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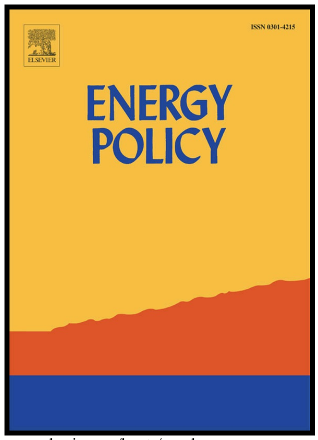

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PII: S0301-4215(18)30201-5
DOI: https://doi.org/10.1016/j.enpol.2018.03.068
Reference: JEPO9908

To appear in: *Energy Policy*

Received date: 12 October 2017
Revised date: 13 March 2018
Accepted date: 28 March 2018

Estimating temperature effects on the Italian electricity market

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Abstract

This paper provides empirical evidence of the effects that weather conditions exert on the electricity market, offering a new contribution to the understanding of hourly regional price formation in the day ahead market in Italy. The empirical estimation uses a new data set of hourly data on both market variables and temperature variables.
There is a vast body of literature on the effect of temperature on final consumers and on wholesale electricity market equilibrium. However, the influence of temperature on the behavior of the wholesale electricity market has not been studied at the hourly level. A new econometric estimation shows some evidence of different effects of temperature and provides a more accurate estimation of the hourly prices. Forecasting out-of-sample performance of the model is satisfactory.
The present results have welfare-improving policy implications, because appropriate policy strategies can help public decision-makers promote regulation, such as issuing public weather alert and designing contingent plans to face extreme weather conditions, which improves production efficiency, network management, and consumer saving behavior, taking specific weather conditions into account.

JEL classification: C32, D4, Q4

Key Words: Hourly electricity market; Temperature effects; Hourly temperature data; Vector autoregression; Non-parametric regression.

1 Introduction

The analysis of the dynamic pattern of electricity prices has developed extensively with the liberalization of electricity markets, exploiting the rich data made available from the organized wholesale markets. In particular, the European market design, as framed by the EU Directive (EU, 2009) and implemented by Member States, explicitly envisions the public release of the relevant market data in accordance with the principles of transparency and promotion of efficiency. In this respect, the Italian Power Exchange market (IPEX) is no exception. Data on prices, quantities, and relevant structural conditions are released by the market operator, GME spa, at an hourly frequency, almost in real time.

There is a large amount of empirical literature investigating several aspects of the liberalized electricity markets. This paper analyzes the stochastic properties of the spot prices, like mean reversion, seasonality, and extreme values, and assess the influence of the weather variables, such as temperature, on the pattern of electricity consumption. While a large amount of literature has addressed the issue of temperature effects by looking at the final consumer behavior at the structural level of monthly or annual data, as argued more in detail in the next Section, there has not been any explicit analysis of the nexus between market prices and temperature effects at the hourly level.

The aim of this paper is to fill this gap, providing empirical evidence of the effects of temperature conditions on the electricity market at the hourly frequency, specifically investigating whether forecasting the temperature effect is a relevant additional variable in the day-ahead price determination at the hourly frequency. In this paper, this aim has been broken down to the following three new research questions:

First, the hourly price forecast is explicitly modeled, both taking into account and testing the specific effect of a function of the hourly temperature. Second, the empirical analysis considers simultaneously regional and hourly data for the longest period available. Data are for six regions and 101,520 hours from January 2005 to July 2016. There are no studies of the Italian market that analyze such a long range of data. Third, the estimation is carried out via a comprehensive model of hourly price determination using data on both market variables and weather forecast variables. In particular, a new hourly measure of heat degree-hours (HDH) and cooling degree-hours (CDH) is computed and used, together with a new measure of extreme weather conditions for six Italian regions.

Results can offer a more accurate forecast of electricity market prices, which can be useful for both private business and public policy-makers. Generation companies can use a more accurate price forecast to improve their profitability strategies and their short-term technical and operational decisions, as well as their long-term investment decisions.

Policy-makers and public agencies (like the Energy Authority and the Renewable Incentive Program Agency) can use more accurate price forecasts to implement better regulation to promote competition and enhance consumer welfare. Consumers will have better choice opportunities. Specific consumer categories can be better protected, like in the case of linking, in a systematic way, the issuance of public weather alerts to real time measures to helping the elderly in extreme weather conditions.

The paper proceeds as follows. Section 2 presents a brief literature review. Section 3 describes the model. Section 4 discusses the methodology applied and the data. Section 5 presents the results. Section 6 concludes and discusses the policy implications.

2 Literature review

The introduction of weather variables in the analysis of electricity consumption and price patterns dates back to the pioneering works of Le Comte et al. (1981), Engle at al. (1986), and Peirson and Henley (1994), who estimated models with monthly data. Since then, there have been three main lines of research on the weather–electricity market variables' nexus.

The first line of research deals with the impact of temperature on residential demand and prices. The data are generally at a monthly frequency (Miller et al., 2017; Son et al., 2017), with a breakdown of monthly sectorial electricity demand and complex functions of the density of temperatures (Chang et al., 2016). Analysis of the sectorial firms' electricity demand with temperature effects has been conducted at the daily frequency in the case of Spain (Moral-Carcedo and Pérez-García, 2015). Also using daily temperature data, Graff Zivin and Novan (2016) assess the impact of temperature on the individual response to the residential weatherization programs designed to encourage conservation. A specific interest in the analysis of demand response in urban areas is provided by Papakostas and Kyriakis (2005), who use HDH and CDH in Greece, with daily data; Veliz et al. (2017), who estimate the effect of climate change on electricity prices in the US, with monthly data; Luiz and Afshari (2015), who measure several hourly weather variables to model and forecast the electricity load within the UAE, using a transfer function method, with daily data; Jovanovic et al. (2015), who analyze the impact of temperature conditions on the consumption of electricity in East Europe, with daily data.

The second line of research analyzes the supply side. Yu et al. (2009) use a data envelope analysis to investigate the impact of weather on the overall efficiency of network utilities, measured with costs and quality of service. Herrerias and Girardin (2013) use temperature to analyze the seasonal character of electricity production across Chinese regions, at the monthly frequency.

The third line of research deals with dynamic modeling and forecasting the electricity price with temperature variables at a higher frequency, generally either daily or weekly. The electricity price is modeled using the stochastic time change method, with the temperature being used as a proxy for the demand (Borovkova and Schmeck, 2017). Figueiredo et al. (2016) provide an updated literature review of the analysis of daily electricity prices and the weather variables, analyzing the Central–West European market with vector auto regressions (VARs), showing that there are also spillover effects across all countries.

The day-ahead spot price dynamics in the German electricity spot market is analyzed with a dynamic structural VAR model by Paschen (2016), who finds that load and spot prices are stationary. Several price variables, peak hours, and daily averages, are analyzed by Huurman et al. (2012) at the daily frequency, who show that temperature information demonstrates predictive power in forecasting electricity prices. Evidence that electricity load and prices are temperature sensitive is reported also in Forbes and Zampelli (2014). Bosco et al. (2010) justify the use of weekly medians of the original hourly time series to avoid intra-day seasonality. A mean reversion of electricity prices in wholesale markets is found in Bosco et al. (2010), Huisman and Mahieu (2003), and Zhang and Lian (2017). The latter authors estimate a general model combining wavelet transformation, a kernel extreme learning machine, and an auto regressive moving average (ARMA), using daily data.

A specific interest in the effects of extreme temperature events on the electricity prices in Latin America is provided by Santágata et al. (2017). Evidence of extreme weather with daily data is provided by Moral-Carcedo and Pérez-García (2015), who analyze the impact on firms' electricity demand in Spain, and by Mansanet-Bataller et al. (2007), who analyze the EUA price levels.

Raviv et al. (2015) challenge the view that hourly prices are independent, because, as they point out, the market process is based on simultaneous bids submitted for the prices of all the hours of the next day in the day-ahead market.

They posit that prices are determined simultaneously and that it is not appropriate to model the hourly prices as single time series. Their line of analysis is geared toward the question of whether hourly electricity prices can be used to predict the daily average price.

In summary, the existing literature does not contain an explicit estimation of the hourly frequency of the electricity price determination with temperature effect. This paper intends to fill this gap.

3 The Model

The general model specification is grounded on the simple textbook supply equation, which can be identified (Fisher, 1966) as a price-quantity relation that excludes a priori specific demand determinants (such as income). In this context, the supply function is specified as follows: price *P* is a function of quantity Q and possibly market structure *M* (as defined in the next section) plus an error term u.

$$P = f(Q, M) + u \qquad (1)$$

The main interest of this paper is to investigate the additional explanatory content of the temperature T, assuming that the supply function includes also the temperature *T*:

$$P = f(Q, M, T) + u \qquad (2)$$

Note that eq. (2) allows us to test empirically whether temperature is an additional significant regressor, together with load, that explains day-ahead prices.[1] In this paper, three specifications of eq. (2), both parametric and non-parametric, are used to assess the impact of temperature on electricity day-ahead prices in the six regions of the Italian electricity market (as explained in detail in the next section)..

First, a non-parametric regression is conducted to compute a kernel estimator of the relation price-quantity and price:

$$E(P|X = x) = f(x) \tag{3}$$

where $X= \{Q, T\}$ and $f(x)$ is a kernel estimator with a Gaussian function.

Second, a simple ARMA(p,q) model is used for each regional price:

$$P_t = \sum_{j=1}^{k} a_j \; P_{t-j} + \sum_{j=0}^{k-1} b_j \; u_{t-j} \tag{4}$$

where $b_0 = 1$, $b_j = 0$ for $j > q$, $a_j = 0$ for $j > p$ and the innovations u_t are independent and identically distributed, with $E[u_t] = 0$.

Third, a VAR(p) model is specified for the six regional prices, or a p-th order VAR, with exogenous variables X:

$$P_t = c + A_1 P_{t-1} + \cdots + A_p P_{t-p} + B_0 X_t + B_1 X_{t-1} + \cdots + B_s X_{t-s} + u_t \tag{5}$$

where P_t is a vector of the six regional prices, with p lags of these variables, c A_j B_j are parameters, and $X_t= \{Q_t, T_t, M_t\}$ are exogenous variables, which include functions of

[1] This is an empirical question, because it cannot be taken for granted that the load incorporates all the relevant information at the time of the day-ahead price formulation. So, adding the temperature forecast in the equation allows its significance to be tested.

contemporaneous and lagged quantities, market structure, and temperatures. The usual assumption holds:

$E(u_t) = 0,\ E(u_t, u_t') = \Sigma, and\ E(u_t, u_s') = 0, \forall\ t \neq\ s$.

It is particularly interesting to assess the effect of forecast temperature on the electricity day-ahead market prices. Weather forecasting is crucial to both the demand and the supply sides of the electricity market. On the demand side, traders and distributors are sensitive to weather conditions, for their customers in the retail market are affected by temperature and, therefore, both traders and distributors are exposed to the risk of unbalancing costs. On the supply side, energy companies and generating utilities obviously face operational challenges related to unexpected changing weather conditions. It is assumed that market operators formulate weather forecasts using the available temperature data at the time of decision. Therefore, this paper considers how temperature forecasting is incorporated in the agents' decision process, taking into account the relevant works of Wilks (1995) and Campbell and Diebold (2005), who used a time series approach to forecast daily temperatures.

To this end, three different temperature forecasting behaviors in the electricity market are considered: (i) A short-term memory, i.e., using past temperatures of previous hours—this model is intended to capture an autoregressive expectation formation about the temperatures during the next day, at the time of the day-ahead market formation; (ii) A long-term memory with perfect foresight using contemporaneous and lagged temperature values—this model implies perfect foresight at the time of the day-ahead market formation and incorporates the realized value of the temperature in the observed hour; and (iii) A long-term memory plus a specific alert mechanism for extreme weather conditions. This model includes a specific determinant for the periods of extreme values of the temperatures, which are very low in the winter in the Northern regions and very high in the summer over the entire country.[2]

4 Data and Methodology

The dataset used is constituted by the hourly day-ahead market outcomes in Italy, taken from the Italian market operator, GME spa, and spans the longest period available since the start of the Italian Power Electricity Exchange market (IPEX). The 2004 data are discarded, because the market was not completely operational in the initial period, with only the generator allowed to bid in the market. Thus, the data on hourly prices and quantities are collected for the period January 2005 to July 2016, for a total of 101,520 hourly records.

The Italian day-ahead market determines the hourly equilibrium price and quantity as the balance of the supply and demand bids, aggregated according to the ascending and descending merit order, respectively. Bids can be freely revised until the closure deadline, which is 12:00; i.e., the market closes on average 24 hours before operations start. In case of line congestion, a market segmentation solution with different regional prices is implemented. Notice that Italy is a narrow country stretching from North to South, with the two largest islands (Sicily and Sardinia) in the Mediterranean Sea; so the zones of possible congestion are pre-defined in six regions—North, Center-North, Center-South, South, Sicily, and Sardinia—by the system operator, TERNA spa.[3] This means that different prices can occur only across the six regions and not within a region. The regional prices occurring in the 6 regions are labeled PNORD, PCNOR, PCSUD, PSUD, PSICI, and PSARD, respectively. Note that different market segmentation resulting in different

[2] Exceptional weather conditions in Italy can occur in the winter as a result of exceptional North-east wind storms originating from a Siberian anticyclone (Makrogiannis et al., 1980) and in the summer as a result of African heat waves originating from the African anticyclone hitting the Mediterranean Sea.

[3] Sicily is connected to the South, and Sardinia is connected by two HVDC lines to Center-North and Center-South, respectively.

prices can occur across the adjacent regions due to different patterns of line congestion. The most frequent occurrence is the two-market segmentation between Continental Italy + Sardinia and Sicily [for a detailed analysis, see Bigerna et al. (2016a)]. Therefore, there are six regional price series in every hour.

The market structure variable is captured by the Herfindahl index, as published by the Market operator for each hour and region (GME, 2017). This variable summarizes the market conditions in terms of concentration and congestion.[4]

Hourly temperature data are provided by the Italian Military Airforce General Office for Meteorology for six airports located in the center of the six regions analyzed. Data are registered at a frequency of 20+ minutes within the hour; thus, they have been preliminarily averaged the data at the hourly level. Hourly temperature data have been used to compute two other variables: the HDH and CDH values, with the reference temperature at 18° Celsius, defined as the differences between hourly average temperatures and the base temperature:

$$CDH_h = (T_h - T_r)^+ \quad (6)$$

$$HDH_h = (T_r - T_h)^+ \quad (7)$$

where T_h is the average hourly temperature and T_r=18 is the reference temperature, as defined above. The “ $^+$ “ superscript shows that only positive values are considered in each formula.

In summary, the data used are the hourly prices, quantities, temperature, HDH, CDH, and market structure for the six regions, for a total of 609,120 elementary observations for each variable (101,520 hours *x* 6 regions).

A preliminary data analysis with a simple scatter plot analysis reveals that prices move with temperatures in different seasons and regions. In winter, prices move upward with lower

[4] Similar considerations on the Italian market can be found in Gianfreda and Grossi (2012) and Bigerna et. al. (2016b).

temperatures, and more so in the North, while prices move upward with higher temperatures in the summer, and more so in the South (Figure 1). Focusing on the time series properties, there is a vast body of literature on unit root tests applied to energy data, as reviewed by Smyth and Narayan (2015). There is evidence of both stationary and non-stationary pattern of quantities at both the country and the sector level. For the electricity markets the evidence shows typically that market series exhibit mean reversion and are stationary [an example for Italy is reported in Gianfreda and Grossi (2012)]. Another debated issue is the power of the unit root test in the presence of time series of spatial data. For instance, the analysis of large multi-country panels shows both stationary and non-stationary patterns, with a Seemingly Unrelated Regressions (SUR) Augmented Dickey–Fuller (ADF), or SURADF, test.[5] Along these lines, it is reasonable to consider that the regional prices are undoubtedly affected by some common decision process in the market, and, thus, may have to be considered as a regional panel of time series; the situation is similar with multi-country energy data. In addition, there is the issue of non-linearity, certainly grounded on the basic features of convexity of the underlying supply functions and demand functions that determine the equilibrium outcomes. Non-linearity has been analyzed, in the case of exchange rate data, with the non-linear test by Kapetanios et al. (2003), who pose, as an alternative to the unit root hypothesis, the hypothesis of non-linear but globally stationary ESTAR (exponential smooth transition autoregressive). This may be a relevant case if the speed of mean reversion is not invariant to the distance from the equilibrium. In this case, non-linearities can arise, perhaps due to market frictions, like transmission line congestions, agents' heterogeneity, and the influence of regulatory interventions in the market (Taylor, 2010).

[5] The SURADF test is advanced by Breuer et al. (2001), which incorporates the efficient SUR estimator and is reported to be potentially more powerful than the ADF test alone (Hsu et al. 2008).

Based on previous considerations, the six regional prices and the six regional quantities are first tested for stationarity with the ADF test and then for cointegration with the Engle–Granger test. Each hour is considered separately. Given that the regional variables for prices and quantities may be correlated, the SURADF test (Hsu et al. 2008) is performed, considering a panel of 6 regional variables through time. Finally, the Kapetanios test is used for non-linearity but global stationarity. All tests are reported in Tables 1 and 2. The first three columns of Table 1 report the ADF tests for prices, quantities, and temperature in the 6 regions. The fourth column reports the Engle–Granger test for the cointegration vector price-quantity-temperature. The four columns of Table 2 report the same tests for each hour separately; there are 4,230 observations in the sample. To save space, results are reported only for 4 hours of the day (00.00; 6:00; 12:00; 18:00); the others are available upon request. In addition, columns five and six of Table 1 report the non-linear Kapetanios tests for price and quantities, and the last two columns, seven and eight, report the SURADF test for the six regional price and quantity variables.

Findings show that, for all variables, ADF and SURADF tests reject the null hypothesis; thus, the conclusion is in favor of stationarity, even taking into account the panel feature of the regional variables. This is in line with a similar analysis by Kyritsis et al. (2017). There is also a rejection of unit root and some indication in favor of non-linear stationarity, less so in the case of log transformation. On the basis of these results, logs of the six regional price variables are taken.

5 Estimation results

The data set described in the previous section is used to estimate different models, both to assess their relative performance in estimating prices and to choose the most appropriate empirical representation of the price generation process.

First, a non-parametric kernel regression is estimated, with relative bandwidth data driven [chosen according to the classic rule of thumb of Silverman (1986)] for each regional price (Table 3). For a recent non-parametric analysis of energy variables see Mohammadi and Ram (2017).

Study of the density functions of the six regional prices allows us to check for the time patterns, as shown in Figure 2. The shape of the distribution has not changed significantly between 2006 and 2016, for all regions with a tendency to higher peaks in the most recent period, with the exception of the Sicily distribution, which is definitely less dispersed in 2016 than in the previous periods. The accuracy of the estimation is somehow poor, as shown by the RMPSE values in Table 3, especially in tracking the spikes and the pattern in the Island, see Figure 3.[6]

Second, a simple ARMA(24,12) model is estimated for each regional price (Table 3). In principle a Seasonal ARMA(P,Q)s, considering s=24, i.e., considering the influence of the same hour of the day before, can be also investigated. As examples, note that Janczura et al. (2013) and Nowotarski and Weron (2016) discuss the daily seasonality of the electricity day-ahead prices. As the focus in this paper is not on the de-seasonalized properties of the series, this issue is not pursued further. The maximum order lag for autocorrelation was chosen as one full day, p = 24 (and q=12), determined using the usual Schwarz Information Criterion tests for the null hypothesis of absence of autocorrelation until order 48 (essentially, two days). The estimated series are plotted against the historical values for 2 representative hours of the day: 00:00 and 12:00 (Figure 4). The goodness of fit is somewhat better than with the non-parametric kernel estimation, but it is quite low, as shown by the r-square and root mean square percent error (RMSPE) values reported in the last column of Table 3.

[6] Note that, in Figure 3 (and following), each box shows the regional price pattern. As price variability is different in each region, the scale of each box is automatically adjusted to enhance the visual impact of the line.

Third, focusing on the VAR models of the six regional (log) prices, five variants of the theoretical models (1) and (2) are estimated, labeled VAR0, VAR1, VAR2A, VAR2B, and VAR2C (Table 4). The first estimation, VAR0, is a basic model with contemporaneous and lagged quantities as exogenous variables. The order of lag chosen to set a parsimonious parameter specification is: 0, 1, 2, and 24. The second estimation, VAR1, corresponds to equation (1), which includes the market structure variable (as in Gianfreda and Grossi, 2012).

Fourth, the temperature effect is added to the model, as in eq. (2), considering a short run forecast of temperature, model VAR2A. In this case, the temperature variable lags reflect the current information presumably available at the time of closure of the day-ahead market (at midday) and are chosen as 12, 24, 25, and 30. Fifth, a long memory forecast with perfect foresight is considered in model VAR2B. In this case, the temperature lag structure is more complex, ranging from the contemporaneous temperature to a maximum lag of 30. Therefore, the lags are 0, 1, 6, 12, 18, 24, 25, and 30. Values of the temperature variables every six hours have been used to mimic the typical frequency of the meteorological forecast issued by the Italian Military Navy meteorological service. This has been done because, and this has to be stressed, the day-ahead market data are determined the day before the actual recorded date, so the contemporaneous temperature is not known at that time. In other words, the realized temperature value in each hour can be assumed to be the perfect foresight value determined the day before.

Sixth, regional dummy variables have been computed for extreme critical conditions of very low temperature in the Northern regions (below -5° Celsius) and very high temperatures in the whole country (above 30° Celsius). These occurrences are seen in approximately 5% of the whole sample. The model that includes of the extreme weather condition is model VAR2C.

The relevant diagnostics for these five VAR models are shown in Table 4. Note that VAR0 is theoretically unfounded and that VAR2A is a significant generalization of the basic model VAR1 (which includes the market structure variable), on the basis of the LR test. In other words, temperature has a significant additional effect on price determination.

The empirical results of models VAR2A, VA2B, and VAR2C are new in the analysis of the Italian electricity day-ahead price. These results undoubtedly show that temperature is significantly determining prices. The LR ratio tests are all in favor of the highest level of generalization. This confirms the relevance of extreme weather conditions in shaping the market outcome.

In addition, the single equation diagnostics of the VAR1 and VAR2C estimations are reported to appreciate better the improvement in the price estimation provided by the inclusion of the temperature effect (Table 5). The VAR2C model exhibits lower r-square and RMSPE values and better DW. Note the high significance of the block exogeneity test for the inclusion of lagged values of the other prices. The accuracy of estimation of VAR2C is good, as shown in Figure 5, for two hours of the day for the six regions.

It should be noted that the dynamic specification of the VAR2C model involves the estimation of 145 parameters for each region, given the complex lag structure. Detailed parameter results (which are jointly statistically significant, as shown by the LR tests of Table 4) are available upon request. The simulations of shocks on the exogeneous variables are shown in Table 6, which provides averages (and standard errors) of the effects of the market structure, CDH and HDH to prices (simulated values are averages for the last year of the sample). These values are marginal effects, ceteris paribus, taking as given the quantity effects. The relative contribution of the market structure is reported in col. 1 of Table 6, and it shows that an increase of 10% in the

Herfindahl index, which can be interpreted as a lowering of competition, brings about an increase of 1%–1.5% in the electricity price in the Central and Northern regions of the country. Thus, an increase in concentration has a positive effect on prices. In the South, which is a region where the gas and electricity distributor Enel has a relevant position there is a small negative effect on prices. Differently from the other regions, the highest values of the Herfindhal index occur in the South during the night hours. Therefore, in these hours it happens that Enel bids its relatively more efficient generation units, pushing down the equilibrium price down, but at the same time pushing up the Herfindhal index. The relative contributions of an increase of 1 degree Celsius of CDH and HDH are reported in cols. 2 and 3 of Table 6. Note that in general, the effects are relatively higher for the CDH than HDH. This is in line with expectations, for in Italy air conditioning uses electricity more than heating (which uses also natural gas). Note that the effect of CDH and HDH is relatively lower in the central part of the country (C-north and C-south), showing that the need for comfort requires a relatively more moderate increase in price. In particular, the HDH effect in the South is negligible. In addition, note that in the islands, Sicily and Sardinia, an increase in the heating requirement, even if the winter season is short, spurs a relatively higher price increase. This can be triggered by the increased need for local generation, which may costlier. In addition, in Sicily the HDH effect is relatively greater than the CDH effect, possibly because higher temperature in the summer is concomitant of a larger share of solar generation, which partly moderates prices.

It is appropriate to evaluate the relative influence among the six regional electricity prices in the long-run using the impulse response and the forecast error variance decomposition (FEVD) of the estimated VAR2C. The former is useful to trace the effect that either an exogenous shock or an innovation in one of the variables has on the others. The latter shows the proportion of the forecast error variance of each variable that can be explained by some exogenous shocks to another variable. The impulse response and the FEVD for the six regional prices of model VAR2C are reported in Figure 6 and Table 7, respectively.

Analysis of these impulse responses highlights that a shock to the price in the North fades away rather quickly, while it is more persistent in the other regions. This is plausible, because the North is highly interconnected with other foreign markets. Prices in Sicily and Sardinia do not significantly react to a permanent 1% shock in the price of their adjacent regions; South and Center-South, respectively. All shocks fade away within the day.

To assess the forecasting performance, the model has been re-estimated, excluding the last six months of the sample and rolling one month ahead in each trial. Operationally, model estimation has been carried up to December 2015, then up to January 2016, and so on up to May 2016. Then, the model has been dynamically simulated to forecast zonal prices one month ahead, i.e., the forecasting horizon is 720 hours ahead, using historical values of the structural and temperature variables. The RMSPE values are higher than is the in-sample error (values range from .04 to .10 for all zones, except for Sicily, which is .20). Analyzing the decomposition of the mean square error, the fraction due to bias is approximately .5 for all series, while almost all the rest of the fraction is due to difference covariation. Correcting for the bias, the RMSPE is halved. The actual and forecasted corrected values for the 720 hours forecast for January 2016 are shown in Figure 7. The estimations for the other periods are quite similar. In general, the forecast appears to be satisfactory, (except for two isolated spikes) confirming the relative accuracy of the estimated model.

6 Conclusions and policy implications

In this paper, an hourly model of price determination in the Italian electricity market has been estimated for six regions. The main novelty of this work has been the incorporation of hourly temperature variables as a measure of the weather forecasting behavior of agents into the determination of the day-ahead price in the electricity market. This differs from previous studies, which have analyzed the impact of temperature on the market at either daily or weekly frequencies. Given that relevant temperature fluctuations occur within the course of one day, while daily averages show less pronounced changes, this result sheds new light on the understanding of hourly price formation.

In this paper, the hourly price determination is modeled simultaneously for the six regions in the Italian electricity market, considering the approach of Ravin et al. (2015), and it is related to the interesting work of Papakostas and Kyriakis (2005), who use heating and cooling degree hours to analyze residential behavior.

The empirical estimation of electricity prices has taken into account not only the main characteristics relative to the cointegration but also the parametric relationships between the electricity market and temperature variables, as recognized in the literature at daily and monthly frequency. The new results at hourly frequency show that temperature has a significant explanatory power alongside traditional load variables and other structural variables. The marginal effects of the temperature on prices are on average in the order of one percentage point, higher for cooling-degree hours and lower for heating-degree hours. The forecasting performance of the model out-of-sample is, in general, satisfactory.

Thus, possible future lines of extension of this work could be to develop further models of temperature forecasting, and also to simulate a kind of stress-test for extreme weather conditions.

If the forecast temperature affects the day-ahead price and this feeds back to the reaction of the policy-maker, a rational expectations framework could be devised, whereby market agents react to the policy response triggered by the private agent forecasts.

These results are relevant to formulating suggestions to policy-makers based on a better understanding of the relevant impact of temperature variables on the process of price determination, for four reasons.

First, a more accurate model of price forecast not only helps to design better deregulation policies and price setting enacted by the Government and/or the Energy Authority but also improves the acceptance of consumers, who can see a better and more transparent impact on their electricity bills. It should be remembered that a mission of the Italian Energy Authority is to promote competition. This can also be accomplished with more accurate information. If Italian consumers learn and understand that temperature is a relevant determinant of their electric bill, i.e., that, for example, high temperatures mean higher generation costs, this can be conducive to a more favorable attitude toward the transition challenges of the electric market, including a favorable response to real time pricing (Allcott, 2011). Indeed, any improvement in the credibility of the regulatory action is expected to have a positive impact on efficiency and welfare in the marketplace.

Second, better knowledge of market price models can help managers of generators and utilities refine their pricing strategies and, ultimately, improve their profitability. In other words, these results suggest that there is valuable information in the temperature variables to formulate business decisions, paving the way for further development of modeling other weather-related variables, such as humidity, insolation, wind speed, and so on.

Third, and closely related to the previous issue, it is reasonable to assume that weather-related variables, such as temperature in this study, will become increasingly relevant with the further development of renewable sources on the supply side of the market. This is rather obvious, for the availability of renewable sources depends on natural forces on Earth. Thus, the previous paradigm of complete human control of conventional generation technology may be increasingly challenged by the shift toward more reliance on renewable sources. Hence, there is a need to develop the analysis of the relationship between temperature and both the level and the composition of the electricity generation to design adequate risk control measures, to cope with increased volatility, and to face undesired consequences of policy actions. In this context, it is important to strengthen the relationship between short-term temperature effect and long-term investment decisions. Even if this argument may give rise to skepticism at first sight, we must recall that market prices, and especially the day-ahead prices, have been considered**,** within the liberalization of the electricity markets, as the signaling variable to spur future investment. Consequently, a better understanding of the driving factor of price formation is bound to have an effect on investment decisions.

Fourth, a more accurate understanding of the impact of extreme weather conditions can help public decision-makers enact better regulation to improve consumer welfare. As the Italian Energy Authority is involved in the definition of the policies in favor of specific groups, such as poor and weak consumers, it can help accomplish its mission by taking care of sensitive issues related to either the elderly or those affected by long-term illness, who may suffer in critical weather conditions, and enacting specific tariff structures and rebates related to weather conditions.

In conclusion, this paper has provided new empirical evidence of the significant impact of temperature in the hourly price determination in the electricity market. The results quantify the additional explanatory power of temperature with respect to the traditional load variable and other structural variables and demonstrate the possibility of obtaining more accurate short-term price forecasts at an hourly frequency. Better information and better forecasts is the basic way for the regulator to encourage supply competition and enhance consumer welfare. This work opens a fruitful line of future research to analyze further the link between the day-ahead electricity price formation and temperature forecasting at an hourly frequency.

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Figure 1 Price and temperatures in Winter and Summer at 12:00 – North and South -2005-2016 (*) (*) Price on the horizontal axis in Eur/MWh and temperature on the vertical axis in Celsius

Figure 2 - Kernel estimation of regional prices

Figure 3 - Regional price estimation with kernel regression – period 2006-2016 (*) (*) price in Eur/Mwh on the vertical axis

Figure 4 - Regional price estimation with ARMA model – period 2006-2016 (*) (*) price in Eur/Mwh on the vertical axis.

Figure 5 - Regional price estimation with VAR2C model – period 2006-2016 (*) (*) price in Eur/Mwh on the vertical axis

Figure 6 - Impulse response of VAR2C model

Figure 7 – Zonal prices - out-of-sample dynamic forecast Jan 2016 - one month ahead (*) (*) price in Eur/Mwh on the vertical axi

Table 1- Cointegration and Non-linearity tests – regional series

Test value	ADF price	ADF quant	ADF temp	EG P-Q-T	KAP price	KAP quant	SURADF price	SURADF quant
24 lags								
North	-21	-64	-5	-16	-18.9	-3.0	-62.1	-152.1
C-North	-21	-54	-9	-17	-19.3	-3.9	-80.1	-165.1
C-South	-21	-31	-10	-16	-19.5	-3.8	-84.2	-114.8
South	-20	-18	-10	-16	-26.2	-3.8	-100.8	-117.1
Sicily	-15	-26	-11	-17	-23.9	-4.2	-66.9	-107.6
Sardinia	-20	-10	-10	-21	-23.9	-3.2	-89.8	-120.7

Note: all values are significant at 1% level
Cols.1-3: ADF, augmented Dickey Fuller on price, quantity and temperature, no constant, (critical level= -3.4). Col. 4: EG, Engle Granger cointegration test on price, quantity and temperature vector. Cols. 5-6: Kapetanios test on price and quantity, significance level at 1% = -2.8. Cols. 7-8: SURADF test on system of regional price and quantity.

Table 2 - Cointegration tests – hourly regional series

Test value	ADF price	ADF quant	ADF temp	EG P-Q-T
7 lags				
Hour 1:00				
North	-5.1	-13.4	-5.2	-5.2
C-North	-5.3	-10.2	-6.2	-5.5
C-South	-5.5	-8.0	-6.1	-5.9
South	-6.5	-4.5	-5.5	-6.8
Sicily	-9.7	-7.8	-5.2	-10.9
Sardinia	-11.0	-4.9	-5.9	-12.7
Hour 6:00				
North	-6.6	-12.2	-5.2	-6.9
C-North	-6.9	-9.9	-6.2	-7.0
C-South	-7.3	-7.9	-6.0	-7.4
South	-7.9	-4.9	-5.1	-7.9
Sicily	-10.8	-7.9	-4.9	-11.3
Sardinia	-11.6	-4.6	-6.4	-13.0
Hour 12:00				
North	-8.6	-9.9	-5.3	-8.5
C-North	-8.1	-8.9	-5.3	-8.8
C-South	-7.8	-6.3	-5.4	-7.8
South	-8.1	-5.3	-5.9	-8.2
Sicily	-7.8	-7.9	-5.0	-9.5
Sardinia	-9.2	-5.1	-5.2	-9.5
Hour 18:00				
North	-6.1	-10.5	-4.7	-7.1
C-North	-5.6	-8.9	-5.4	-6.9
C-South	-5.5	-6.7	-5.1	-5.7
South	-6.0	-5.1	-5.3	-6.7
Sicily	-7.0	-7.1	-4.8	-9.4
Sardinia	-8.8	-4.9	-5.1	-9.6

Note: all values are significant at 1% level
Cols.1-3: ADF, augmented Dickey Fuller on price, quantity and temperature (no constant). Col. 4: EG, Engle Granger cointegration test on price, quantity and temperature vector

Table 3 - Estimation diagnostics - Single regional equations

Test value	logL	r-square	No. Coeff.	DW	rmspe
North					
Kernel	..	.57	..	..	6.9
ARMA	-360965	.89	36	1.9	0.9
C-North					
Kernel	..	.64	..	..	6.2
ARMA	-367636	.89	36	2.0	1.5
C-South					
Kernel	..	.35	..	..	32.0
ARMA	-369306	.89	36	2.0	7.3
South					
Kernel	..	.49	..	..	72.2
ARMA	-371526	.89	36	1.9	2.0
Sicily					
Kernel	..	.58	..	..	65.2
ARMA	-443316	.82	36	2.0	28.1
Sardinia					
Kernel	..	.42	..	..	26.7
ARMA	-425720	.1	36	2.0	8.9

Note: Kernel Gaussian regression, data determined bandwidth. AR (24,12) single equation estimation. Col.1: Log likelihood values. Col. 2: r-square. Col. 3: number of parameters. Col. 4: Durbin-Watson test. Col. 5: root mean square percentage error.

Table 4 - Estimation diagnostics - VAR system of regional equations

Test Value	logL	LR test	No. Coeff.	Schwarz B.I.C.
VAR0: simple p,q	477126		222	-475649
VAR1: add mkt structure	478847	3442(72)	294	-476891
VAR2A: add short run temperature effects	479402	1110 (276)	576	-475570
VAR2B: add long run temperature effects	479999	1194 (282)	858	-474291
VAR2C: add extreme temperature effects	480055	112 (54)	912	-473987

Note: VAR specifications: VAR1 from eq. (1); VAR2A, VAR2B, VAR2C, from eq. (2), 24 lags with quantities and temperature.
Col.1: Log likelihood values. Col. 2: LR test with degrees of freedom (d.f.) in parenthesis; all tests are Chi-square and significant at 1% (critical values are: 81.1for d.f.=54; 102.8 for d.f.=72; 359.9 for d.f.=300. Col. 3: number of parameters. Col. 4: Schwarz B.I.C.

Table 5 - Estimation diagnostics of VAR models - Single regional equations

Test value	R2	No. Coeff.	DW	Block exog F	rmspe
North					
VAR1	.91	49	1.82	15.4	0.02
VAR2C	.92	152	1.84	14.9	0.01
C-North					
VAR1	.90	49	1.84	51.8	0.038
VAR2C	.91	152	1.86	54.5	0.037
C-South					
VAR1	.90	49	1.86	53.1	0.039
VAR2C	.90	152	1.87	51.7	0.038
South					
VAR1	.87	49	1.89	70.9	0.055
VAR2C	.87	152	1.89	70.9	0.054
Sicily					
VAR1	.85	49	1.97	105.1	.12
VAR2C	.86	152	1.97	99.4	.11
Sardinia					
VAR1	.86	49	1.92	161.3	0.039
VAR2C	.86	152	1.92	169.7	0.038

Note: VAR1 and VAR2C: VAR specifications as in table 4. Col.1: R square. Col. 2: number of parameters. Col. 3:Durbin-watson test. Col. 4: block exogeneity F test for significance of lagged values of other dependent variables. Col. 6: mean square percentage error.

Table 6 – Estimate of the effect of market structure and temperature in model VAR2C

	Increase of 10% in Herfindhal index	Increase of 10 C in Cooling-degree-days	Increase of 1^0 C in Heating-degree-days
		Percentage effect on price	
North	1.2 (0.09)	1.36 (0.01)	0.22 (0.02)
C-North	0.3 (0.02)	0.64 (0.08)	0.10 (0.08)
C-South	1.5 (0.05)	0.73 (0.09)	0.17 (0.02)
South	-0.3 (0.04)	2.44 (0.02)	0.07 (0.01)
Sicily	0.1 (0.002)	0.62 (0.02)	2.39 (0.01)
Sardinia	1.1 (0.02)	1.05 (0.01)	0.93 (0.01)

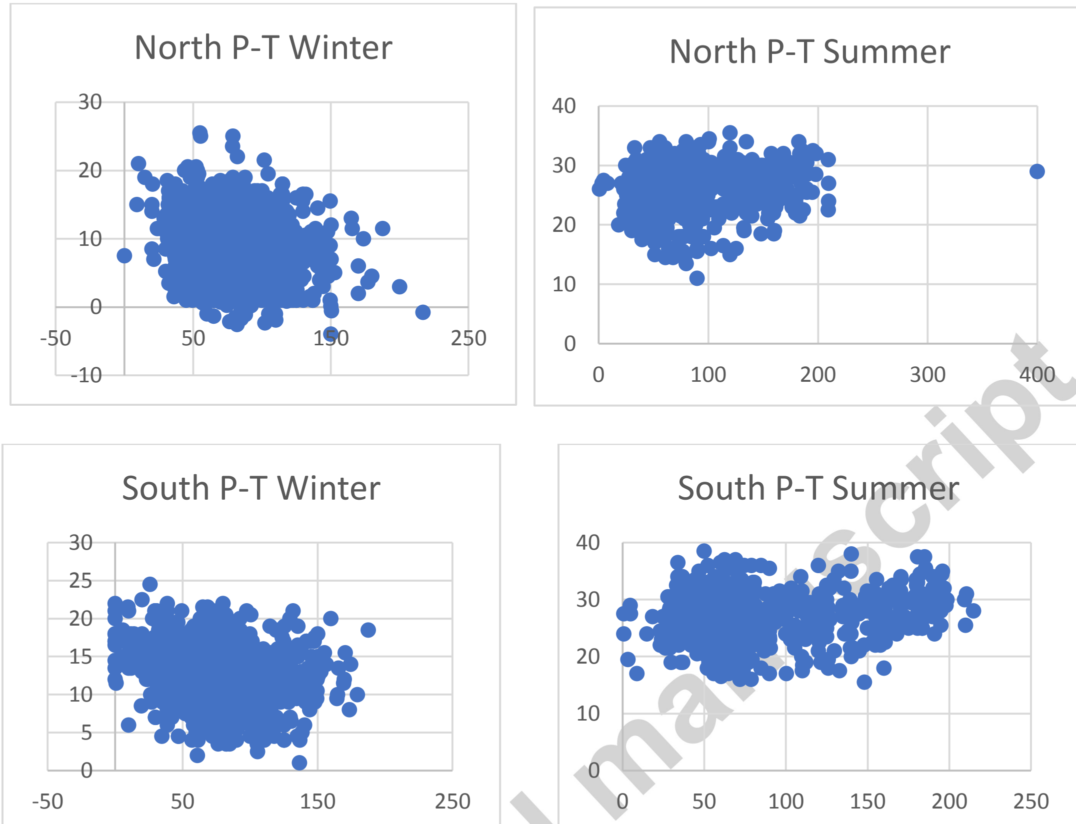
Note: simulation of the single regional equation of theVAR2C model, with shocks on the regressors shown in columns. Values are averages (with standard errors in parenthesis) of the percentage difference between actual and simulated values for the last year of the sample.

Table 7 - Single regional equations forecast error variance decomposition from model VAR2C

Variation in the row variable explained by column variable

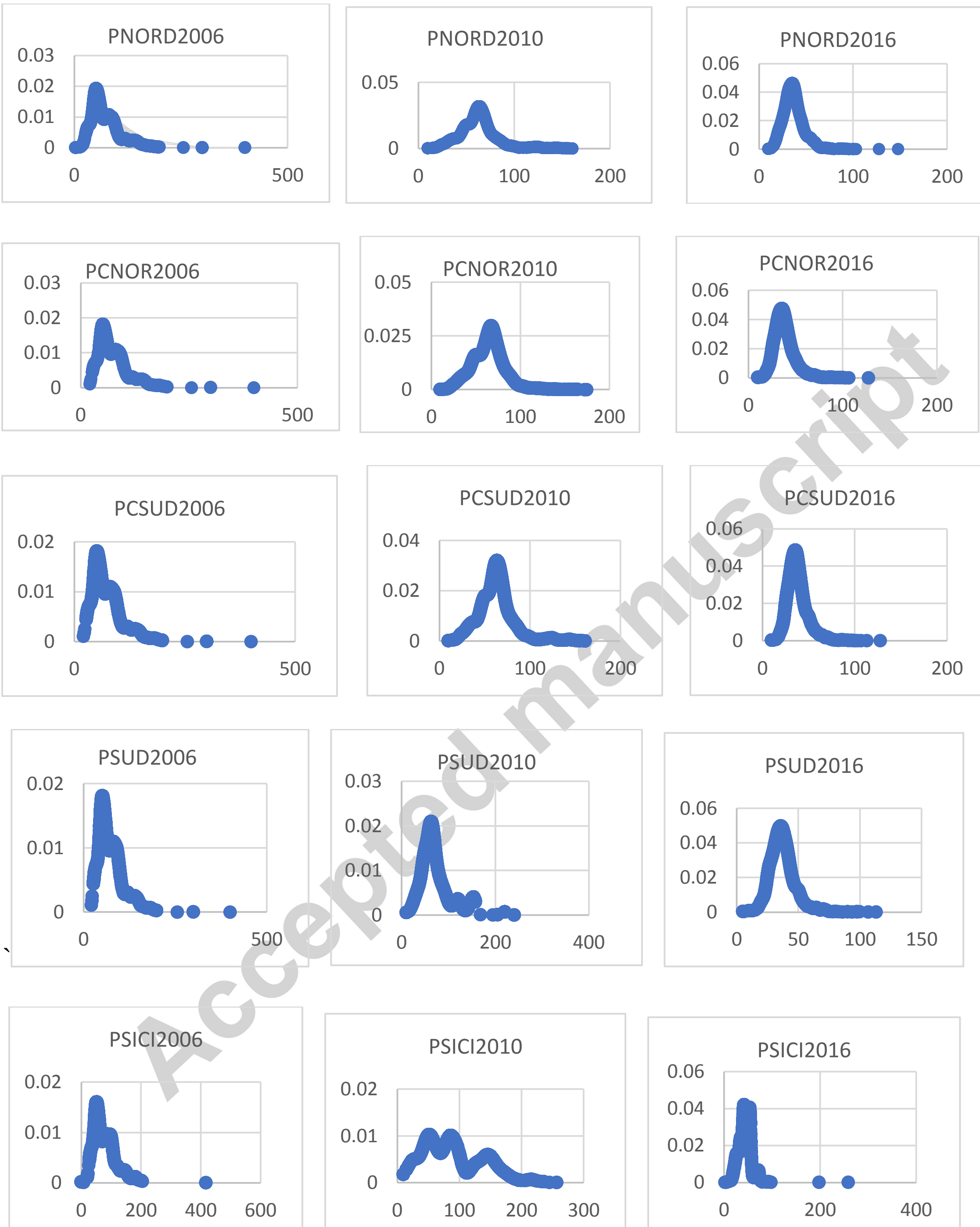
	North	C-North	C-South	South	Sicily	Sardinia
North	0.2	99.6	0.1	0.0	0.0	0.1
C-North	0.2	72.1	27.5	0.0	0.1	0.1
C-South	0.2	54.1	17.4	28.3	0.1	0.0
South	0.3	33.0	10.3	18.3	38.4	0.0
Sicily	0.3	7.3	1.6	2.9	5.1	83.0
Sardinia	0.3	25.3	9.4	13.7	0.5	0.0

Figure 1 Price and temperatures in Winter and Summer at 12:00 – North and South -2005-2016 (*)



(*) Price on the horizontal axis in Eur/MWh and temperature on the vertical axis in Celsius

Figure 2 - Kernel estimation of regional prices



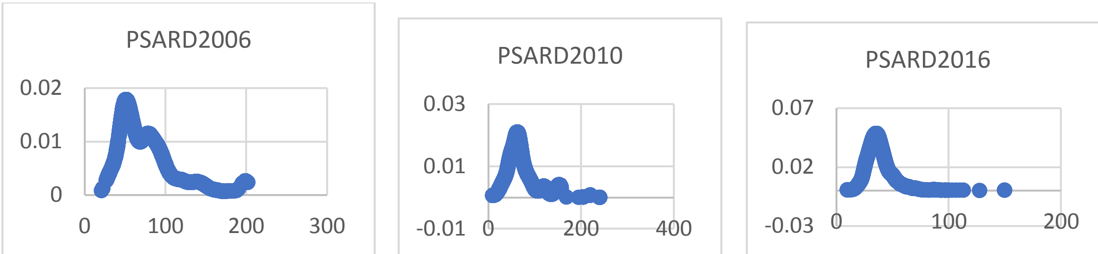
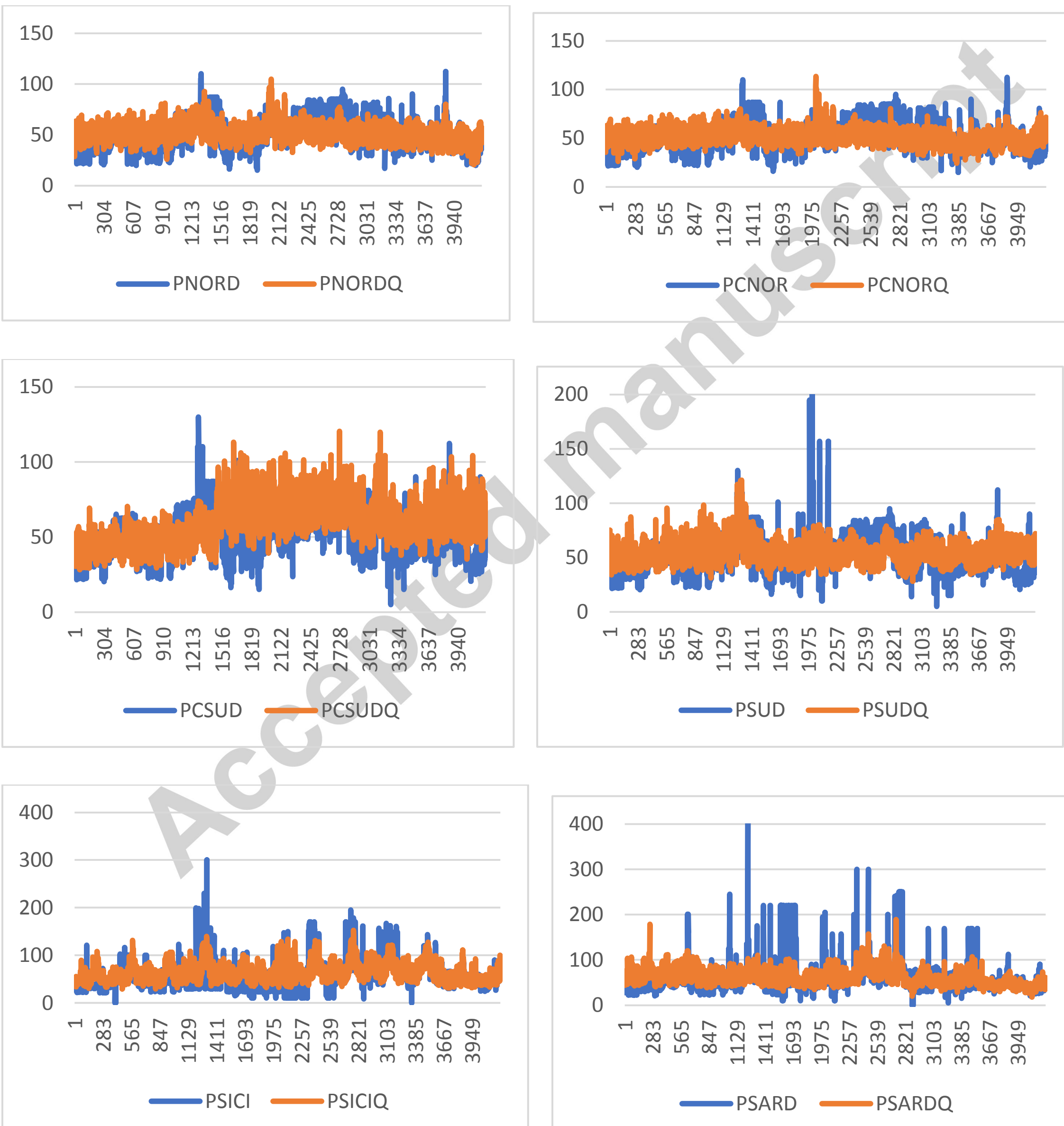
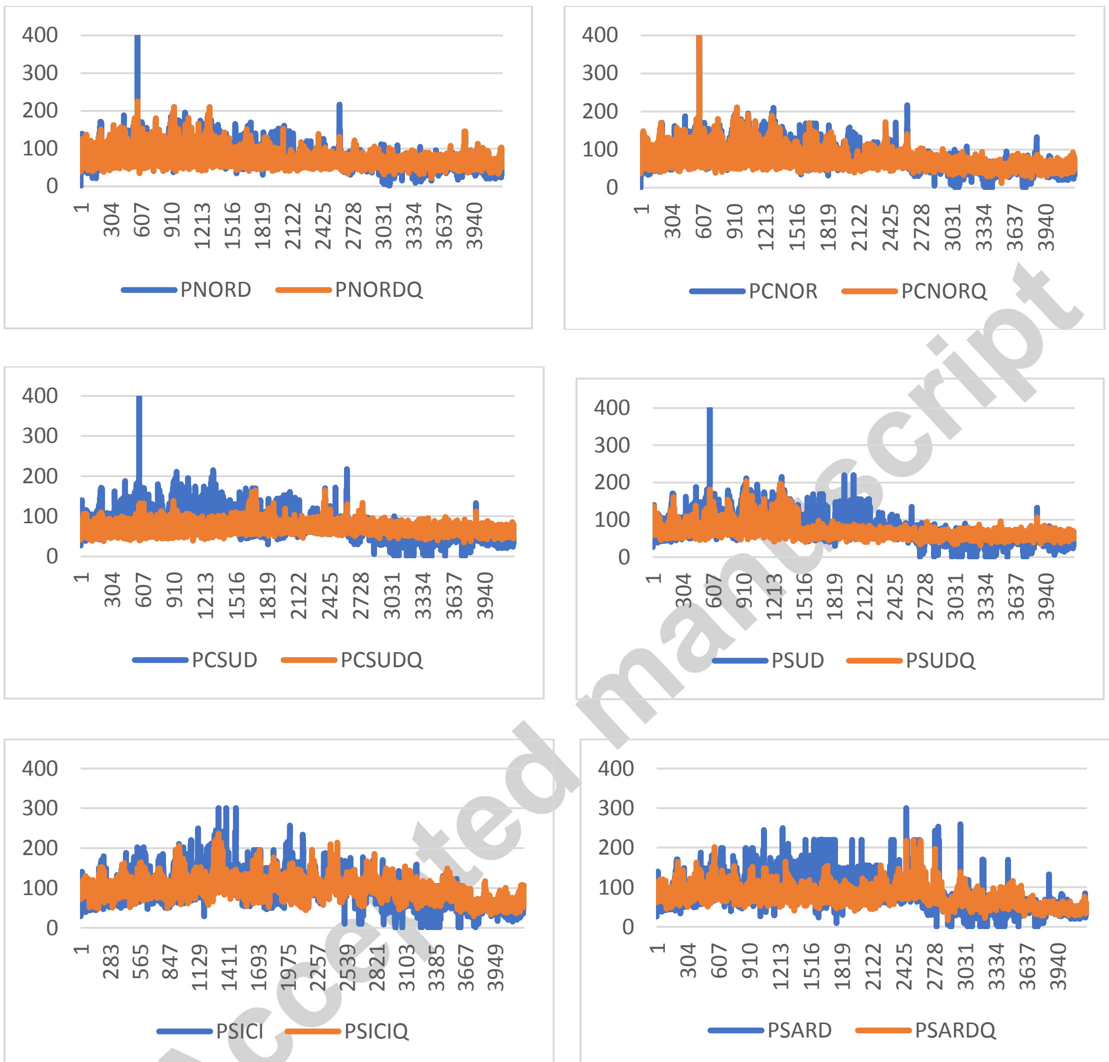


Figure 3 - Regional price estimation with kernel regression – period 2006-2016 (*)

Panel A – hour 00:00



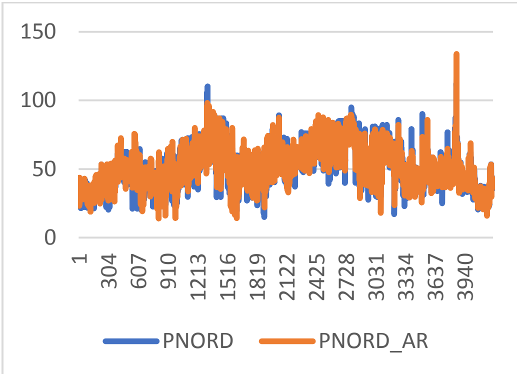
Panel B – hour 12:00

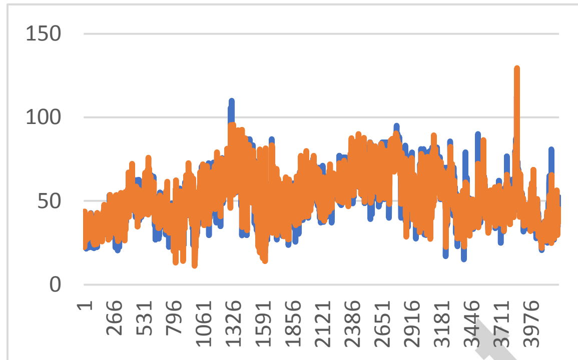


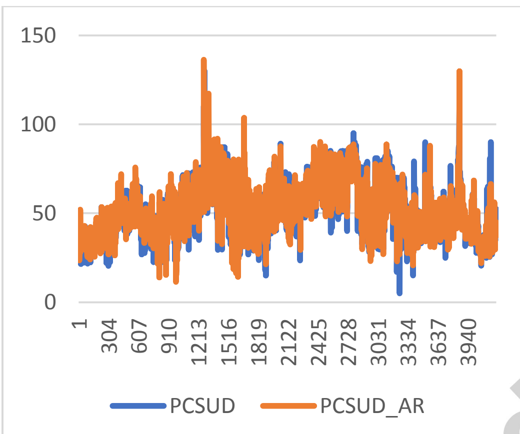
(*) price in Eur/Mwh on the vertical axis

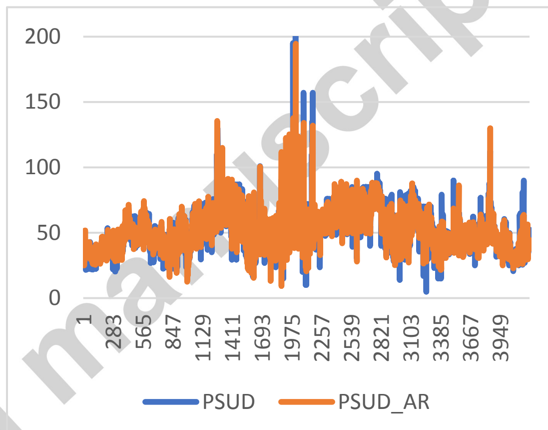
Figure 4 - Regional price estimation with ARMA model – period 2006-2016 (*)

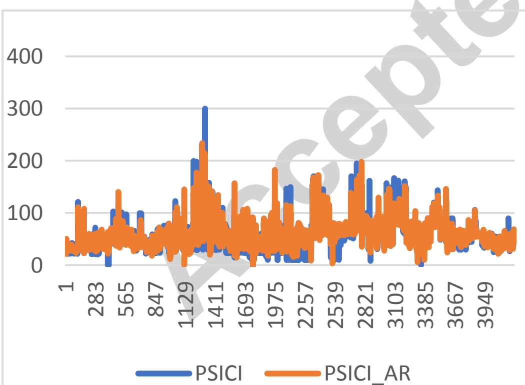
Panel A – hour 00:00

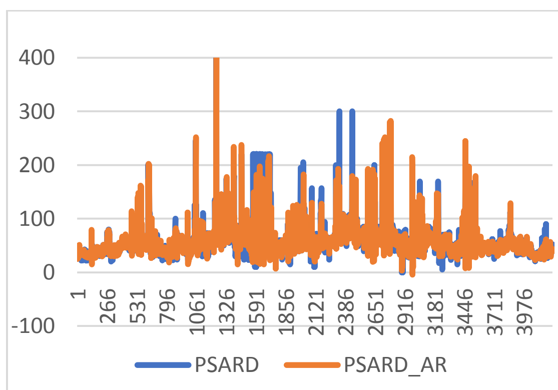




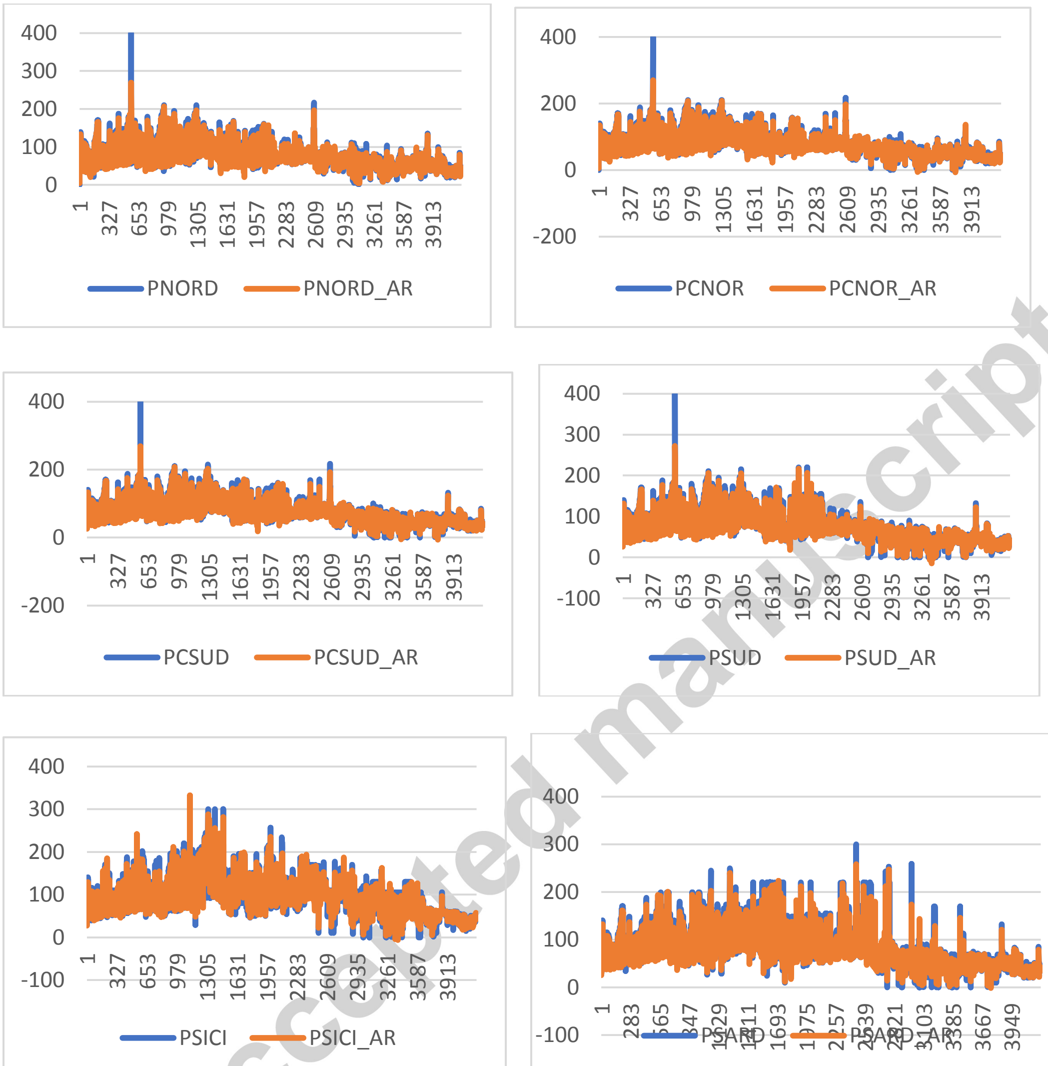








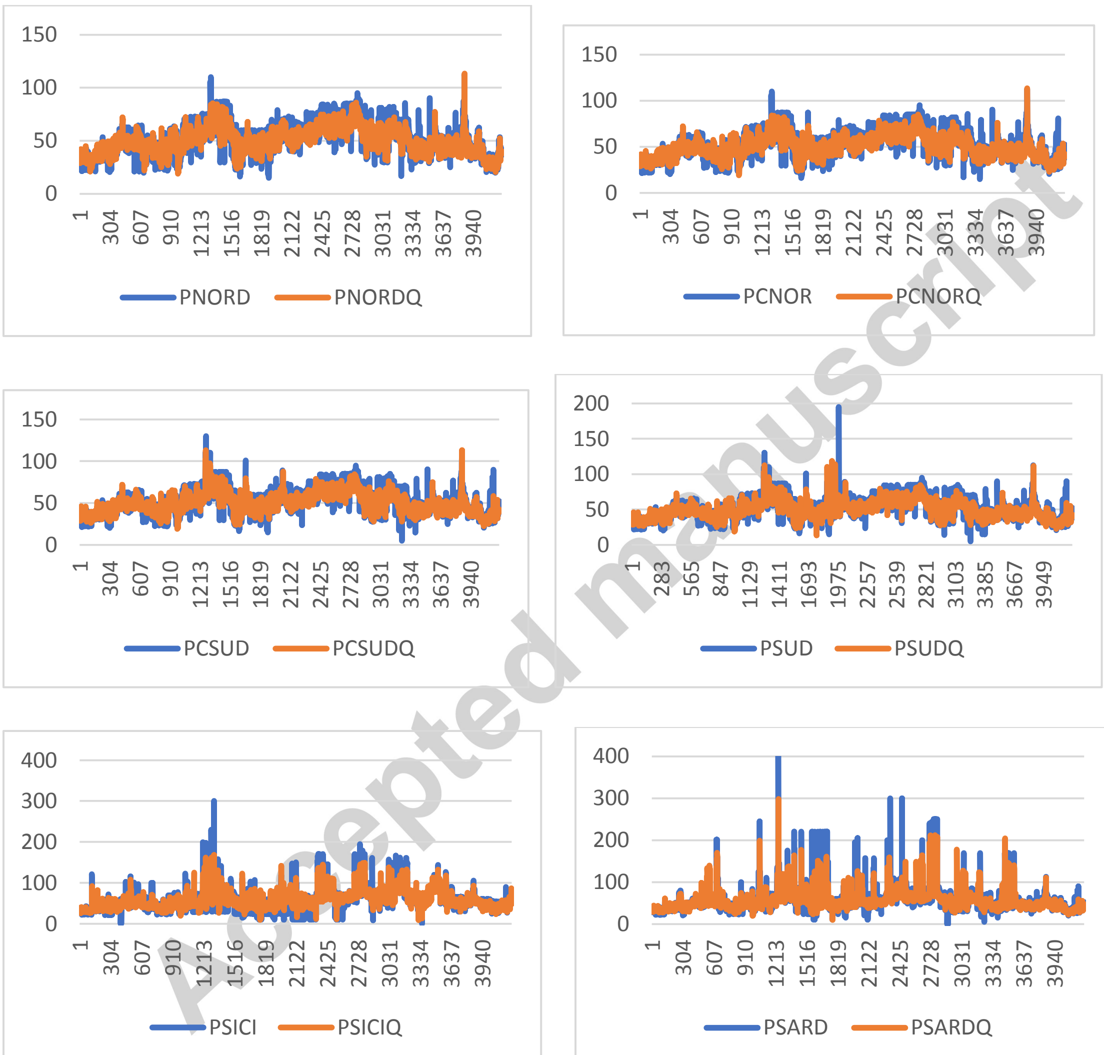
Panel B – hour 12:00



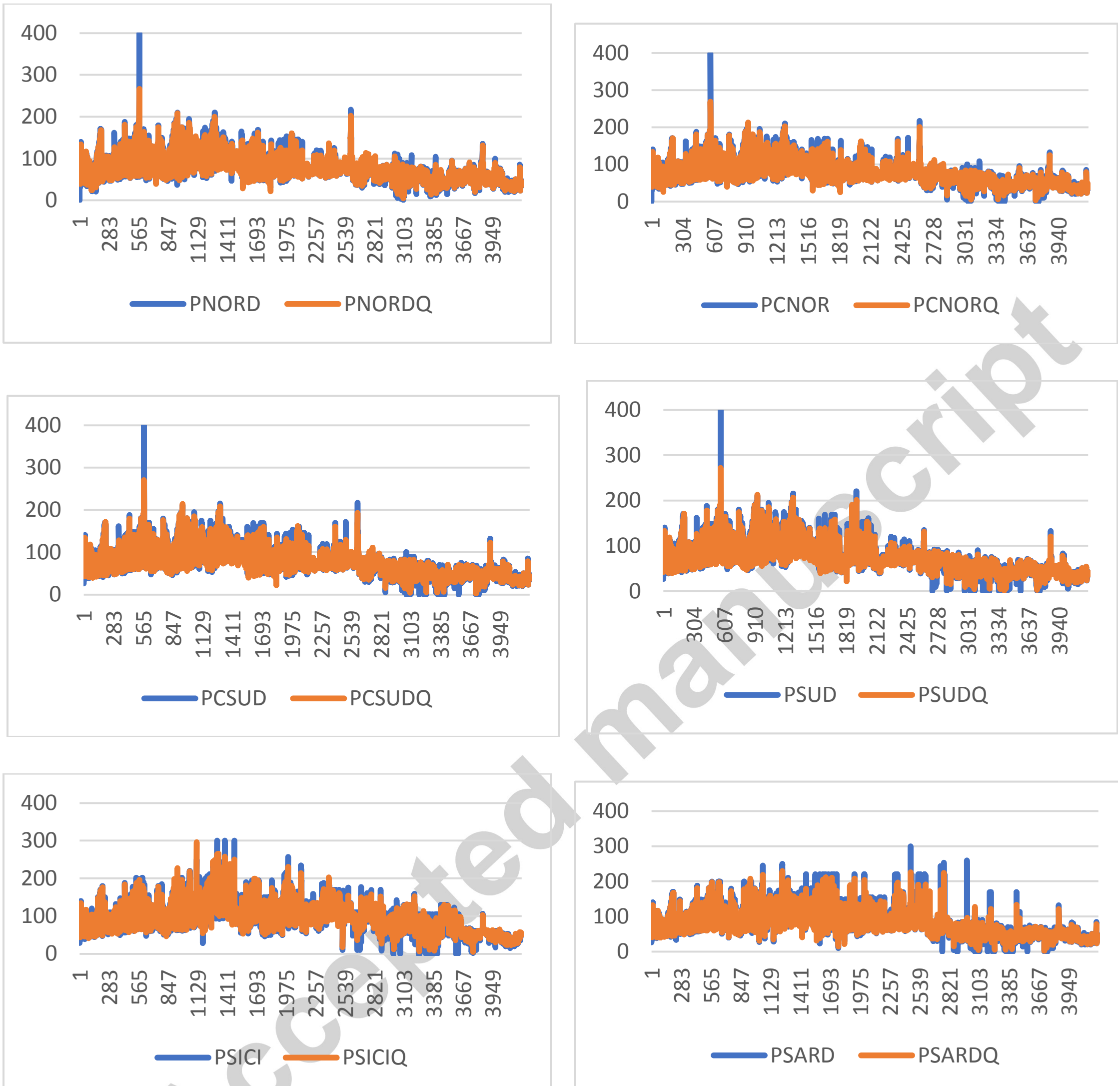
(*) price in Eur/Mwh on the vertical axis

Figure 5 - Regional price estimation with VAR2C model – period 2006-2016 (*)

Panel A – hour 00:00



Panel B – hour 12:00



(*) price in Eur/Mwh on the vertical axis

Figure 6 - Impulse response of VAR2C model

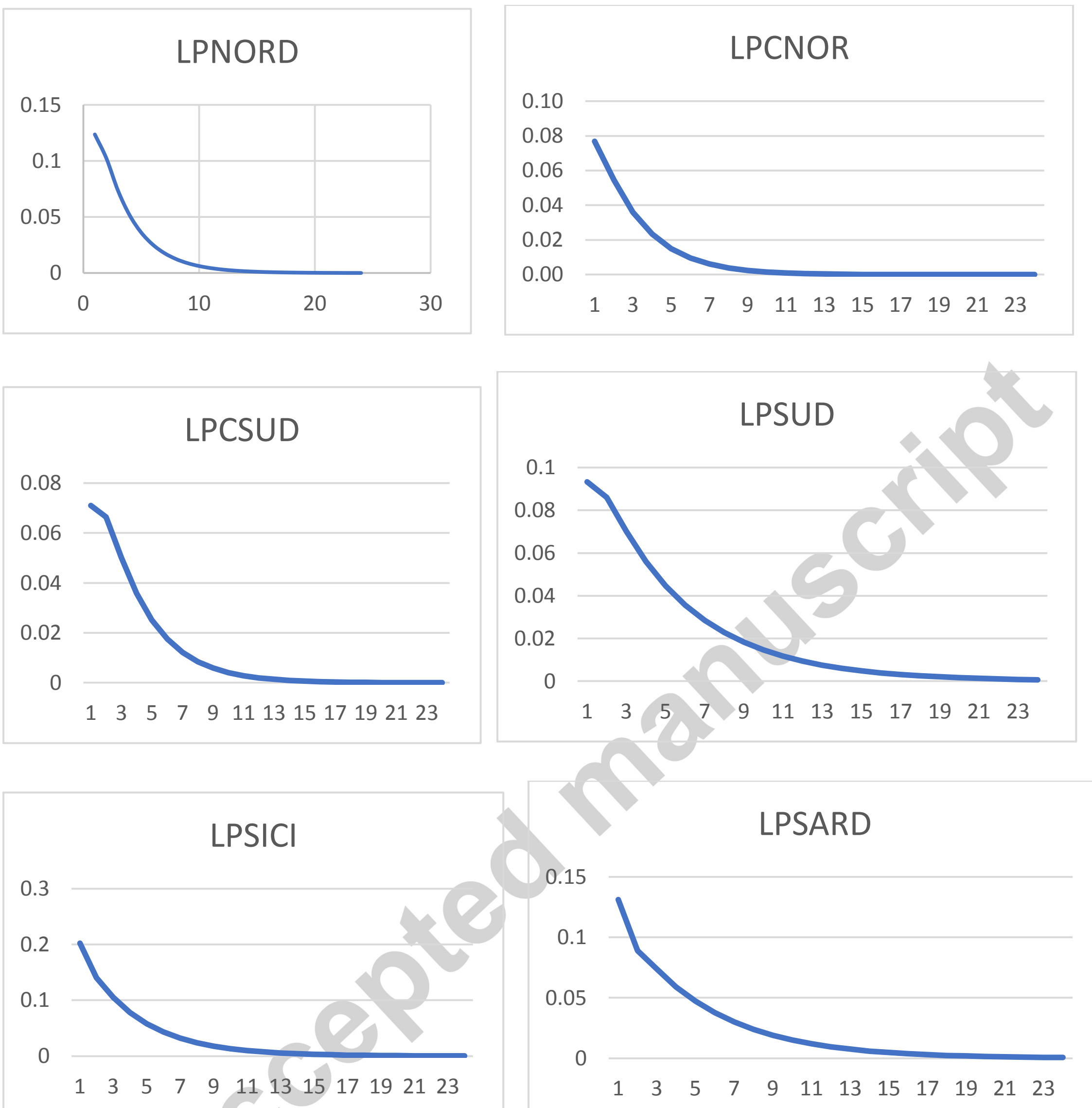
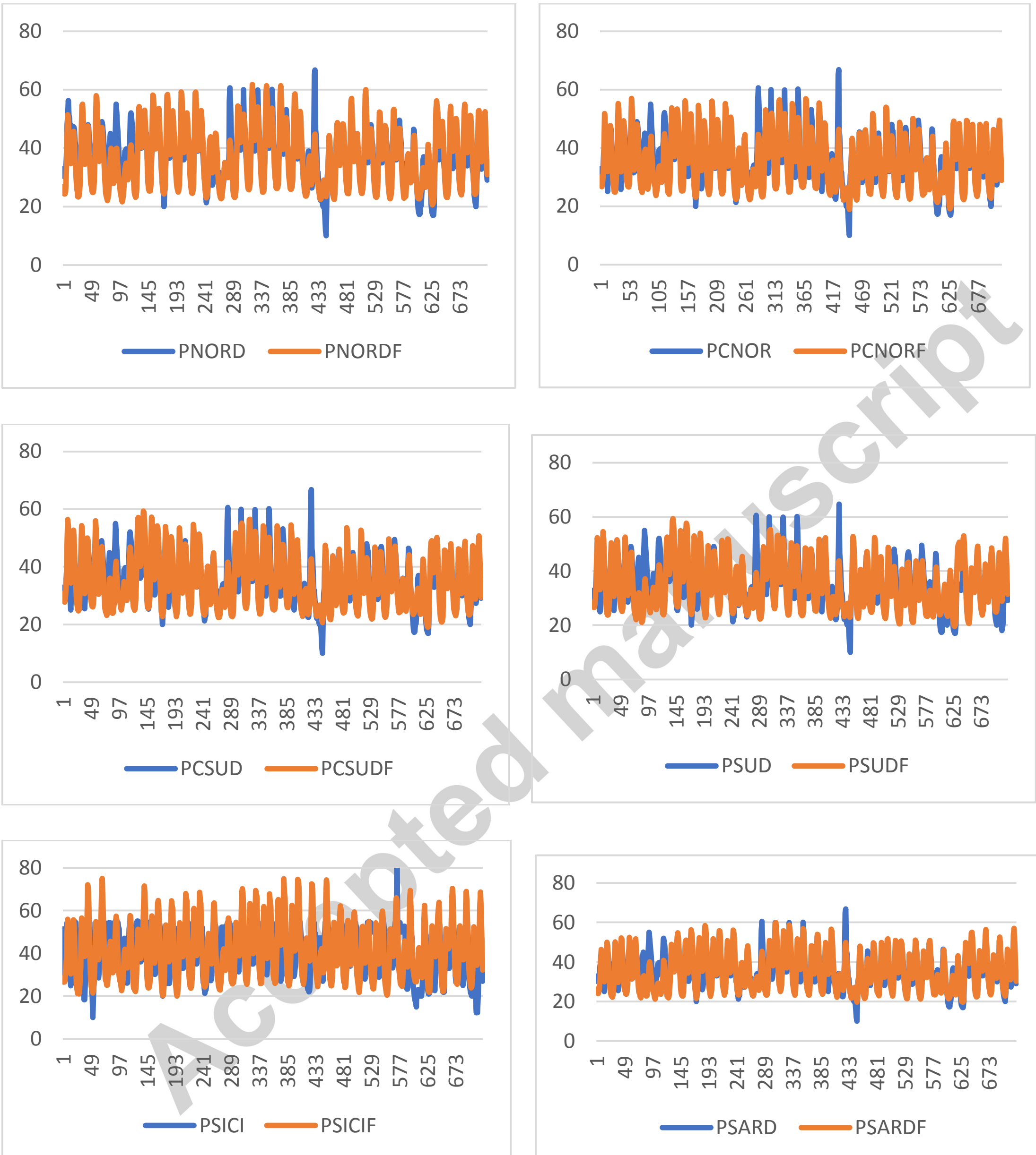


Figure 7 – Zonal prices - out-of-sample dynamic forecast Jan 2016 - one month ahead (*)



(*) price in Eur/Mwh on the vertical axis

Highlight

Price formation in the hourly electricity day ahead market is function of temperature

Accurate estimation of the hourly prices allows good forecasting out-of-sample

Results can help policy makers to improve production and network efficiency

Model can help in issuing public weather alert and design contingent plans for emergency