Modelling and forecasting the Italian electricity price

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Abstract

As a consequence of the liberalization which took place in Italy at the end of the 90s the Italian electricity market has seen a huge increase in the trading volumes. Jointly with the increased availability of gas in the European spot market, this pushed the Italian electricity market to integrate more closely with other European power markets and international fuel markets. First, this paper investigates the impact of the 2008 brent crisis on the determinants of the Italian electricity price. We detect a structural break in February 2009, after which gas fuel price and loads result the only determinants of the Italian electricity price. Second, we use data on fuel prices and loads to estimate an ARMA-X model with GARCH residuals to model the electricity price from 2009 to 2011. Finally we use these results jointly with the load forecasts, to project the Italian power price for the first six months of 2012. Our results show that after the brent crisis, gas and loads are the best predictor of the Italian electricity price. Moreover, the forward electricity price is not significantly related with the spot price once gas is included in the analysis. This results can be interpreted as a linkage between the Italian and the fuel prices as well in a greater exposure of the Italian electricity price to fluctuations in the international fuel markets.

1 Introduction

Italy is not self sufficient in energy so the country depends on foreign suppliers for about 85 percent of its needs, as stated in the National Energy Agency report.[1] These imports mainly consist of oil and natural gas, while some electricity (around the 15% of the total consumption) is imported from abroad.

In recent years, the Italian electricity sector has been subject to a wide reorganization, following the implementation of EC Directive 96/92 for the creation of a single electricity market, which set minimum goals for the opening of the national market to competition in order to achieve harmonization among the legislation of the Member States required for the creation of an integrated European electricity market.

Further, Legislative Decree n. 79 of March 16, 1999 (Bersani Decree) liberalized the activities of electricity production, import, export, purchases and sales and set an antitrust ceiling on the business of the dominant operator implementing a series of measures meant to enhance competition. The partial success of the Bersani Decree could be seen by the substantial increase in the number of electricity operators that both added new plants in the generation sector and have determined the reorganization of existing enterprises. In fact, various electricity companies have split their operations, establishing separate production entities, while only a few companies have merged or have incorporated smaller enterprises.

As a consequence of all these legislative measures, during the last six years Italian power market has seen a strong increase in the number of participants and in the liquidity, as shown by the following Table.

Table 1: Italian electricity market main indicators (2004-2012)

Year	PUN (€/MWh)			Total Volumes (MWh)	Liquidity (%)	Participants (31 Dec)
	average	min	max			
2004	51.6	1.1	189.19	231572	29,1	73
2005	58.59	10.42	170.61	323185	62,8	91
2006	74.75	15.06	378.47	329790	59,6	103
2007	70.99	21.44	242.42	329949	67,1	127
2008	86.99	21.54	211.99	336961	69,0	151
2009	63.72	9.07	172.25	313425	68,0	167
2010	64.12	10	174.62	318562	62,6	198
2011	72.23	10	164.8	311494	57,9	181
2012	75.48	12.14	324.2	298669	59,8	192

Source: GME, 2013
Data for 2004 are from April to December

Moreover, recent changes on international fuel markets have affected the Italian electricity price. First, both the spot and the forward gas European markets (ICE) have dramatically increased their traded volumes from 2007 on. This, in turn, affected the linkage between gas and brent price series. Second, the oil market incurred in huge crisis in 2008 when the price of the oil fell from 140 to 80 dollars per barrel.

This paper aims to analyze how the changes Italian electricity market and international fuel markets affected the determinants of the Italian electricity price (PUN). We then use these results to forecast the Italian electricity

[1]See ENEA (2009).

price for the first 6 months of 2012.

First we analyze the relationship between the Italian electric prices and the international gas and oil dynamics. As the international gas markets become more competitive and open, the Italian power plants may partially substitute long term gas contract (brent indicized) with gas directly bought in the spot market. This substitution effect should impact on the PUN predictors, that should switch from oil to gas.

Second, the paper tests whether the reforms in the Italian power sector jointly with the structural changes in the oil markets in 2008 and 2009 had an impact on Italian power prices.

The outline of the paper is as follows. Section 2 describes the data, Section 3 presents the model and the estimation results for the electricity price. The results of the forecasts are presented in Section 4. In section 5 there are the results of the load forecasts and Section 6 concludes.

2 Data description

Information on hourly data on loads and spot electricity prices come from the market operator's website (`http://www.mercatoelettrico.org/En/Default.aspx`), as well as daily data on forward electricity price. Spot prices are available from 2004, data on the cooling and heating degree days used to forecast the loads were available from 2008 on. Data on fuel prices come from the Thompson-Reuters database. Specifically, gas prices are from the UK HUB and brent prices are from ICE. All information on prices is on a daily basis. Since fuels are traded Monday through Friday, whereas electricity is traded on weekends as well, we set the weekend prices equal to those of the previous Friday. Table 2 summarises the data for the electricity price (both spot and forward) and loads, gas and brent.

Table 2: *Summary statistics (2008-2011), €/MWh*

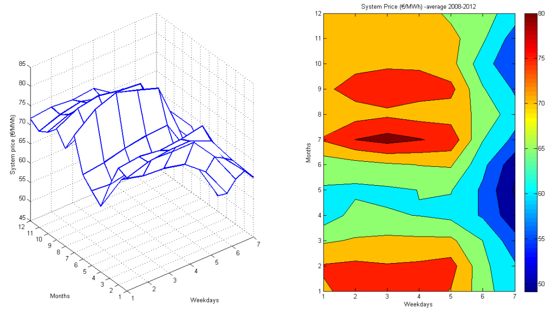
Variable	Obs	Mean	Std. Dev.	Min	Max
PUN (€/MWh)	3409	68.73	15.28	1.21	142.60
Brent spot (€/MWh)	3072	37.70	11.32	16.66	63.63
Gas spot (€/MWh)	3072	18.77	7.67	3.37	87.46
Loads (MWh)	3197	35852	4677	23075	46311
HDD	1648	2.96	3.71	0.00	16.07
CDD	1648	2.29	2.98	0.00	10.38

Cooling and heating degree days were available from the website () from 2008 on.

3 Load modeling and forecasting

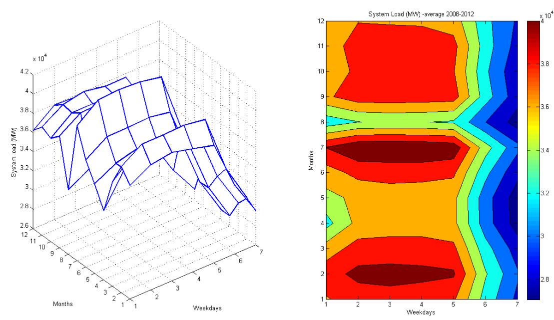
Load forecasting is necessary in order to forecast the price of electricity. Data on gas forward are available from the market, whether data on the volumes of electricity consumed in the future should be projected. The linkage between the electricity prices and volumes is shown by Figure (1) and Figure (2), that also highlight the seasonal components of the two series.

Figure 1: *PUN distribution - average 2008-2012*



The series shows strong cyclical components, as it is higher during the weekdays than during the weekends. Moreover, it is interesting to notice that in Italy the peak of the electricity price is reached in July , due to the massive use of air conditioning both in the industrial and in the commercial sectors. Traditionally, August is the month in which both the industrial and the commercial sectors close for holidays, which explains why the price of electricity decreases during that month compared to the peak of July. The pattern followed by the Italian electricity price is strongly related both to Italian loads and international fuel prices, as highlighted by Figures (2-4) below.

Figure 2: *Loads distribution - average 2008-2012*



Again, July is the month with highest electricity consumption, and the consumption during the weekends is significantly lower than during the weekdays. These findings are not surprising, as there is much research indicating that the main factors characterizing the electricity prices are the loads, the fuel prices and the seasonality. [2]. In order to model loads correctly, we control for the difference sources of seasonality. Following Lotufo and Minussi (1999), Juberias et al. (1999), Ling et al. (2003) and Liu et al. (1996), we use data available from the site (`http://www.degreedays.net/` to estimate the determinants of the Italian loads. Cooling degree days are defined as the number of degrees that a day's average temperature is above 65 Fahrenheit (18 Celsius) and people start to use air conditioning to cool their buildings. In the same way, heating degree days are the number of degrees that a day's average temperature falls below 15.5 degrees, and people need heating to heat their buildings. Then, we use the estimated coefficients to project the load series through the first 6 months of 2012. As done for the electricity

[2] See Weron (2006)

price, we adopt an ARMA-X to estimate the relation between loads, cooling and heating degree days and seasonal dummies as:

$$L_t = \alpha + \beta CoolDegree_t + \gamma HeatDegree + \sum \kappa^s D_t^s + u_t \tag{1}$$

where $u_t = \rho_0 u_{t-1} + \rho_1 u_{t-6}$ L_t is the load series, CoolDegree is the indicator for the cooling degree days and ϵ_{t-1} is the error term that characterize the MA component of the selected ARMA-X model. No structural breaks were detected for the loads, so we estimate the complete series from 2008 to 2011. The model selection procedure consists of two steps. First, ARMA-X (p, q) processes with p and q ranging from 0 to 10 are calibrated to the stochastic components. Next, the goodness-of-fit is measured by the AICC and BIC criteria. Also, we calculate the PAC and AC statistics for the residuals, and found that the optimal specification was to include the 6th lag in the disturbance. As usual, the model is estimated with the maximum likelihood estimator. Estimation results are shown in Table (3).

Table 3: Estimation results: loads

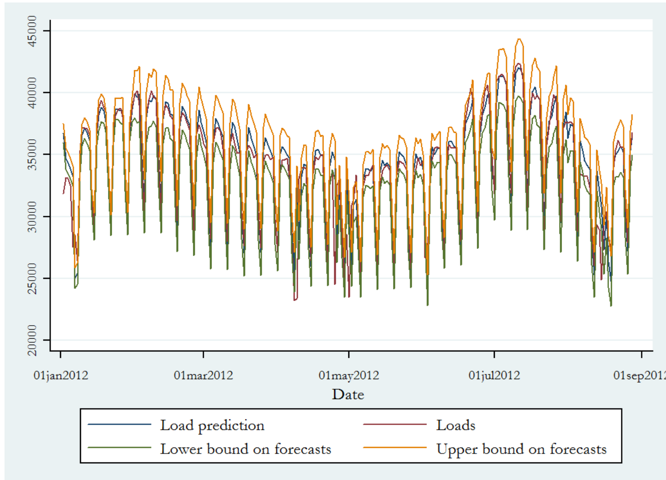
CoolDegree	169.5*
	(95.35)
HeatDegree	191.4***
	(65.73)
Cool*Weekdays	YES
Heat*Weekdays	YES
WeekDummies	YES
MonthDummies	YES

The forecast results are summarized in Table(**??**):

Variable	Obs	Mean	Std. Dev.	Min	Max
Loads	240	34018	4302	23247	42392
Load forecast	240	34251	4210	24067	42048

Finally, Figure 3 shows the forecasted loads and the confidence intervals of the forecasts

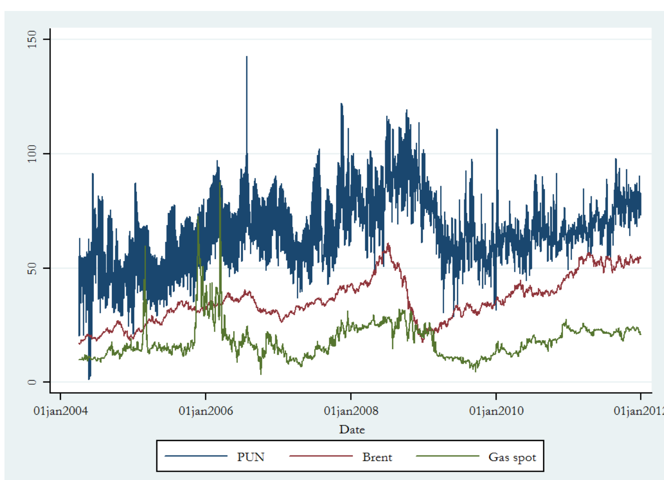
Figure 3: *Load forecasting*



4 PUN modeling

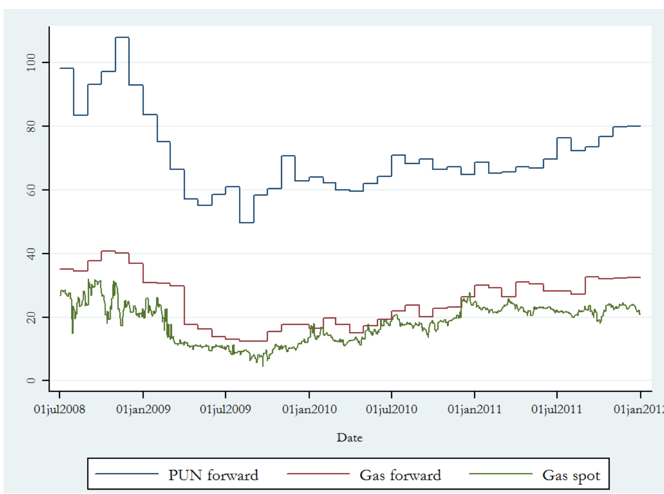
The recent increased liquidity of international natural gas markets has increased the possibilities for generators to hedge the power plants against the risk of rising the fuel prices. On the other hand, the financial crisis started in 2008 has potentially affected the determinants of the Italian electricity price in irreversible way. Fig.(4) shows the dynamics of the Italian electricity price and of the main fuels used in the generation process from 2007 to 2011. The electricity price series shows a structural break at the beginning of 2009, following the collapse of oil (and gas) prices in the summer of 2008.

Figure 4: *PUN, gas and brent (2007-2011) €/ MWh*



The most popular test for the presence of structural breaks is the one introduced by Chow (1960). However, this test is exogenously determined, as the researcher has to choose a plausible date for the structural break , then check for the presence of differences between the series before and after the break. Both Zivot and Andrews (1992) and Baum (2001) have introduced tests to identify unit roots in the presence of structural breaks. The Clemente and Rao test detects the presence of a structural break in the shadow price series on the 8th of February 2009, whereas the Zivot test finds a break on the 12th of the same month. All the tests suggest a structural break in a similar period in February 2009; however these tests reject the hypothesis of the presence of a unit root in the series. The same tests on the gas price series shows that the presence of the structural break cannot be rejected at the 5% level for the end of December 2008. This is plausible, as the price of electricity in Italy follows the gas distribution on the forward markets, which is strongly related to spot prices.[3] Following the results of the previous tests, we look for the presence of structural breaks on the 12th of February 2009. The Chow test rejects the null hypothesis of absence of structural breaks with an F statistic equal to 130.66. The lag in the PUN reaction may be explained considering the existing lag in the gas formula adopted by power plants to hedge their position, which is based on the dated brent contracted 9 months before the PUN. We therefore estimate the model excluding the data prior to the identified structural break, in order to exclude potential sources of errors in our model. We don't include the forward electricity price in our analysis, as the correlation coefficient between the forward and the gas prices (both forward and spot) is very high (0.78) and therefore including both leads to multicollinearity problems. The relation between these markets is shown by Figure (5).

Figure 5: *PUN forward, gas forward and gas spot (2008-2011) €/ MWh*



Data on PUN forward are available from 2008 on

As highlighted by Karakatsani and Bunn (2008), Swider and Weber (2007) and Weron and Misiorek (2008), the electricity prices are characterized by path dependence and strong volatility. There is no consensus in the literature on the most appropriate model to use to forecast electricity prices. Nogales et al. (2002) used ARMA-X and AR-X models for predicting hourly prices in California and Spain. Both model results were significantly better than for

[3] The Clemente and Rao test statistic for pun rejects the hypothesis of the presence of a unit root in these series at the 5% level. ADF test rejects the presence of unit root test both before and after the structural break. The ADF associated to the period before the structural break is -15.036, with a test statistic equal to -3.430. After the break, the test statistic is equal to -14.601.

the ARIMA and ARIMA with load as an explanatory variable models proposed by Javier Contreras and Conejo (2003). In another study Conejo et al. (2005) compared different time series specifications (ARMA-X, AR-X and ARIMA) and a wavelet multivariate regression technique. For their sample, the time series models with exogenous variables was the outperforming model. Adam et al. (2006) included the weekly seasonality. Their result couldn't be compared with ARMA-X and AR-X models of Nogales et al. (2002) because of different time-lag specification. However Weron (2006) pointed out that ARMA-X and AR-X calibrated to spike preprocessed data lead to significant improvement in the results. In this case, it is important to test the spike pre-processing procedure as the model predictability should be influenced by this procedure. In our sample, spikes are quite limited and we didn't find evidence of improvements in the forecast performance of our model with the spike preprocessing.

Finally, Schmutz and Elkuch (2004), included in their model gas price, nuclear available capacity, temperature and rain as regressors and a mean-reverting stochastic process for the residuals as exogenous variables. However, the strong volatility associated with the electricity price and the dependency of the volatility from its own past suggest the adoption of a GARCH specification for the residuals. This intuition is supported by different works. Knittel and Roberts (2005) consider an AR-EGARCH specification and a seasonal ARMA model with temperature, squared temperature and cubed temperature as explanatory variables to explain the electricity price in California. Interestingly, they found all temperature variables to be highly significant during the pre-crisis period (April 1998 to April 30, 2000), but the relation between electricity prices and temperature broke down during the crisis (May-August 2000). We observed a similar behaviour looking at the relation between brent and electricity price in Italy before and after the brent crisis in June 2008. Knittel and Roberts (2005) also found evidence on the AR-EGARCH specification outperformed the ARMA model only in the presence of high price volatility (i.e. crisis period). [4]

Finally, Swider and Weber (2007) compared the explanatory in-sample power of ARMAX and ARMAX-GARCH models in Germany. They concluded that ARMAX-GARCH models improved the representation of the identified fat tails in the price distributions, however, including Gaussian mixtures or regime-switching components in the ARMAX specification yielded yet better (in-sample) results.

We adopt the ARMA-X specification, with ARCH modelisation of the residuals. This captures the impact of fuel prices and loads on the electricity price and models the electricity price dynamics correctly. In order to get the appropriate lags order and the correct specification for the residuals we took the log of the variables, and we tested different specifications (ARMA-X, AR-X and ARMAX-GARCH) with different exogenous variables. We estimated two models. The first for the period before the identified structural break (12 February 2009) and the other one for the period after that date. We use the last model to forecast the PUN for the first six months of 2012. Nevertheless, the estimation of the Italian electricity price for the period before the structural break is interesting in order to

[4]Other works which investigates the behaviour of the residuals during crisis are Karakatsani and Bunn (2008), Bystrom (2005) and citeMugele2005, who test different distribution for the residual with ARMA-GARCH fitted model. However, there is no specification that clearly outperform the others in their sample

understand how the determinants of the PUN changed across the years. We estimate the follow equation:

$$PUN_t = \alpha + \beta L_t + \gamma Gas_{t-1} + \delta Brent_{t-1} + \sum \kappa^s D_t^s + u_t \tag{2}$$

where: PUN_t is the electricity price, L_t are the loads, Gas_{t-1} and $Brent_{t-1}$ are the gas and the brent day ahead prices and D is a set of dummies to account for weekly and monthly seasonality. The residuals are modelled as follows:

$$\begin{aligned} u_t &= \theta_0 u_{t-1} + \theta_1 u_{t-7} + \varepsilon_t \sigma_t \\ \varepsilon_t &\sim N(0,1) \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{2} \alpha_i u_{t-i}^2 + \sum_{j=1}^{1} b_j \sigma_{t-j}^2 \end{aligned}$$

As Table (4) shows, before the brent crisis, both gas and brent were determining the Italian electricity price.

Table 4: Results before the structural break (1st April 2004- 12th February 2009

Loads	1.252***
	(0.0234)
Gas_{t-24}	0.0213*
	(0.0115)
$Brent_{t-24}$	0.133**
	(0.0542)
Constant	-9.509***
	(0.259)
AR(1)	0.681***
	(0.0196)
AR(7)	0.278***
	(0.0169)
MA(1)	-0.161***
	(0.0341)
ARCH(1)	0.644***
	(0.029)
ARCH(2)	-0.531***
	(0.0289)
GARCH(1)	0.908***
	(0.0115)
Dummies	YES
Obs	

Table (5) shows the result of the same regression after the structural break of 12 February 2009.

Table 5: Results after the structural break: 12th February 2009 - 31st December 2011

Loads	0.681***
	(0.0436)
Gas_{t-24}	0.109**
	(0.046)
$Brent_{t-24}$	0.0355
	(0.0827)
Constant	-3.236***
	(0.53)
AR(1)	0.885***
	(0.0259)
AR(7)	0.0685***
	(0.022)
MA(1)	-0.551***
	(0.0463)
ARCH(1)	0.203***
	(0.047)
ARCH(2)	-0.0795*
	(0.0478)
GARCH(1)	0.853***
	(0.0243)
Dummies	YES
Obs	

These results show that after the structural break of February 2009 only loads and gas price are significantly related with the Italian electricity price. Brent turns out to be not significant after the 2008 crisis. As mentioned above, the structural break in the PUN series is mainly the result of the fall in the brent prices in the summer of 2008. In Italy, the gas contracts signed by power generators were usually long term contracts (i.e. more than 30 years) indicized to brent in order to hedge the power plants from the risk of abrupt price changes. Up to 2008, brent was one of the determinants of the Italian electricity price, thus it is not surprising the negative shape of the PUN series after the brent crash in June 2008. The instability of the brent price jointly with the high liquidity in gas market have concurred in reducing the explicative power of brent on the Italian price series. Then, after February 2009, the PUN is only related to loads and gas, which are the variables we consider in order to forecast the electricity price in 2012.

5 PUN forecasting

Italian market liberalization has made the short run forecasting a necessity for all the active market players. Even if the gas availability on the spot markets has reduced the risk of players that signed a long-term contract, as they can partially adjust their needs before the delivery of the contract, the liberalization of the electricity markets has increased market volatility and the cost of selling or buying power which is the company hedging strategy from over or under contracting.

We use the variables that emerged as determinants of the Italian electricity prices from our previous analysis to forecast the PUN for the first 6 months of 2012. The results of the forecasts are shown in Figure 6;

Figure 6: *PUN forecasts*

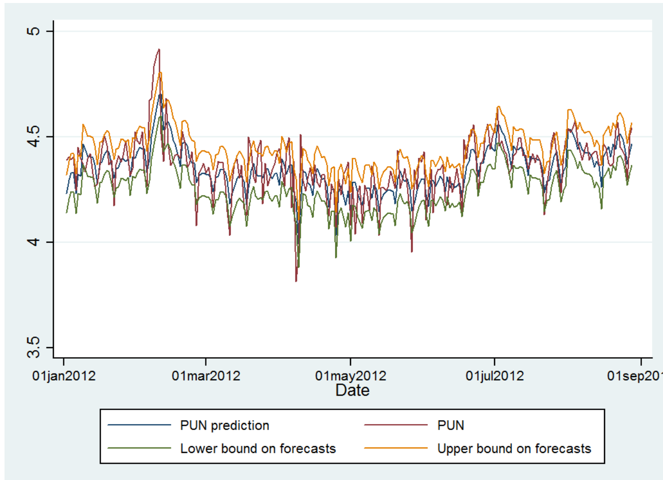


Table 6 shows the statistics calculated to evaluate the forecast performance.

Table 6: Summary statistics, PUN and PUN forecasted

Variable	Obs	Mean	Std. Dev.	Min	Max
PUN forecast	240	4.36	0.14	3.81	4.92
PUN forecast	240	4.35	0.10	3.99	4.72

Our forecast shows that gas has become the best predictor of the Italian power price. This result can be expected since more generation companies are hedging their asset on the liquid gas market.

Comparing our final estimates to other studies that consider the same exogenous variables leads to some interesting conclusions. The forecast errors are quite stable during different days of the week, as shown by Table (7). [5]

Table 7: Forecast errors by weekdays

Day of the week	Forecast error
Sunday	0.050
Monday	0.051
Tuesday	0.051
Wednesday	0.051
Thursday	0.052
Friday	0.052
Saturday	0.050
Average	0.051

On average, these results are slightly higher than in Weron (2006) who finds forecast errors on average equal

[5]The mean absolute forecast error has been calculated as :

$$MAE = \frac{1}{N}\sum_{i=1}^{7}(PUN_t - PUNfor_t) \tag{3}$$

to 0.047. However this may be explained considering that in his work Weron (2006) forecasts over a more stable period.

6 Conclusions

In this paper we model and forecast the Italian electricity price. We use a calibration period from the 12th of February 2009 to the 31st of December 2011 to estimate the relation between the PUN and several exogenous variables to forecast the price series for the first 6 months of 2012. First, our work shows how the presence of the structural break at the beginning of 2009 has changed the determinants of the Italian electricity price. Before the crisis of the brent and the subsequent fall of the PUN in 2008, both the brent and the gas prices were significantly related to the PUN, due to the presence of long-term contracts in the supply of gas for the Italian generators. After 2009, the volatility of brent jointly with the great liquidity available on the ICE gas market made the brent price insignificant in determining the Italian electricity price. Thus, we change the calibration period and we use the coefficients estimated from 2009 to 2011 to forecast the PUN through 2012. Second, our paper shows that the forward price is not statistically significant in determining the spot electricity price. in other words, the main determinant of the PUN forward price appears to be the natural gas forward price. Then, our results show that temperature data and gas prices are the only variables which significantly determine the Italian electricity price, once controlled for the weekly and monthly seasonality.

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