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IMPACTS OF SUBSIDIZED RENEWABLE ELECTRICITY GENERATION ON SPOT MARKET PRICES IN GERMANY: EVIDENCE FROM A GARCH MODEL WITH PANEL DATA

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Thao PHAM[1] Killian LEMOINE[2]

***ABSTRACT**:*
Electricity generated by renewable energy sources creates a downward pressure on wholesale prices through - the so-called "merit order effect". This effect tends to lower average power prices and average market revenue that renewables producers should have received, making integration costs of renewables very high at large penetration rate. It is therefore crucial to determine the amplitude of this merit order effect particularly in the context of increasing burden of renewable support policies borne by final consumers. Using hourly data for the period 2009-2012 in German electricity wholesale market for GARCH model under panel data framework, we find that wind and solar power generation injected into German electricity network during this period induces a decrease of electricity spot prices and a slight increase of their volatility. The model-based results suggest that the merit-order effect created by renewable production ranges from 3.86 to 8.34 €/MWh which implies to the annual volume of consumers' surplus from 1.89 to 3.92 billion euros. However this surplus has not been re-distributed equally among different types of electricity consumers.

Keywords: German electricity markets, Intermittent generation, Feed-in tariff, Merit-order effect, GARCH, panel data.

1. INTRODUCTION

The European electric power sector has experienced an exceptional policy trend that fundamentally reshaped the industry over the last decade: the intrusion of environmental-related policies. Germany is perhaps the most distinguished example of this energy policy trend. The next day of nuclear catastrophe in Fukushima in 2011, the German government decided to accelerate the phase-out of nuclear fleet by 2022, starting with the immediate closure of the eight oldest nuclear plants. Although fossil fuels fired energy has to put in place during the transitional period, renewable electricity generation is being considered as cornerstone of current and future energy supply. In 2011, wind, hydro and solar supplied together 20% of electricity consumption in Germany and this share should increase to 35% by 2020 and 80% by 2050. This is apparently ambitious.

Developing renewable energy taking into account all challenges requires a carefully designed connection policy. In Germany, a lot of support policies for the development of renewable electricity

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generation have been put in place. The perhaps most popular support scheme has been "feed-in-tariff" mechanism put in place since 1991. The conditions of the German support scheme were revised in 2000, 2004 and 2010 (See more in Fulton, Capalino and Auer [2012]; The Renewable Energy Sources Act (Erneuerbare Energien Gesetz - EEG, [2012]). According to this law, all electricity generated from renewable energy sources must be purchased and transmitted with priority by the grid operators at a guaranteed feed-in-tariff. The loss suffered by the system operator due to the difference between market price and tariff is compensated by all consumers.

On one hand, this support scheme has increased the burden borne by final consumers. In the period from 2007 - 2012 for instance, the net support expenditures for renewable electricity rose from 3.6 to 18 billion euros, the highest level in Europe. Over 2008-2012, household electricity bills increased by over 22% largely due to the surcharges of renewable subsidy. This has raised concerns over the efficiency of the renewable support schemes. On the other hand, an important aspect that must be considered in the discussion is that electricity generated by renewable energy sources creates a depressive effect (or merit-order effect) on power prices. This effect, in turn, increases consumers' surplus while raising high integration cost of renewables to the power system. In this context, an economic assessment of the merit order effect is necessary.

There have been several papers attempting to evaluate this effect, among those are, for example, Sensfuss, Ragwitz and Genoese [2008] and Weigt [2009] using electricity simulation models; Gelabert, Labandeira and Linares [2011], Wurzburg, Labandeira and Linares [2013], Cludius, Hermann, Matthes and Graichen [2014], Ketterer [2014] using econometric regressions. This paper applies the latter approach. Though each paper takes different approaches, they essentially come up with similar conclusions: there is a decrease of electricity spot prices as wind power penetration increases. However, regarding econometric modeling, none of these papers take into account the distinguished feature of the data in electricity market. Indeed, electricity is the unique market where there exist 24 different prices for 24 hours per day due to the combination of strong variability of demand for electricity and non-storability of electricity. Most papers employ daily aggregated data or single pooled time series. Using average data might remove the variation of parameters in short run and treating the hourly prices as a single time series is not an appropriate methodology as prices for 24 hours of the following day are determined *simultaneously* on the day ahead. Any attempt to model electricity price should take this into account.

In this paper, we consider a different modelling strategy: we treat the data as a ***panel framework*** and apply the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model for the panel dataset. This modelling approach is not only highly relevant with data on electricity spot market but also allows taking into account the variation of hourly solar production.

The paper proceeds as follows. Section 2 describes the merit order effect and its impact on market values of renewables. Section 3 discusses different models to evaluate the merit-order effect of the intermittent electricity generation that have been employed in literature. Section 4 describes the data and specifications for modelling strategies. Section 5 employs the GARCH model to estimate the relationship between spot prices and wind/solar power generation for panel dataset from October 2009 to December 2012 in German wholesale electricity market. Section 6 concludes the paper.

2. MERIT-ORDER EFFECT AND ITS IMPACT ON MARKET VALUE OF RENEWABLES

Electricity generated from renewable, though being inexpensive in term of variable cost, is very costly to develop in large scale due to its unpredictability and intermittence[3]. This creates a

[3] The overnight costs for offshore wind power plants are also very significant.

discouragement for suppliers to invest in this type of energy. In this context, energy policies must give enough incentives so that wind companies would be likely to guarantee their profits to offset the disadvantages borne from the intrinsic lower value of intermittent output.

In Germany throughout the past 15 years, the development of renewable energy has been driven mainly by Feed-In Law[4], first introduced in 1990, otherwise known as the Electricity Feed-In-Law. This law was modified in several ways in April 1998 and in 2000, with the introduction of the Renewable Energy Sources Act (Erneuerbare Energien Gesetz (EEG)) in response to the deregulation of German electricity market in 1998. Feed-in law is a mechanism which assures the obligation and priority of the integration of electricity output produced by renewables into the market no matter how conditions of classic thermal capacities are. The technical and commercial responsibility of this integration is supported by the system operator, who has been obliged to take the delivery of renewable electricity generation and put it immediately on the market. The German wind/solar generators sell their output to the system operators at a guaranteed tariff. The conditions of the German feed-in tariffs were revised in 2004, 2009 and 2011. The latest EEG amendment (EEG 2012) dates from 20 December 2012[5]. This mechanism is financially neutral for renewable producers because they are paid at fixed tariffs which are independent from the conditions of supply and demand that determine the market price. If the market price is lower than the tariff, the loss suffered by the system operator is compensated by all consumers. Renewable generators will have no incentives to restrain their output, even if market conditions are particularly unfavorable. Thanks to the support scheme, the installed wind turbine capacity in Germany has increased with a factor of five over the last ten years, from 6 GW in 2000 to 31.3 GW in 2012, and that of photovoltaic has raised from only 100 MW in 2000 up to 32.6 GW in 2012.

The implementation of feed-in-tariff support scheme; however, has received a lot of critics. First, the burden borne by final consumers are too high. It is important to note that German retail prices of electricity is at the highest level in Europe except those of Denmark - European champion for CO2 emissions and the development of wind power. The extra costs that German final customers have to bear due to the difference between market prices and guaranteed tariff for renewable generators made retail prices even higher. This extra cost, the EEG-Umlage, is expected to increase from 5.3 ct/kWh in 2013 (20% of total 2013 price) to around 6.2 ct/MWh in 2014. Electricity prices for household consumers in Germany comprise around 40 - 45% of all taxes and levies, of which the EEG-Umlage constitutes about 30 - 40% according to the data from Eurostat. Over 2008-2012, the electricity bills for median household consumers (whose consumption is between 2500 kWh and 5000 kWh) increased by over 22% largely due to the surcharges of renewable subsidy. Other issues bound to renewable production and its support scheme are the perverse effect on equilibrium prices (the phenomenon of negative prices) and negative externalities on neighboring network systems. Negative prices are the consequence of two coincident events: a low demand and a very high level of wind which makes off-shore wind turbines in the Baltic run at full speed. When this situation occurs, the conventional thermal plants are required to back down. Since the temporary shut-down of a base load plant can become more expensive than maintaining operations without revenues, some conventional generators, prefer to produce and pay an operator who could accept to take the electricity rather than shut down their plants and suffer the startup costs. It would be the Swiss

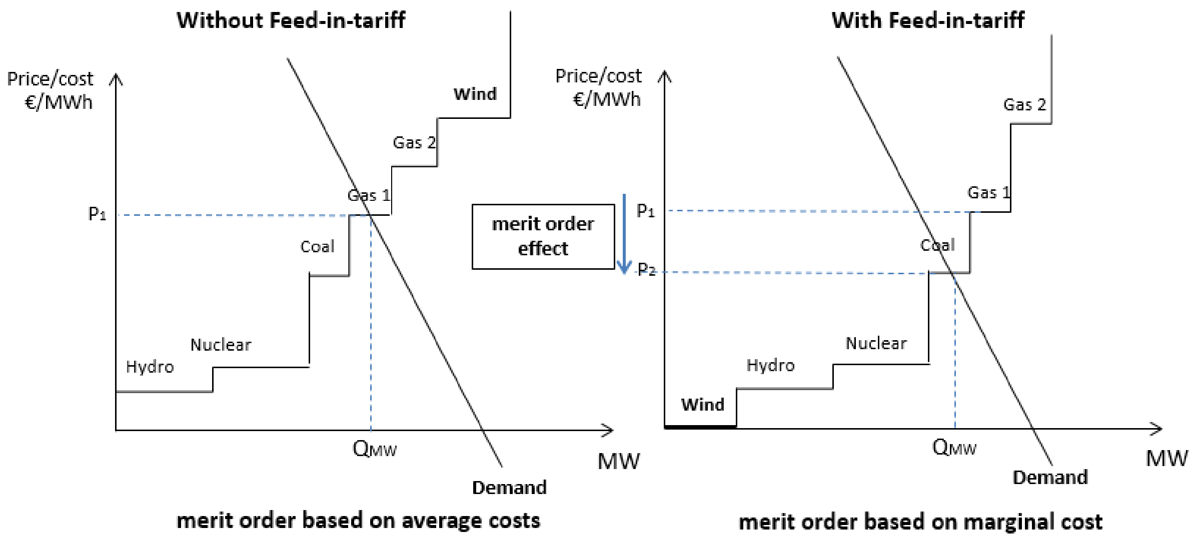
[4] Other means of support can be different kinds of low-interest loans and financing packages for investments in installations for electricity production from renewable energy sources.

[5] The EEG 2012 also introduced "feed-in premium" mechanism to encourage the direct sale of renewable electricity on the spot market. Under the market premium model, renewable power producers sell their electricity directly into the wholesale market and are paid at market spot prices plus the "market premium" payment which is equal to the difference between the feed-in tariff and a "reference price", calculated at the end of each month.

generators, who dispose a high capacity of pumped storage hydroelectricity, would be paid for evacuating this excess electricity. This phenomenon represents a de-optimization of electricity system and induces growing concerns over the efficiency of the support scheme as long as the solutions to economic storage of electricity in large scale are not available yet. Furthermore, a network externality occurs as electricity generated from wind turbines in the Baltic Sea cannot be evacuated directly to the locations of high consumption in the southern of Germany. Given the interconnected European network system, this electricity would be transported via Poland or the Czech Republic before reaching the final consumers in the Southern locations - big industries in the state of Bavaria. Any issue induced by the network is now mutualized. The customers in these neighboring countries would have to participate in the costs of reinforcing the transmission lines so that foreign generators could deliver their excess electricity.

These observations are quite disturbing for the development of renewable energies through feed-in tariff scheme. However, an important aspect that must be considered in the discussion is that electricity generated by renewable energy sources creates a downward pressure on wholesale prices through the so-called merit order effect. While wind generators are paid at a fixed tariff and do not participate directly to spot market, wind output does have impact on the spot market prices. In fact, when wind generation is put in the merit order, it takes the value of "zero marginal cost", and since it will be the first to be dispatched, generation from other energy sources must move to the right of merit order curve. This analysis is applied analogously to other types of intermittent generation.

Figure 1. Merit order with and without fed-in wind tariff

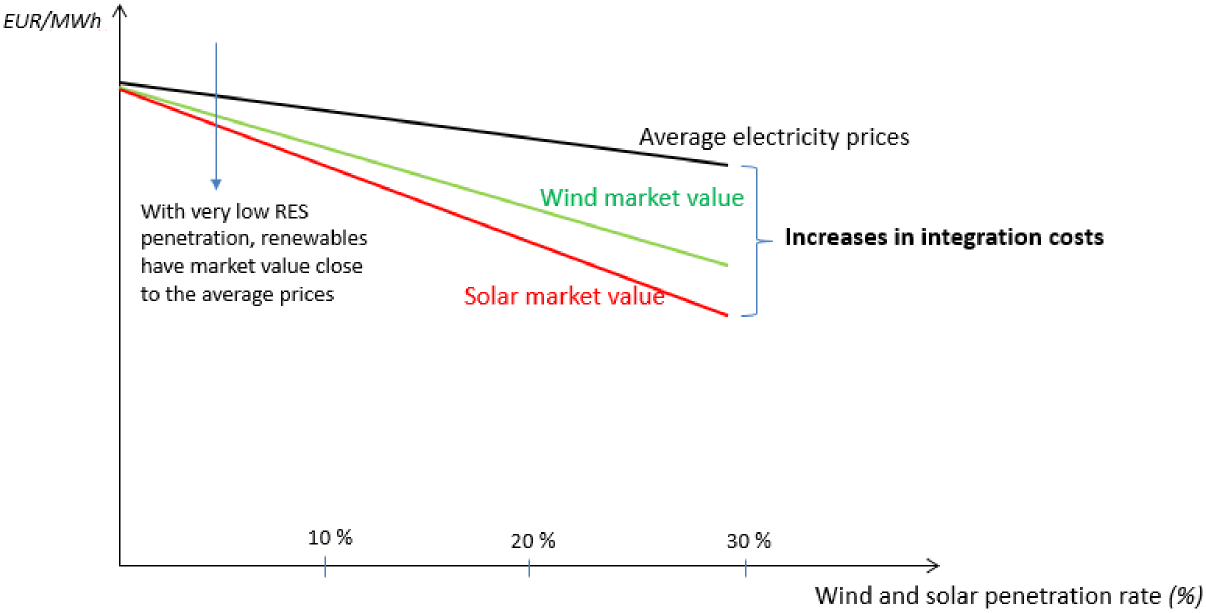


Source: Benhmad and Percebois (2013)

Figure 1 illustrates the difference between a logic of merit order based on average costs and a logic of merit order based on marginal cost. Electricity generated by wind energy, albeit zero fuel cost, has the highest average cost because the overnight cost (unit capital cost) is relatively high, particularly wind off-shore, and its load factor is relatively low: 26% and 43% for onshore and offshore as compared to 85% of nuclear or other thermal plants (OECD-IEA [2010]). However, in a logic of merit order based on marginal cost, wind generation will be the first to be dispatched since it takes the value of "zero marginal cost". As consequence, generation from other sources must move to the right of merit order curve, thus at a given demand, market price decreases. This is illustrated in figure 1.b where merit order effect is represented by the difference between P_1 and P_2.

Merit order effect tends to create surplus for consumers who buy electricity at wholesale prices. However, this increase is not equivalent to increases in total net welfare. Conventional producers are receiving lower profits because a part of their surplus is transferred to the consumers. The costs for the overall system will increase with high integrated renewable largely due to this merit order effect. This observation refers to market value loss of intermittent renewable, which has been discussed recently in Hirth [2013 and 2015]. In fact, merit order effect lowers average power prices and average market revenue that renewables producers should have received. The gap between them refers to market value loss or integration cost of renewables. The gap exists because when intermittent penetration rate increases, the drop in the volume weighted average revenues of intermittent renewables outweighs the drop in yearly-weighted average prices that they create. Figure 2 depicts this effect.

Figure 2. Difference between RES market value and average electricity price



Source: Own illustration

Intuitively, this is because during the periods when high demand of electricity coincides with low output from intermittent generation, the system has to resort to high cost fuel-fired plants. Prices during these periods would be high because such plants have high marginal costs, and/or scarcity would push the prices even higher. Intermittent generators, however, would not benefit from these high prices since they occur when their output is low. In contrast, when high demand coincides with high renewable output (this is particularly true for solar), merit order effect will drive the prices downs during these periods, lowering marginal revenue for renewables (market value of renewables)[6]. In an electricity system where intermittent generation comprises a small share of total output, the high variability of renewable will have little impact on the average base prices and market value of renewables, the gap between them is low. However, if the share of intermittent generation is significant, this gap might be significant, as illustrated in Figure 2. Measuring merit order effect in this context is of high importance. In the next section, we attempt to evaluate the magnitude of this effect.

[6] This effect can be illustrated clearer as compared with peak-load plants running during high demand level, the revenue received by these plants will be very high because prices will be high during these periods. The volume wighted average revenue paid to peak-load plants shoud thus be equal to yearly average market price. This is not the case of intermittent renewables.

3. LITERATURE REVIEW ON QUANTITATIVE ANALYSIS OF THE MERIT ORDER EFFECT

The merit order effect has been recently discussed in a number of articles about renewable energy. Two broad methods to estimate the merit order effect of renewables have been used in literature: electricity market modelling and econometric analysis of historical time series data. Using electricity modelling requires precise calibration of costs and especially definition of reasonable scenarios. A lot of assumptions bound to the models can negate the certitude of conclusions. Regression models, on the other hand, employ historical data and do not require assumptions about alternative developments. However, only short-term relations between renewables and spot prices are considered. Besides, other factors such as costs and network congestion are often neglected.

Sensfuss et al. [2008] carry out a calibrated PowerACE model[7] to run simulations of German electricity market with and without fed-in wind generation in order to estimate the merit order effect of wind power from 2001-2006. They find that in the year 2006 the reduction in the average market price reaches 7.83 €/MWh. The results also suggest that the total volume of merit order effect grows from 1 billion Euro in 2001 to about 5 billion Euros in 2006.

Weigt [2009] analyzes the potential of wind energy to substitute fossil fuels and the cost saving that this effect would bring about. Using data from German electricity system from 2006 to the first half of 2008, he employs an optimization model with the objective function of minimizing costs, subject to demand level and capacity constraints of different power plants. The results show that wind generation creates a reduction effect on both prices and generation costs and that during the examined period, the total saving reaches 4.1 billion euros.

Regarding econometric analysis, Gelabert et al. [2011] employ an OLS regression of daily average prices on renewable generation outputs for 2005-2009 in Spain. They find that the spot electricity prices decrease by almost 2 €/MWh per additional 1GW renewables fed into the system and that the effect is greater for hours with high demand. Earlier papers on Spanish electricity markets found also the reduction effect: Sáenz de Miera, del Río González and Vizcaíno [2008], for instant, estimate a market price reduction of 11.7%, 8.6% and 25.1% in 2005, 2006 and 2007 respectively. Using the similar regression model to Gelabert et al. [2011], on German-Austrian joint dataset from July 2010 to 30 June 2012, Wurzburg et al. [2013] find an overall reduction of 7.6 €/MWh in the electricity spot price induced from fed-in renewable. Cludius et al. [2014] analyze the merit order effects of wind and photovoltaic electricity generation for 2008-2012 in Germany by OLS regression models using daily average prices. They specify that on average, day-ahead prices of electricity decrease by 0.8 to 2.3 €/MWh per marginal GWh of renewables fed into the system. The total merit order effects of wind and photovoltaic increases from 5 €/MWh in 2010 to more than 11 €/MWh in 2012. They extend the analysis out to 2016 forecast and suggest that total merit order effects are likely to lie between 14 and 16 €/MWh, depending on the assumptions about capacity extensions of wind and PV as well as load development. Using OLS regressions with daily prices over the period 2005 –- 2013 in Italian power market, Stefano, Alessandra and Pietro [2015] find that an increase of 1 GWh in the hourly average of daily production from solar and wind sources has, on average, reduced wholesale electricity prices by respectively 2.3€/MWh and 4.2€/MWh.

Jónsson, Pinson and Madsen [2010] take a slightly different approach. Using forecasted data of wind generation and spot prices (day-ahead) for 2006-2007 in West Denmark, they carry out a non-parametric regression model to estimate how the spot prices in West Denmark are affected by wind

[7] The PowerACE is a research project conducted during 2004 - 2007 which develops a simulation model of the German electricity system and specially focus on the impact of emissions trading and the increased use of renewable energy sources on markets and power generation structures. Many research institutions were involved in the projects team and it was funded by Volkswagen Stiftung.

power forecasts. They also find a significant price effect when the wind power penetration exceeds 11% of the total power demand.

More recently, Ketterer [2014] and Benhmad and Percebois [2013] analyze the impact of wind generation on the spot market prices in Germany. Using GARCH model on average daily data, they find that on average the fed-in wind power has negative impact on the price level and positive effect on the price variance. Studies are also employed for the wholesale electricity markets in Texas (Woo, Horowitz, Moore and Pacheco [2011]) and Australia (Forrest and MacGill [2013]); both papers use an AR(1) process.

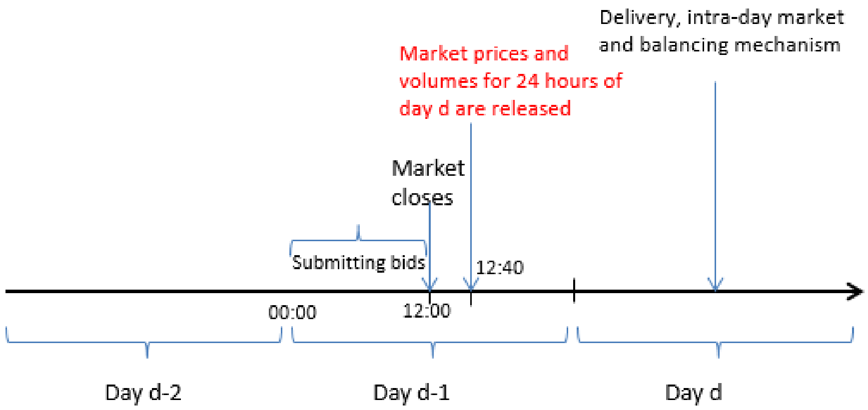
Though each paper takes different approaches and uses different methods, they essentially come up with similar conclusions. The general suggestion in all of those papers is that there is a decrease of electricity spot prices as wind power penetration increases. However, none of those using econometric models takes into account the distinguished feature of the data in electricity market. Electricity is the unique market where there exist 24 different prices for 24 hours per day due to the combination of strong variability of demand for electricity and non-storability of electricity. Any attempt to model electricity price should take this into account.

There have been three broad modeling strategies of electricity spot prices in the existing literature, of which the most common method is to model one daily average price series. Other methods that have been employed, though not necessarily concern merit order effect analysis, are the treatment of the hourly prices as a single time series, for example, Nogales, Contreras and Conejo [2002], Conejo, Contreras, Espinola and Plazas [2005], Liu and Shi [2013], Steen [2003]; or a treatment of the hourly prices separately, for example, Crespo Cuaresma, Hlouskova, Kossmeier and Obersteiner [2004], Weron and Misiorek [2008], Karakatsani and Bunn [2008], Bordignon, Bunn, Lisi and Nan [2012].

Averaging hourly observations to obtain one average daily price is the least complicated way to treat the dataset and this also introduces smoothness into the data by dampening the fluctuations in the hourly data. However, manipulation the data in this way might remove the possible short run dynamic across hours. Indeed, the magnitude of price reduction effect created by wind power is different during the day depending on which power plants are mobilized in the merit order. For this reason we are not considering this method.

The treatment of the hourly prices as a single pooled time series is not being considered in this paper either. In fact, we are modelling the day-ahead market, where equilibrium prices are determined one day before the delivery through an auction mechanism. In the morning of each day, buyers and sellers submit their bids (price and quantity combination) for each hour of the forthcoming day. The market is closed at 12:00 noon in Germany. Epex Spot then aggregates demand and supply curves. The results of equilibrium price and volume for each hour of the forthcoming day are published by Epex Spot from 12:40 pm for **simultaneous** 24 hours (figure 3). Thus, the information of price for 24 hours is released at the same time. This is why considering the hourly prices as a continuous single pooled time series is not an appropriate methodology.

Figure 3. Time framework of market information release



Modelling a multivariate model is appealing because this allows capturing precise coefficients for separate hours. However, the burden on calculation might be too heavy due to the enormous number of parameters to estimate.

An assumption under which the issue of having too many parameters can be solved is **contemporaneous correlation** between the error terms. This assumption says that the error terms in different equations (hours), at the same point of time, are correlated. The economic intuition behind this is quite straightforward. These errors contain the influence on demand and supply that have been omitted from the model, such as changes in market regulation, the general state of the economy, etc. Since the individual hourly prices share common dynamic in many respects, it is likely that the effects of the omitted factors on hour, say h8, will be similar to their effect on hour h9. If so, then the error terms in these two hourly equations will be capturing similar effects and will be correlated. This motivates us to implement a panel data model, as done in Huisman, Huurman and Mahieu [2007] or more recently Meritet and Pham [2015].

4. DATA AND MODELLING PROCEDURES

4.1. Data

The data concerns the period from 26/10/2009 to 31/12/2012, largely because of the availability of data on solar power generation. Hourly data of electricity spot prices (in €/MWh) in German wholesale electricity market is collected from the European Exchange market. The data of wind and solar power generation in quarter-hour is collected from different TSOs (Tennet TSO, 50 Hertz, Amprion, EnBW) and via EEX for validation. We take the average of four quarter-hours to get the hourly data.

One great advantage of modeling panel data over daily average series is that panel data takes into account the variation of solar power generation across the hours. Unlike wind, solar output is zero during the night from 09pm to 5am while being very high around mid-day. Using panel framework allows capturing this factor.

The 24 hourly power consumed by the network (including the network losses but excluding the consumption for pumped storage and excluding the consumption of generating auxiliaries) is published by ENTSO-E. We use the data of total load as the main determinant of equilibrium prices. Indeed, total load gives information on which technology should be mobilized in the merit order, thus contributing to determine the marginal plant as well as marginal cost[8]. To avoid endogeneity problem, we use lag-1 values of load.

Table 1. Summary statistics for sample variables

	PRICE	LOAD	WIND	SOLAR
Unit	€/MWh	GW	GW	GW
Mean	45.54569	54.91237	4.900346	1.96345
Median	46.04	54.998	3.056	0.1223
Maximum	210	79.884	24.021	22.1523
Minimum	-221.99	29.201	0.093	0
Std. Dev.	16.53413	10.07668	4.31388	3.548788
Skewness	-1.989811	-0.072376	1.445615	2.258021
Kurtosis	32.60875	1.916716	4.940433	7.958007
Jarque-Bera	1037995	1389.153	14921.43	52614.08
Probability	0	0	0	0

The whole sample spans from 26 October 2009 to 31 December 2012, yielding $T=1163$ for each hour and 27912 observations for the whole panel dataset.

Table 1 gives summary statistics for sample variables. Several unit root tests (Augmented Dickey-Fuller, Phillips Perron) are applied to each variable, all series are found stationary at the usual significance levels (the results are available upon request). The information of Skewness, Kurtosis as well as Jarque-Bera on price data shows that its distribution is far from normal: the skewness is substantial at -1.99 and the kurtosis is much greater than 3 (at 32.6). The statistical information on each series of price also suggests that the normal distributions are rejected: the skewnesses are highly negative and the kurtosises are far from 3, particularly from 00am to 09am where the kurtosis is at over 50.

4.2. The model and estimation procedures

We employ generalized autoregressive conditional heteroscedasticity models GARCH to estimate the effects created by wind generation on electricity spot market. The argument to justify this choice of model are: (1) Electricity spot prices display a "leptokurtosis" feature; that is, they have distributions that exhibit fat tails and excess peakedness at the mean (table 1); (2) There is also "volatility clustering" attribute - the tendency for volatility to appear in bunches: the current level of volatility tends to be positively correlated with its level during the immediate preceding periods. For those reasons, we use GARCH model, which are also popular to modelling and forecasting volatility of spot prices (Liu and Shi [2013], Garcia, Contreras, Van Akkeren and Garcia [2005], Tan, Zhang, Wang and Xu [2010]).

With 24 series dataset, an appropriate model would be multivariate GARCH, which has been developed in the literature to model the time dependent variance-covariance; for example, the VECH and the diagonal VECH model of Bollerslev, Engle, and Wooldridge [1988]; the BEKK model of Engle and Kroner [1995] and the constant correlation (CCORR) model of Bollerslev [1990]. However, one problem of these models is that as the number of series employed in the models increases, the estimation of these can quickly become infeasible. For example, a 24-price set yields 180300

[8] Others variables that should have been taken into account in price function are fuel costs such as coal or gas prices. However, none of these is included in the model. First, the share of gas generation technology accounts for a small part in the total annual marginality duration in Germany. A simple OLS regression of German electricity spot prices on gas prices shows a non-significant effect. Second, though hard coal and lignite plants tend to have a major marginality, the unavailability of the coal price on daily basis and the fact that weekly coal prices are rather stable during the examined period except in 2012, we are not considering this variable.

parameters to estimate under VECH (1,1) and 900 parameters under diagonal VECH (1,1) model. This is practically daunting.

Cermeno and Grier [2001 and 2006] and extended traditional GARCH models, as applied recently in Lee [2010], to a panel context. By assuming a common dynamics between hours, this model allows to capture the average effect of renewable on the spot price across hours and to reduce significantly the number of parameters to be estimated. Besides, this model specifies also equations for how the covariances move over time.

For a cross-section of *N=24* hours and *T* time periods, the conditional mean equation for price (P_{it})can be expressed as a dynamic panel with fixed effects[9]:

$$P_{it} = \mu_i + \sum_{l=1}^{L} \emptyset_l P_{i,t-l} + \beta X_{it} + \beta_{wind} Wind_{it} + \beta_{solar} Solar_{it} + \epsilon_{it} \qquad (1)$$

$$i = 1, \dots, N \, ; t = 1, \dots, T$$

The model is defined by the first equation (1) - mean equation- with μ_i captures possible hours-specific effect; β are constant parameters associated with X_{it} - exogenous variables in the system. To control the bank holidays effects, we include a dummy variable which takes value of 1 on weekend and on Public holidays in Germany and 0 otherwise. The autoregressive terms $P_{i,t-l}$ with associated parameters $\emptyset_l$ (l=1…L) are included in the mean function. β_{wind} and β_{solar} are the parameters measuring the price effects created by the wind and solar power generation.

The disturbance term ϵ_{it} had zero mean and normal distribution with the following conditional moments:

$$E[\varepsilon_{it}\varepsilon_{js}] = 0 \qquad for\ i \neq j\ and\ t \neq s, \qquad (2)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = 0 \qquad for\ i = j\ and\ t \neq s, \qquad (3)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = \sigma_{i,t}^2 \qquad for\ i \neq j\ and\ t = s, \qquad (4)$$

$$E[\varepsilon_{it}\varepsilon_{js}] = \sigma_{ij,t} \qquad for\ i = j\ and\ t = s, \qquad (5)$$

Assumption (2) assumes no non-contemporaneous cross-sectional correlation while assumption (3) assumes no autocorrelation. Assumptions (4) and (5) define a very general conditional variance-covariance process. The conditional variance and covariance are assumed to follow a GARCH (1,1) process:

$$\sigma_{it}^2 = \alpha_i + \lambda_{wind} Wind_{it} + \lambda_{solar} Solar_{it} \gamma \sigma_{i,t-1}^2 + \delta \varepsilon_{i,t-1}^2, \qquad i = 1, \dots, N, \qquad (6)$$

$$\sigma_{ij,t} = \varphi_{ij} + \eta \sigma_{ij,t-1} + \xi \varepsilon_{i,t-1} \varepsilon_{j,t-1}, \qquad i \neq j, \qquad (7)$$

Modeling the conditional variance and covariance processes in this way is quite convenient in a panel data context since by imposing a common dynamics to each of them, the number of parameters is considerably reduced as compared with VECH or CCORR models. In this case there are $\frac{N(N+1)}{2} + 5 = 305$ parameters in the variance-covariance matrix to be estimated. Renewable output variables are also included in the variance equation (6) to estimate whether wind generation fed into the electricity system increases the volatility of electricity spot prices.

In matrix notation, equation (1) can be expressed as:

[9] We justify this choice by Hausman specification test (1978), which assume random effects (RE) estimator to be fully efficient under null hypothesis. The results of the Hausman test give the overall statistics, chi squared (9) having p-value=0.000. This leads to strong rejection of the null hypothesis that RE provides consistent estimates. We are considering therefore the fixed effects model.

$$P_t = \mu + Z_t\theta + \epsilon_t \qquad t = 1 \dots T \qquad (8)$$

where $Z_t = [P_{t-1} \vdots X_t]$ is a $N \times (K + 1)$ matrix with their corresponding coefficients in $\theta = [\emptyset \vdots \beta']$. The *N*-dimentional vector ϵ_t has a zero-mean multivariate normal distribution and variance-covariance matrix $\boldsymbol{\Omega}_t$ denoted as $\epsilon_t | I_{t-1} \sim N(0, \boldsymbol{\Omega}_t)$ where I_{t-1} represents the information available at time *t-1*, so that the latest information is taken into account. The log-likelihood function of the fixed-effects panel model with the time-varying conditional covariance can be expressed as:

$$L = -\frac{1}{2}NT\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln|\Omega_t| - \frac{1}{2}\sum_{t=1}^{T}[(P_t - \mu - Z_t\theta)'\Omega_t^{-1}(p_t - \mu - Z_t\theta)] \qquad (9)$$

The estimation of this model is conducted by direct maximization of the log-likelihood function given by (9). To make sure that GARCH-type model is appropriate for the data, we employ the Engle (1982) test for ARCH effects on equation (1). Both the F-version and the LM-statistic are very significant, suggesting the presence of heteroscedasticity or ARCH effect in spot market prices. The choice of optimal lag number L for the autoregressive terms in the mean equation is justified based on the minimization information criteria (Hannan-Quinn). The results show that the best lag number is l=7 which correspond to weekly frequency of 7 days. To make sure that there is no autocorrelation, we employ the unit root test for the residual ϵ_{it} of the mean equation (1). The results from both correlogram and unit root test suggest the absence of autocorrelation.

5. RESULTS AND DISCUSSIONS

5.1. Estimation results

The estimation results of GARCH(1,1) model for panel dataset are reported in table (2).

Table 2. Estimation results for the GARCH dynamic panel data model

Variables	Parameters	Std deviation	Student	P-value
		Mean Equation		
AR(1)	0.3176	0.0081	39.1810	0.0000
AR(2)	0.0166	0.0070	2.3776	0.0087
AR(3)	0.0677	0.0065	10.4563	0.0000
AR(4)	0.0577	0.0063	9.1471	0.0000
AR(5)	0.0520	0.0066	7.9034	0.0000
AR(6)	0.0615	0.0063	9.7811	0.0000
AR(7)	0.1934	0.0049	39.6539	0.0000
Load	0.0862	0.0236	3.6400	0.0010
Wind	-0.9287	0.05125	-18.290	0.0000
Solar	-0.4451	0.0180	-24.660	0.0000
$\mu_i(24)$	...			
		Variance Equation		
ARCH (1)	0.0253	0.0018	13.9377	0.0000
GARCH (1)	0.0242	0.0250	0.9675	0.1666
Wind	0.0262	0.0019	14.0216	0.0000
Solar	0.0244	0.0026	9.2529	0.0000
$\alpha_i(24)$	...			
		Covariance Equation		
ARCH (1)	0.0109	0.0019	5.6931	0.0000
GARCH (1)	0.0438	0.0543	0.8063	0.2100
$\varphi_{ij}(276)$	...			

The coefficients of both wind and solar are highly significant and negative as expected. The model-based result suggest that on average, day-ahead prices of electricity decrease by 0.93 and 0.45 €/MWh per marginal GWh of wind and solar respectively fed into the system.

The coefficients of autoregressive part are generally significant, particularly AR(1) and AR(7) because the prices at the day t depends on the prices of the day before (t-1) and those of the same day the week before.

The results also suggest that the integration of renewable power generation induces an increased volatility of electricity spot prices in German market. This is shown by the coefficients of wind and solar outputs in the variance equation which are statistically significant and positive.

The coefficients ARCH associated with $\sigma^2_{i,t-1}$ and $\sigma_{ij,t-1}$ in the variance-covariance equations are highly significant and positive, which justify the model we have chosen, though GARCH effects, $\epsilon^2_{i,t-1}$ and $\epsilon_{i,t-1}\epsilon_{j,t-1}$, are statistically insignificant.
The volatility of prices across hours is given in figures 3 and 4 in the appendix which represent how conditional variance changes over time for each hour. Day ahead prices experience more "shocks" during the night and early morning (from 00am to 9am) than the rest of the day. Conditional variances are also higher in the 26/27 December for each hours. These observations correspond with the large changes in price level due to negative prices (which occur mostly during the night) and due to the holiday effects.

Other interesting observations show up in the cross-sectional correlation matrix of the error term as specified in (7). The conditional covariance constant coefficients $\boldsymbol{\varphi}_{ij}(276)$ are highly significant, which shows evidence for a clear cross-sectional correlation structure in hourly electricity prices.

As explained above and justified in many papers, for example Jónsson et al. [2010], Jonsson et al. (2012), Nicolosi and Fursch [2009], and Ketterer [2014], the combination of renewable generation and the total electricity load plays an important role in price behavior. For this reason, we use also the ratio between wind/solar and total load to estimate how the share of wind in the load portfolio effect the prices as done in Ketterer (2012). Indeed, the same level of wind and solar power will result different impacts on the price depending on the level of electricity demand. The results are shown in table (3)[10]. The coefficient of fed-in wind and solar share in the total load portfolio is highly significant. On average, an increase by 1% of the share of wind and solar power generation in the total load would lead to a decrease of spot price by 1.5% and 0.69% respectively.

Table 3. Estimation results for the GARCH dynamic panel data model

Mean Equation				
Variables	'Parameters'	'Std deviation'	'Student'	'P-value'
Wind share	**-1.5486**	0.12964	-11.9500	0.0000
Solar share	**-0.6900**	0.5310	-13.000	0.0000
AR(1)	0.251	0.0055	45.838	0.0000
AR(2)	0.080	0.0051	15.603	0.0000
AR(3)	0.058	0.0053	10.978	0.0000
AR(4)	0.061	0.0045	13.707	0.0000
AR(5)	0.060	0.0045	13.145	0.0000
AR(6)	0.050	0.0042	11.832	0.0000
AR(7)	0.208	0.0039	53.922	0.0000
μ_i (24)	...			
Variance Equation				
ARCH (1)	0.0929	0.0034	27.4383	0.0000
GARCH (1)	0.0641	0.0086	7.4509	0.0000
Wind	**0.0672**	0.0137	4.8899	0.0000
α_i (24)	...			
Covariance Equation				
ARCH (1)	0.0228	0.0034	6.6342	0.0000
GARCH (1)	0.3216	0.0348	9.2293	0.0000
φ_{ij} (276)	...			

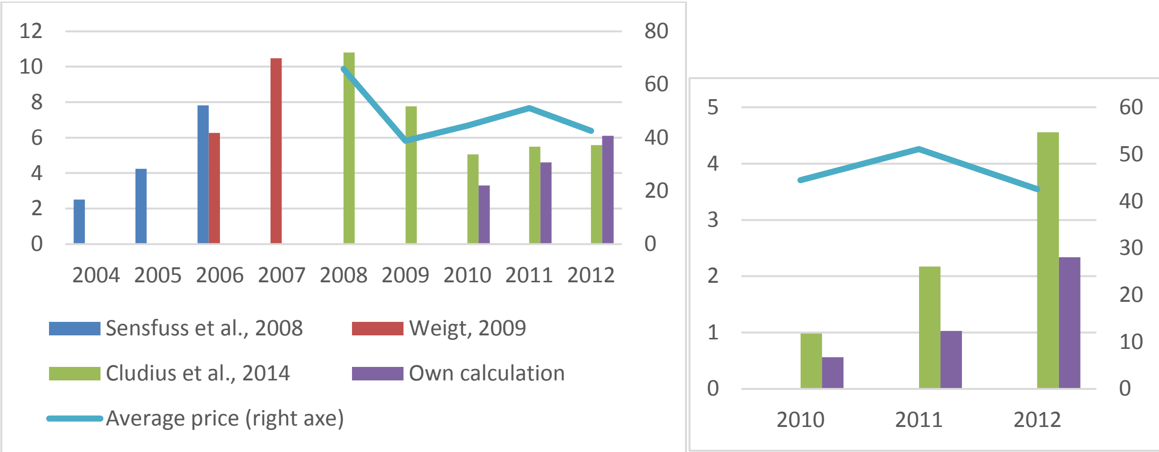
We implement four sub-panel datasets corresponding to four demand profiles: the morning peak (from 7am to 11am); the afternoon trough (from 12am to 5pm); the evening peak (from 6pm to 11pm) and the night trough (from 00am to 6am), whose the details are reported in the tables (5) and (6) in the Appendix. The results suggest that the impact of wind power on price level is more significant in the morning from 7am to 11am. This could be explained by the fact that during the peak demand period, the marginal cost curve is steeper, thus the merit order effect would be more significant. The impact of wind power generation is particularly high during the night with very low level of demand (from 00am to 6am) due to the "shocks" created by negative prices.

5.2. Discussions

Our results are correspondent with findings from literature especially for wind effect. Figure 4 plots some results recorded in various studies in Germany on each year between 2004 and 2014 for both wind and solar effects.

[10] We use logarithm of spot prices in this regression to ease the interpretation of coefficients.

Figure 4. Merit order effects of renewables in Germany by year[11]



a. Merit order effects of wind output **b. Merit order effects of solar output**

Regarding merit order effects of wind output (Figure 4a), in general, there has been only slight variation among papers which employed the data on the same year. The level of average price reduction created by wind power generation increased substantially from 2004 to 2008, ranging between 2.5 €/MWh in 2004 up to 10.8 €/MWh in 2008. This could be explained by very expensive fuel prices and high CO2 prices (especially in 2007-2008) that make the marginal cost curve of electricity generation become steeper during these years. The effect of switching merit order would be consequently higher. This effect remained relatively high in 2009 despite lower demand. Indeed, average day ahead prices in 2009 were at particularly low level (38.86 €/MWh) as compared with the rest of period mainly because of low demand. However, the merit order effect remained comparatively high largely due to very high frequency of negative prices phenomenon observed in 2009, which were results of combination between high wind fed-in and low demand.

Merit order effect of wind power was smaller between 2010 and 2012 as the slope of marginal cost curve was less steep as result of cheap coal and sharp fall in CO2 prices (since mid-2011). A slight increase of merit order effect was however observed from 2010 to 2013 due to the shutdown of 8 nuclear power reactors in March 2011, which was substituted largely by massive integration of wind output (from 4.3 GW in 2010 to 6 GW in 2013). At the end of 2014, price reduction created by wind power generation lied from 4.1 to 6.3 €/MWh. The merit order effect induced by solar output was in general less significant than that of wind (Figure 4b). This effect has significantly increased between 2010 and 2012, rising from around 0.8 €/MWh on average in 2010 to around 3 €/MWh after 2 years. There is a larger variation between our findings and the ones form literrature (Cludius et al. [2014]) because we treat the data as panel framework while Cludius et al. [2014] used daily average data. The outcomes from these two ways of treatment are particularly obvious when we incorporate solar data, which take significant values around mid-day and almost zero the rest of the time. Averaging hourly data to get daily values tends to overestimate the average effect.

It is important to note that the renewables' coefficients associated with the regression describe the effect of marginal wind/solar increase of 1GWh on spot prices, not to estimate what happens when wind/solar generation replaces another technology. Based on the results obtained from the regression, the total average effect and the annual financial volume of the merit-order effect can be estimated as in Sensfuss et al., [2008] and Cludius et al. [2014] by:

$$v = \sum_i MOE * load_i$$

[11] The results in some papers are converted into homogeneous units (average price reduction €/MWh) so that common patterns and trends can be identified.

$$MOE = \beta_{enr} * \overline{ENR}$$

where v refers to the annual financial volume of the merit-order effect created by wind/solar power generation in the wholesale market (in €); MOR – average merit order effect price (measured in €/MWh) equals to marginal effects (β_{enr}) multiplied by the volume weighted average wind/photovoltaic generation.

The results are given in table (4) for each year. The merit order effect created by solar, though less significant than that of wind, has increased substantially from 2010 to 2012. The total annual financial volume is estimated at 1.86 to 3.91 billion euros, a non-negligible amount. In term of surplus for consumers, assuming that local demand curve is linear with a downward slope, this price reduction would imply an equivalent increase in consumers' surplus of 1.26 to 3.16 billion euros between 2010 and 2012 in Germany. This increase in consumers' surplus does not necessarily an increase of total welfare. German electricity producers are receiving lower profits and final consumers are paying more surcharges.

Table 4. Total annual financial volume of merit order effect

	2010	2011	2012
Wind_Average merit order effect (€/MWh)	-3.25	-4.61	-6.01
Solar_Average merit order effect (€/MWh)	-0.56	-1.03	-2.33
Annual financial volume (€billion)	1.86	2.73	3.91
Increase in consumers surplus (€billion)	1.26	2.07	3.16
Total EEG-Umlage cost (€billion) (Costs for household consumers)	2.9	4.82	4.91

The substantial annual financial volumes estimated in table (4) benefit mainly the privileged group of consumers - who are energy intensive companies in the wholesale market. These companies do not bear the surcharge of feed-in-tariff payments: they pay very little amount of the EEG-Umlage: 0.05 ct/kWh which considerably (100 times) lower than that of households. Therefore, the consumers that buy electricity on the wholesale market are not only privileged under the EEG-Umlage but also enjoy lower prices created from merit order effect of renewables. On the other hand, many households have been paying significant surcharges whilst not necessarily benefiting from lower wholesale price. This latter is not fully passed through in the final electricity bill.

In order to distinguish the effect of wind and solar power generation on different types of consumers (household and industry) in monetary terms, we compare the total consumers' surplus (that benefits mainly industrial groups) stemming from the merit order effects of renewable production with the cost of EEG-Umlage charged on households' electricity bills. The latter is calculated by multiplying the EEG-Umlage for households (€/MWh) by the household consumption (MWh) in a given year[12]. We find that the total costs for household consumers to finance investments in renewable energy production have been substantial. And even if the reductions in the wholesale prices caused by the merit order effect could be adequately passed through to non-privileged electricity consumers, the total surcharges would still outweigh the possible savings (in the financial terms).

Our findings suggest that the burden borne on final consumers could be reduced if the surcharges paid by privileged consumers in the wholesale market took into account the merit order effect of renewables. This could alleviate some of the extra costs caused by the EEG surcharges, thus reducing

[12] The EEG-Umlage for households was at 20.47; 35.3 and 35.9 \euro /MWh for 2010, 2011 and 2012 respectively and the household consumption of electricity was at 141.7;c 136.6 and 137 TWh for 2010, 2011 and 2012 respectively (Data from Netztransparenz and Eurostat).

the wealth transfers from residential and small business consumers to large energy-intensive industry.

6. CONCLUSION

This paper quantifies the impact of the supported wind and photovoltaic electricity generation on spot prices in Germany during period from October 2009 to December 2012, using GARCH model for a panel data framework.

The model-based results suggest that wind and solar power generation fed in to the system during the examined period decreased the level and increased the volatility of the spot prices. The merit order effect created by renewable electricity ranges from 3.86 to 8.34 €/MWh which implies to the increase of consumers' surplus of 1.26 ~ 3.16 billion euros. This effect varies across hours during the day depending on the demand level. These findings are of interest in the context of the German Renewable Energy Sources Act (EEG) which levies a surcharge on final consumers for the support of renewable energy sources. Different welfare transfer occurred. Firstly, there have been likely wealth transfers from non-privileged consumers (residential and small business consumers), who are paying high surcharges and not benefiting from merit order effects, to privileged consumers (large energy intensive industry), who are benefiting from merit order effects but being exempted from EEG surcharges. Our results suggest that the supporting costs borne on final consumers could be reduced significantly if the surcharge paid by privileged consumers in the wholesale market took into account the merit order effect of renewables; or if the relations between electricity spot and forward prices were adequately close. Secondly, a part of consumers' surplus was transferred from the profits of electricity producers. In the long term perspective, when renewables penetration rate is sustainably higher, this effect could imply significant integration costs because the gap between average power prices and average market value renewables becomes larger. The need for renewables supporting scheme could probably be permanent (cannibalization effect). However, the methodology used in this paper does not permit to extend the analysis to long term perspective where the level of intermittent generation will increase and conventional generation should be adapted. As an interesting topic for further research, the volume of the merit-order effect created by wind power in the future under different scenario of development would also be worth estimating.

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Appendix

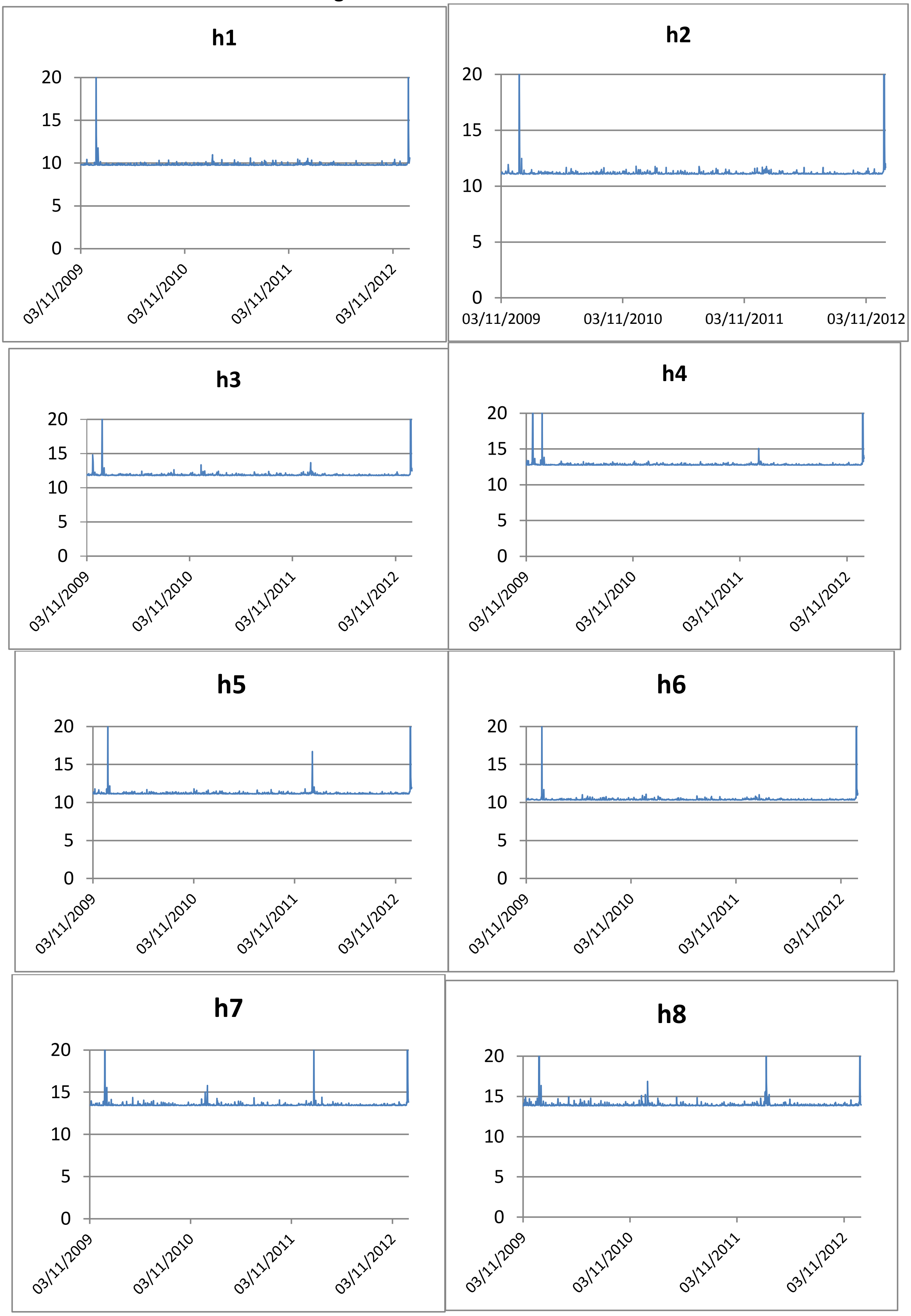
Table 5. Estimation results for GARCH model-morning and afternoon

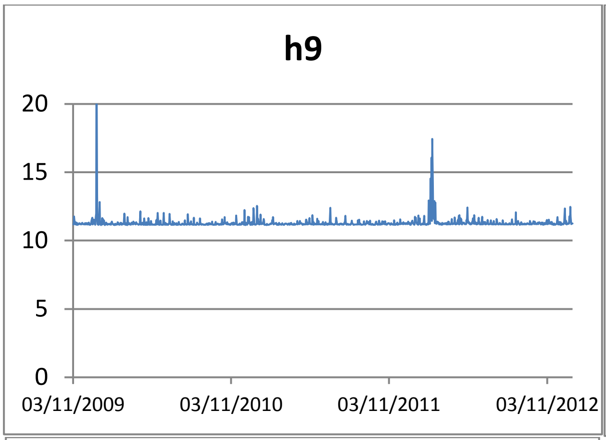
Morning					Afternoon				
	Mean Equation					Mean Equation			
Variables	'Parameters'	'Std deviation'	'Student'	'P-value'	Variables	'Parameters'	'Std deviation'	'Student'	'P-value'
Wind share	**-1.6999**	0.1601	-10.62	0.0000	Wind share	**-1.2906**	0.0666	-19.360	0.0000
Solar share	**-0.7968**	0.1280	-6.2200	0.0000	Solar share	**-0.7580**	0.0635	-11.921	0.0000
AR(1)	0.210	NaN	NaN	NaN	AR(1)	0.205	0.0069	29.591	0.0000
AR(2)	0.099	0.0075	13.184	0.0000	AR(2)	0.063	0.0080	7.874	0.0000
AR(3)	0.109	0.0083	13.028	0.0000	AR(3)	0.106	0.0079	13.481	0.0000
AR(4)	0.108	0.0081	13.270	0.0000	AR(4)	0.069	0.0071	9.722	0.0000
AR(5)	0.084	0.0066	12.811	0.0000	AR(5)	0.192	0.0068	28.416	0.0000
AR(6)	-0.037	0.0086	-4.317	0.0000	AR(6)	-0.020	0.0066	-3.106	0.0009
AR(7)	0.167	0.0066	25.144	0.0000	AR(7)	0.169	0.0066	25.432	0.0000
μ_i (6)					μ_i (6)				
	Variance Equation					Variance Equation			
ARCH (1)	0.1323	NaN	NaN	NaN	ARCH (1)	0.3396	0.0165	20.5488	0.0000
GARCH (1)	0.0940	NaN	NaN	NaN	GARCH (1)	0.5029	0.0119	42.2885	0.0000
Wind	**0.0977**	NaN	NaN	NaN	Wind	**0.2497**	0.0192	12.9840	0.0000
α_i (6)					α_i (6)				
	Covariance Equation					Covariance Equation			
ARCH (1)	0.0598	0.0028	21.3803	0.0000	ARCH (1)	0.2623	0.0162	16.1949	0.0000
GARCH (1)	0.3222	0.0174	18.5228	0.0000	GARCH (1)	0.6015	0.0123	48.7311	0.0000
φ_{ij} (15)					φ_{ij} (15)				

Table 6. Estimation results for GARCH model- evening and night

Evening					Night				
	Mean Equation					Mean Equation			
Variables	'Parameters'	'Std deviation'	'Student'	'P-value'	Variables	'Parameters'	'Std deviation'	'Student'	'P-value'
Wind share	**-0.9026**	0.0400	-22.530	0.0000	Wind share	**-2.3208**	0.1884	-12.320	0.0000
AR(1)	0.251	0.0105	23.962	0.0000	AR(1)	0.229	0.0098	23.370	0.0000
AR(2)	0.123	0.0108	11.386	0.0000	AR(2)	0.099	0.0082	12.002	0.0000
AR(3)	0.066	0.0107	6.168	0.0000	AR(3)	0.050	0.0069	7.197	0.0000
AR(4)	0.042	0.0111	3.737	0.0001	AR(4)	0.133	0.0058	22.809	0.0000
AR(5)	0.100	0.0103	9.750	0.0000	AR(5)	0.037	0.0067	5.462	0.0000
AR(6)	0.134	0.0095	14.145	0.0000	AR(6)	0.056	0.0057	9.715	0.0000
AR(7)	0.213	0.0094	22.583	0.0000	AR(7)	0.104	0.0055	19.106	0.0000
μ_i (6)					μ_i (6)				
	Variance Equation					Variance Equation			
ARCH (1)	0.1165	0.0042	27.7916	0.0000	ARCH (1)	0.3372	0.0119	28.3567	0.0000
GARCH (1)	0.8102	0.0057	141.4360	0.0000	GARCH (1)	0.0056	0.0017	3.3731	0.0004
Wind	**0.1269**	0.0067	18.9513	0.0000	Wind	**1.5355**	0.0354	43.3188	0.0000
α_i (6)					α_i (6)				
	Covariance Equation					Covariance Equation			
ARCH (1)	0.0590	0.0050	11.7863	0.0000	ARCH (1)	0.0035	0.0027	1.3032	0.0962
GARCH (1)	0.8792	0.0075	117.8167	0.0000	GARCH (1)	0.4955	0.1244	3.9825	0.0000
φ_{ij} (15)					φ_{ij} (15)				

Figure 5. Conditional variance

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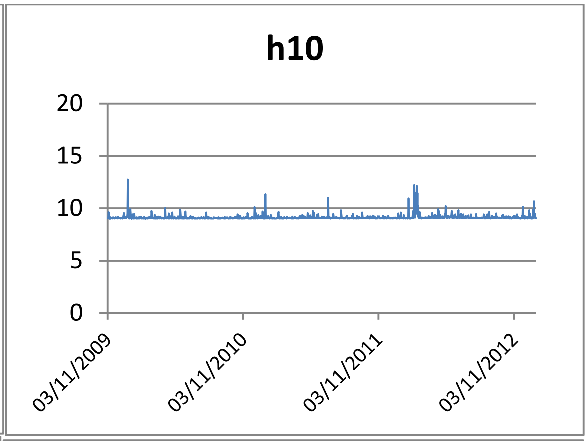
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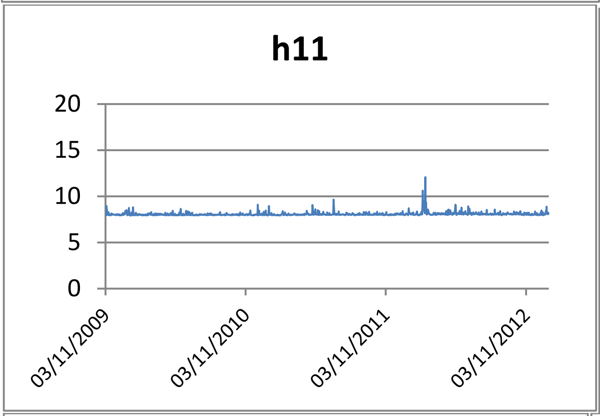
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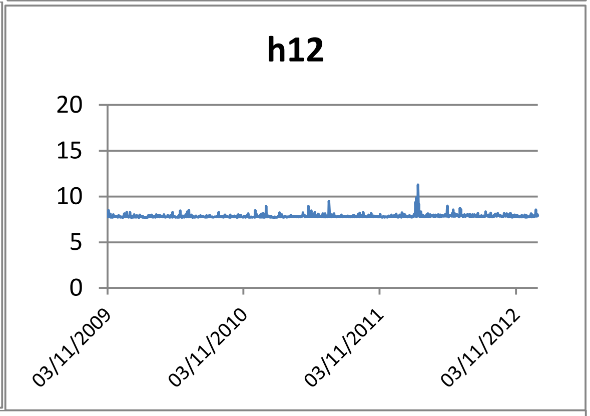
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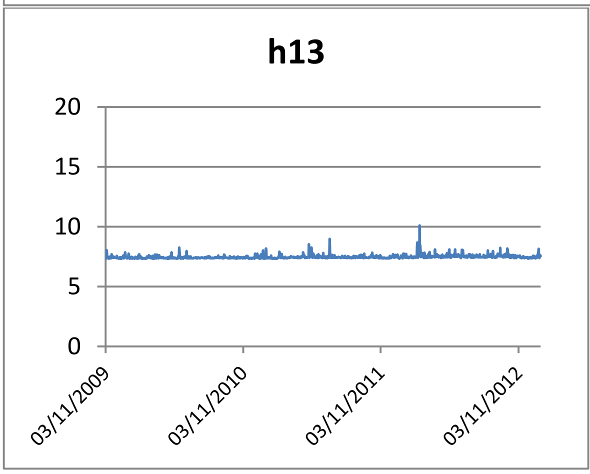
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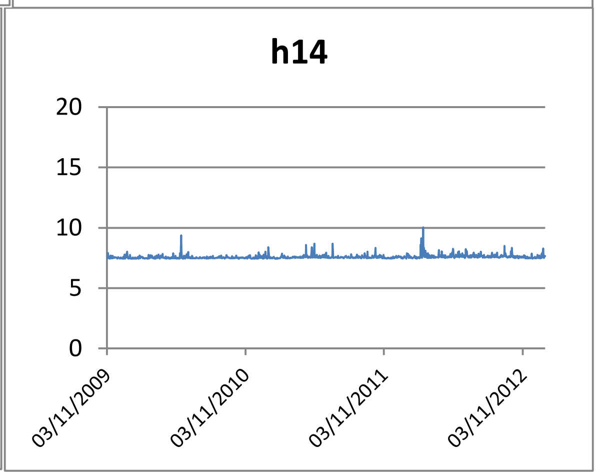
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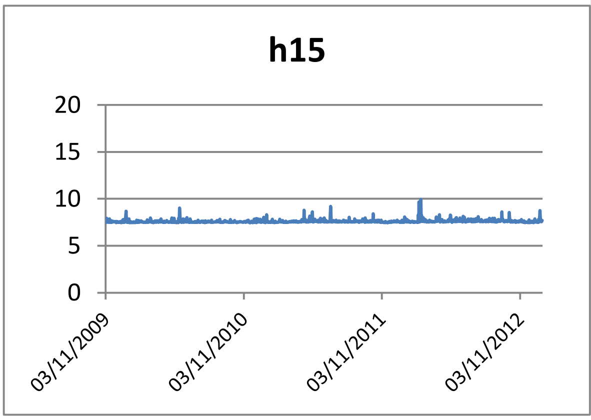
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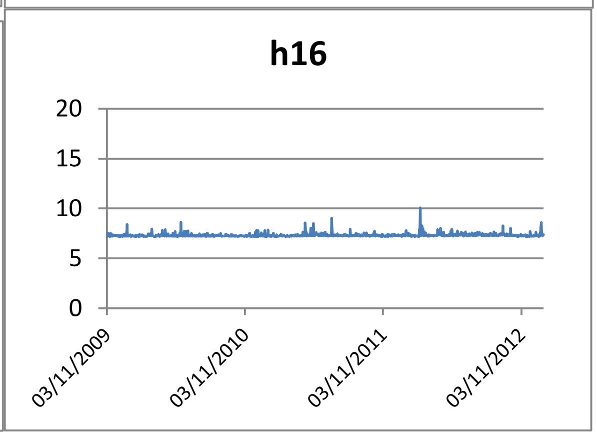
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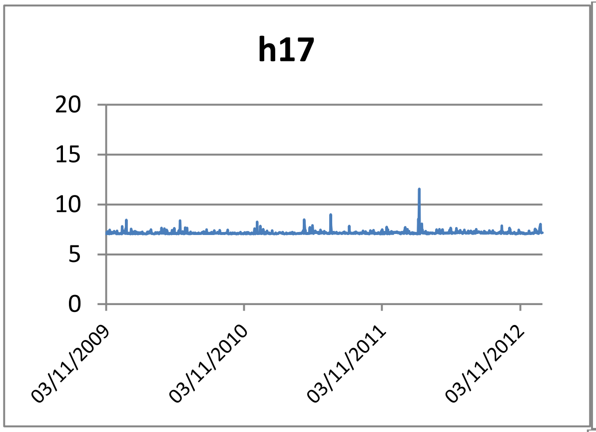
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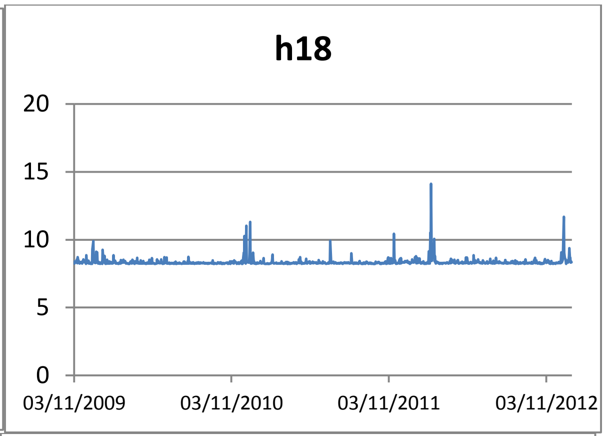
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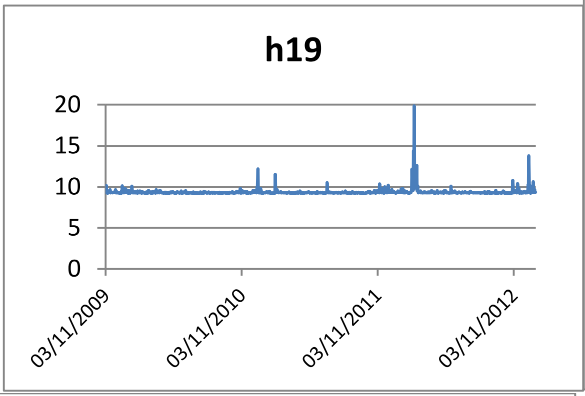
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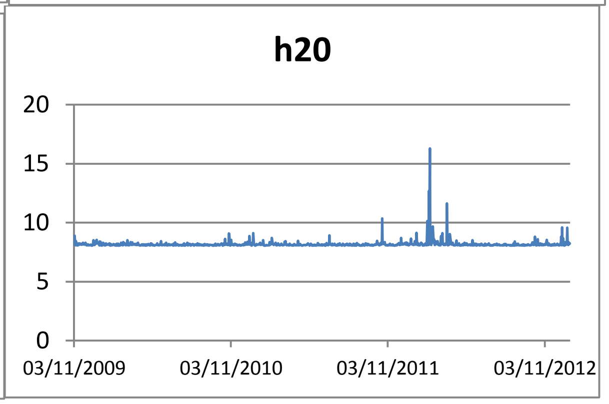
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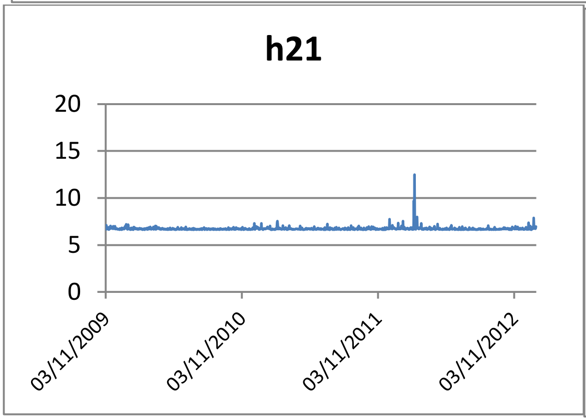
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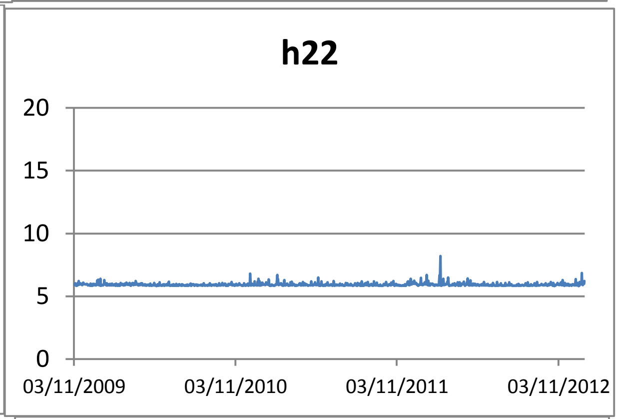
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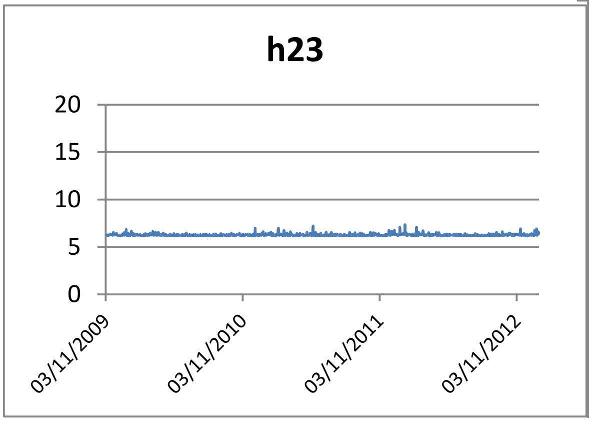
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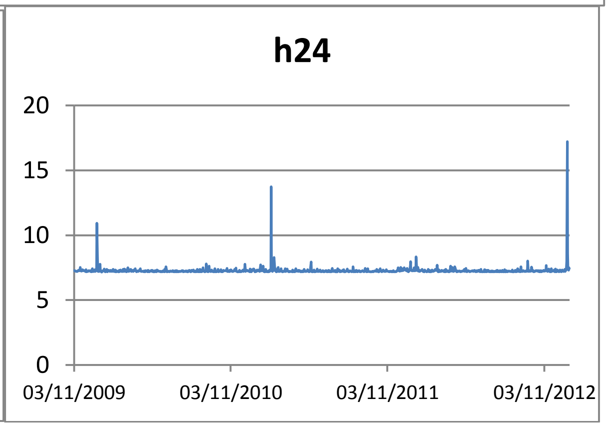
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