.01		-0.06		-0.03
Sep				0.003		-0.02		-0.03*
Oct				-0.01		-0.04		-0.03***
Nov				-0.01		-0.03		-0.03***
Dec				0.06		0.01		0.02
Q(12) p-value	0.45	0.95	0.76		0.71		0.47	
Q(12) squared p-value	0.26	0.52	0.87		0.85		0.61	
Jarque-Bera p-value	0	0	0.01		0.01		0	
Density forecast	NIG(0.21,0.72)	NIG(0.13,0.48)	NIG(0.18,0.56)		NIG(0.18,0.57)		NIG(0.11,0.58)	

Table 39A: Univariate Models results for Finland (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	-0.09
Constant	0.05	Constant	-2.70	speed	3.82**
x_{t-1}	0.46**	β (x_{t-1})	-6.06	sigma	0.43**
variance	0.31***	Threshold Variables (nonlinear part)		Jump variance	1.48
Regime 2		Constant	2.74*	lambda	1.65
Constant	-0.02	$\theta(x_{t-1})$	6.64*	Jump mean	0.82
x_{t-1}	0.82***	Slope ϒ	13.83***		
variance	0.10***	Threshold C	-0.61***		
Probability 1-1	0.68				
Probability 2-1	0.12				
Expected duration 1	3.10				
Expected duration 2	8.66				
Q(12) p-value	0.85		0.45		0.68
Q(12) squared p-value	0.93		0.99		0.28
Jarque-Bera p-value	0		0		0.03
Density forecast	NIG(0.15,0.52)		NIG(0.08,0.46)		NIG(-0.08,0.28)

Table 40A: Evaluations of Univariate Models for Finland

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-0.21	-0.36	**-0.44**	-0.39	-0.36	-0.38	-0.39	**-0.45**
MSE (Out-of-sample)	0.02	**0.01743**	0.0185	**0.01838**	0.025	0.01843	0.024	0.15
LR test	3.36	4.05	3.30	3.10	22.62***	2.60	3.32	1.46
MCS	Eliminated				Eliminated		Eliminated	Eliminated

(x) Models' results for Sweden

Table 41A: Univariate Models results for Sweden (I)

The table reports results of univariate models in the case of Sweden. In the last four rows of the table, we present p-values for correlogram test at 12 lags both for residuals and for squared residuals, p-values for Jarque-Bera normality test and the density forecasted by the model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Variables	Benchmark	mean-reverting	GARCH		TARCH		TARCH-M	
			GARCH	GARCH-Dummies	TARCH	TARCH-Dummies	TARCH-M	TARCH-M-Dummies
LOG(GARCH)							-0.06	-0.06
Constant	0.002	0.01	0.01	0.03	0.02	0.02	-0.20	-0.20
x_{t-1}		0.70***	0.73***	0.70***	0.61***	0.68***	0.80***	0.79***
				Variance Regression				
C			0.01	0.03	0.01**	0.03	0.04***	0.01
RESID(-1)^2			0.05	0.11	-0.15***	0.05	0.14	0.11
I(resid<0)					0.11***	0.17	-0.20***	-0.12**
GARCH(-1)			0.70	0.57***	0.91***	0.56	-0.40	0.07
Feb				-0.02		-0.02		0.02
Mar				-0.02		-0.01		0.03
Apr				-0.05		-0.05		-0.001
May				-0.01		-0.02		0.003
Jun				-0.03		-0.04		0.004
Jul				0.02		0.02		0.05
Aug				-0.06		-0.05		-0.01
Sep				-0.01		-0.01		0.01
Oct				-0.03		-0.03		0.01
Nov				-0.03		-0.03		0.01
Dec				0.01		0.02		0.06
Q(12) p-value	0.66	0.96	0.94		0.85		0.75	
Q(12) squared p-value	0.34	0.87	0.91		0.73		0.95	
Jarque-Bera p-value	0.03	0	0		0		0	
Density forecast	NIG(0.14,0.66)	NIG(0.07,0.39)	NIG(0.09,0.42)		NIG(0.04,0.32)		NIG(0.10,0.51)	

Table 42A:A Univariate Models results for Sweden (II)

The table reports more details about univariate models, such as Markov regime switching model, Exponential smooth transition model and Jump diffusion model. *, **, *** represent significant level 1%, 5%, 10% respectively.

Markov-regime switching model		Exponential Smooth Transition model		Jump diffusion model	
Variable	Coefficient	Variable	Coefficient	Variable	Coefficient
Regime 1		Threshold Variables (linear part)		constant	0.07
Constant	0.04	Constant	-0.01	speed	3.64**
x_{t-1}	0.54***	β (x_{t-1})	0.92	sigma	0.45**
variance	0.25***	Threshold Variables (nonlinear part)		Jump variance	1.33
Regime 2		Constant	-0.10	lambda	2.60
Constant	-0.02	$\theta(x_{t-1})$	-0.98	Jump mean	0.09
x_{t-1}	0.92***	Slope ϒ	1.59		
variance	0.09***	Threshold C	0.18		
Probability 1-1	0.72				
Probability 2-1	0.25				
Expected duration 1	3.61				
Expected duration 2	4.67				
Q(12) p-value	0.85		0.73		0.99
Q(12) squared p-value	0.99		0.87		0.53
Jarque-Bera p-value	0		0		0.81
Density forecast	NIG(0.09,0.44)		NIG(0.09,0.52)		NIG(-0.01,0.04)

Table 43A:A Evaluations of Univariate Models for Sweden

The table reports results of model evaluation methods both in-sample and out-of-sample. In LR test, Null hypothesis: N(0,1,1) distribution., and *, **,*** represent rejection to null hypothesis at 10%,5%,1% significance level. For Model Confidence Set procedure, we report the models being eliminated.

Criteria	Benchmark	mean-reverting	GARCH	TARCH	TARCH-M	Markov-regime switching model	Exponential Smooth Transition model	Jump diffusion model
BIC (In-sample)	-0.31	**-0.42**	-0.26	-0.26	-0.31	-0.31	-0.28	**-0.36**
MSE (Out-of-sample)	0.06	0.054	0.054	0.056	**0.051**	**0.053**	0.056	0.16
LR test	2.06	0.64	0.52	0.42	0.63	0.64	0.98	2.93
MCS	Eliminated							Eliminated