Energy Policy 170 (2022) 113243

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The impact of wind and solar power generation on the level and volatility of wholesale electricity prices in Greece

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ARTICLE INFO

JEL classification:
Q41
Q42
Q48

Keywords:
Wholesale electricity market
Electricity price volatility
Wind power
Solar power
Price-caps
Merit-order effect

ABSTRACT

We investigate the impact of wind and solar power generation on the level and volatility of wholesale electricity prices in the Greek electricity market from August 2012 to December 2018. In the context of a GARCH-in-Mean model the empirical findings suggest the existence of the merit-order effect which is stronger in the case of wind power. Controlling for regulatory mechanisms that may affect price volatility, we find that while overall renewables have decreased price volatility, wind power tends to increase it and solar power tends to decrease it. Furthermore, during peak hours, wind and solar power generation tend to decrease price volatility, supporting the hypothesis that renewables' output reduces the volatility of wholesale electricity prices when it is positively correlated with the electricity load. Finally, we find that the increase in the price-cap of the Greek wholesale electricity market was associated with a reduction in the volatility of wholesale electricity prices. This finding highlights the importance of the market structure and the degree of vertical integration of participants in liberalized electricity markets, which determines their behavior while also affecting market price volatility.

1. Introduction

In the new era that the world has entered with energy shortages and higher prices, renewable energy sources constitute a promising alternative to alleviate the problems, unconstrained by embargoes, wars or other political decisions. The main constraints facing electricity production from renewables are the financing of constructing renewable energy systems and the presence of natural forces, like sun and wind, that make such systems work and produce electricity. The type of renewables along with the level of their penetration when injecting electricity in the grid are likely to impact electricity price and volatility, especially when considering the intermittence feature of wind and solar power systems.

Indeed, the increasing penetration of renewables in electricity generation has brought about new elements into the formation of wholesale electricity prices, regarding their distribution and variability. Numerous studies have shown that wholesale prices are reduced due to the merit-order effect, which stochastically shifts the electricity supply curve outwards (Sensfuβ et al., 2008; Würzburg et al., 2013; Cludius et al., 2014; Benhmad and Percebois, 2018; Bushnell and Novan, 2018). However, less emphasis has been placed on the effect of renewables on the volatility of wholesale electricity prices, which is a fundamental risk factor in electricity markets. Since electricity suppliers are exposed to significant wholesale price risk, the relationship between price volatility and power generation from intermittent renewables has implications for the cost of their risk management strategies (Johnson and Oliver, 2019). Furthermore, increased price volatility may make it more profitable to invest in energy storage or smart grid infrastructure, as the value of transmitting stored energy (or equivalently of demand response) from periods when prices are low to periods when prices are high, increases (Wozabal et al., 2014). A better understanding of the impact of renewables on price volatility also helps policy makers adjusting the rules of operation of wholesale electricity markets to achieve an efficient allocation of resources.

In this paper we examine the impact of wind and solar power generation on the price level and volatility in the Greek wholesale electricity market from August 2012 to December 2018 in the context of a GARCH-in-Mean model. According to Johnson and Oliver (2019), there are two countervailing forces that affect the impact of intermittent renewables on price volatility. First, the volatility of wholesale electricity prices is reduced (stochastic merit-order effect) as intermittent renewables shift the electricity supply curve outwards and the fluctuating real-time

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https://doi.org/10.1016/j.enpol.2022.113243
Received 5 December 2021; Received in revised form 17 August 2022; Accepted 2 September 2022
Available online 13 September 2022

demand curve intersects with the flatter segment of the electricity supply curve.[1] Second, given the demand for electricity, intermittent renewables, having priority in the dispatch, cause the electricity supply curve to shift stochastically, leading to increased price volatility (intermittency effect). It turns out to be an empirical question which of the two impacts prevails on price volatility given the characteristics of electricity supply and demand.

The investigation of the direct impact of wind and solar power on price volatility has not been the subject of many studies. Our analysis is carried out for a wholesale electricity market in which wind and solar power has considerable penetration and seeks to identify and disentangle the impact of intermittent renewables on price volatility. In addition, during the examined period, the Greek wholesale electricity market operated as a mandatory pool with a relatively low price-cap, while negative price offers from producers were not allowed. These characteristics differentiate it from other markets for which the impact of renewables output on price volatility has been examined.

It is worth mentioning that to our knowledge this is the first econometric study that examines separately the impact of wind and solar power on the price level and volatility in the Greek wholesale electricity market. Other studies (Papaioannou et al., 2018; Kalantzis and Sakellaris, 2012) have examined the overall impact of renewables output on the level and volatility of wholesale electricity prices, without considering the unique features of different renewable technologies. As wind and solar power have unique characteristics, the separation of the impact for each renewable technology helps to better understand the process of electricity price formation.

The present work also contributes to the literature by examining the effect of a change in an important regulatory parameter of the Greek wholesale electricity market (i.e., the increase in the market price-cap) on the level and volatility of wholesale electricity prices. Price-caps are applied to wholesale electricity markets in order to limit producers from exercising their potential market power (Wilson, 2000) and in response to socially undesirable high prices in energy. In order to ensure the necessary backup capacity of the power system, in the case producers are not able to recover their fixed cost of capital from the market, regulators often set price-caps in conjunction with capacity payment mechanisms. We examine the effect of the change in price-caps on the level and volatility of wholesale prices of electricity under considerable penetration of renewables to provide evidence that have interesting policy implications.

The structure of the paper is as follows. Section 2 describes the shape of the supply curve and its impact on electricity price volatility. Section 3 provides a literature review on the impact of intermittent renewables on the volatility of wholesale electricity prices. Section 4 offers a description of the Greek wholesale electricity market along with the data and variables used in the study. Also presented are descriptive statistics on prices, electricity load and penetration levels of renewables. Section 5 describes the econometric approach followed and the various version of the basic model. Section 6 presents and discusses the findings of the empirical analysis and examines the impact of the change in the market price-cap on the volatility of wholesale electricity prices in Greece. In the last Section 7, the conclusions and some policy implications are presented.

2. The impact of renewables on wholesale electricity price volatility

In a market environment where prices are already highly volatile, intermittent renewables constitute an additional factor influencing wholesale electricity prices and their volatility. At a theoretical level, according to Green and Vasilakos (2010) the impact of renewables on price volatility, given the demand for electricity, depends on two factors. Firstly, it depends on the variability of renewables power generation and secondly, on the relationship between prices and the supply of conventional (thermal and hydroelectric) power generation, as determined by the electricity supply curve. If there are many hours with similar levels of renewables generation, no significant price volatility is expected during these hours, unless the relationship between prices and supply of conventional electricity generation is very strong, so that even small changes in renewables generation can lead to large price fluctuations. Alternatively, if the electricity supply curve has a relatively flat slope (at least in the part that covers the base and intermediate loads), so that even large changes in conventional power generation have a small impact on price, low variability is expected in the hours that renewables are displacing conventional generation. Accordingly, high price volatility due to renewables requires sufficiently high levels of renewables generation and a strong relationship between prices and the supply of conventional electricity generation.

Fig. 1 shows schematically the effect of renewables' production on the level and volatility of wholesale electricity prices. In Panel A, the hypothetical electricity short-run supply curve S_0 represents the merit order of power plants in an electricity system without renewables. Assuming perfect competition, the supply curve coincides with the marginal cost curve of all electricity producers. The intersection of the supply curve with the short-run electricity demand curve D_0, determines the equilibrium price P_0 in the wholesale electricity market. The demand curve is inelastic, reflecting the lack of instant connection between wholesale electricity prices and final demand. Electricity generation from renewables (RES), at almost zero variable cost, moves the initial supply curve outwards to the position represented by S_1. As a result, the equilibrium wholesale price of electricity decreases from P_0 to P_1. When electricity generation from renewables reaches its maximum capacity (RES max) the supply curve moves further outwards to S_2 and the equilibrium wholesale price of electricity decreases to P_2. The difference between P_0 and P_1 or P_2 is the merit-order effect from electricity produced by renewables and it is greater when the production from renewables increases. However, due to renewables' intermittency, the potential range of output from renewables also implies greater wholesale electricity price volatility since electricity prices fluctuate anywhere between P_0, P_1 and P_2.

The importance of the shape of the supply curve is shown in Panel B of Fig. 1, in which the supply curve is flatter. In this case, renewables move the supply curve from S_0 to S_1, without affecting the equilibrium wholesale price of electricity. For higher levels of renewables generation (supply curve S_2) the wholesale price of electricity falls to P_2. Wholesale price volatility is therefore less compared to the previous case when the supply curve was steeper. It must be noted that a critical element for the above considerations is the relationship between renewables' generation and electricity demand. For instance, if renewables generation is positively correlated with electricity demand then, depending on the shape of the supply curve, we should expect smaller impact or even reduction in wholesale price volatility.

3. Literature review

The reducing impact of renewables on the level of wholesale electricity prices has been extensively studied in a number of markets. Fewer studies, however, have examined the impact of intermittent renewables on wholesale electricity price volatility, with mixed results in terms of the direction of this effect. With this aim various methodologies have been developed which combine the examination of the impact of wind and solar technologies, jointly or separately on both the level and the price volatility. Green and Vasilakos (2010) simulated the impact of wind power generation on electricity prices in the UK for 2020. They relied on actual wind data, information on existing and planned new

[1] This result, as it is related to exogenous shocks in real-time demand (i.e., due to a sudden change in weather conditions), does not apply in the case of the day-ahead wholesale electricity prices which are set on the day preceding the power delivery.

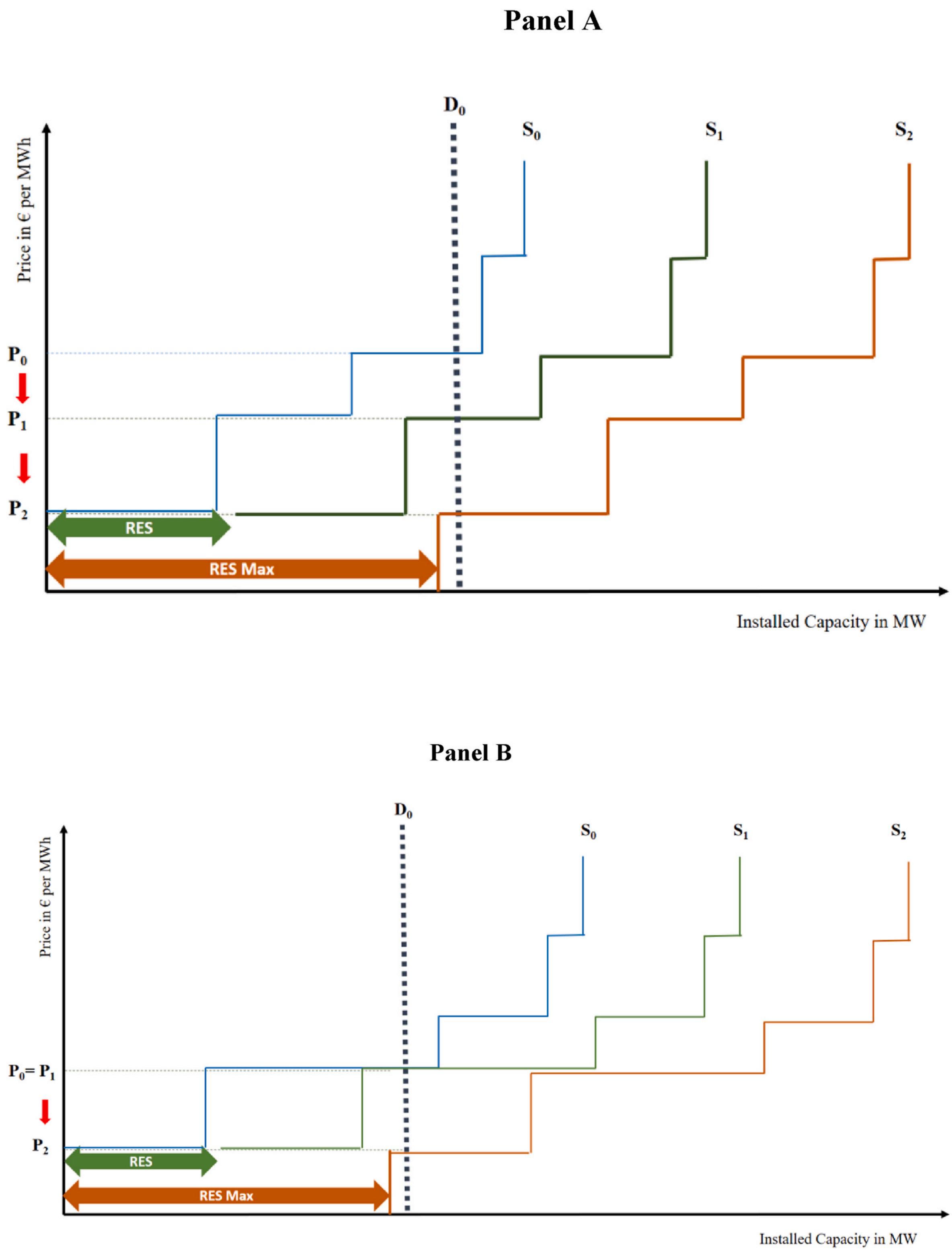

Fig. 1. Illustration of the impact of renewables on wholesale electricity prices and their volatility.

wind power capacity and hourly load data. Their analysis suggests that the volatility of electricity prices increases with the increasing penetration of wind power. However, they argue that the increase in price volatility depends not only on the changes in wind power generation, but also on the electricity market structure. Wozabal et al. (2016) using a static theoretical model with stochastic residual demand for electricity generated by conventional power plants, showed that intermittent renewables can either increase or decrease price volatility. According to their model, the direction of the effect depends firstly on the curvature of the electricity supply curve and, secondly, on the distribution of the stochastic electricity generation from intermittent renewables. Their empirical analysis, using data on daily price fluctuations from the German wholesale electricity market, confirmed the existence of these two effects.

Similarly, Johnson and Oliver (2019) develop a simple theoretical model to explain why the volatility of electricity prices is likely to increase or decrease. More specifically, the power from intermittent renewables shifts the supply curve outwards and as a result the stochastically fluctuating demand intersects more often with its most flatter part, thus limiting the range of electricity price distribution (stochastic merit-order effect). At the same time, however, stochastic changes in the electricity supply curve caused by the intermittent renewables lead to an increase in price volatility (intermittency effect). The authors examined these effects with an econometric model with auxiliary variables, using cross-sectional data for 19 countries over the period from 2000 to 2011. They found a positive and statistically significant relationship between the penetration of intermittent renewables and the volatility of wholesale electricity prices, which suggests that the intermittency effect prevails over the stochastic merit-order effect, thus increasing the price risk in electricity markets, as well as the cost for final consumers in the form of higher risk premiums incorporated in electricity tariffs.

Rintamäki et al. (2017) highlighted the dependence of intermittent renewables' impact on the variability of electricity prices on the particular characteristics of power systems, as well as on the profile of wind and photovoltaic generation in relation to demand. More specifically, using a distributed lag model for the Danish and German electricity markets for the period 2010–2014 (2012–2014 for Germany), they found that wind energy in Denmark reduces daily price volatility, in contrast to Germany where price volatility increases as wind energy has a greater effect on off-peak prices. They attributed these findings to: (a) the different correlation of intermittent renewables generation with the load of the two systems, (b) the existence of large hydroelectric power capacity in the neighboring power systems of Nordic countries, with which the Danish system is interconnected and (c) the smaller, compared to the size of the power system, interconnections of the German system, which limit its flexibility. Furthermore, they found an opposite effect of wind and solar power generation on price volatility in the German market and a positive effect on the weekly volatility of both markets, highlighting the importance of the time horizon of the analysis.

Jónsson et al. (2010) investigated the effect of (forecasted) wind power output on the behavior of electricity prices and their distribution characteristics for the Western Danish price area of the Nord Pool's Elspot market. Their analysis covered the period from January 2006 to October 2007. Using a non-parametric regression model, they concluded that increasing levels of wind power lead, on average but in a non-linear way, to a reduction in the level and price volatility and significantly affect the distribution of prices.

Ketterer (2014) using a GARCH model examined the effect of wind power generation in Germany over January 2006 to January 2012, both in the level and the volatility of wholesale electricity prices. Having isolated extreme values and seasonal cycles from prices, her analysis shows that the penetration of wind power reduces the level, but increases the volatility of electricity prices. Similarly, Kyritsis et al. (2017) investigated the effect of wind and solar power on the daily wholesale electricity prices in Germany over 2010 to 2015. Using a GARCH-in-Mean model they showed that the penetration of wind and solar power led to a reduction in the price level at both peak and off-peak hours. Furthermore, they found that the effect on price volatility varied for each type of renewable technology, with solar power leading to reduced variability by reducing the output of higher variable cost power plants. On the contrary, they confirmed the results of Ketterer (2014) regarding the increase in price volatility brought about by wind power, which necessitates the improvement of power system flexibility.

Woo et al. (2011) also found wind power to increase price variability using a partial adjustment linear regression model in analyzing high frequency data for the Texas Electricity Market (ERCOT). Using the same methodology and data for the Italian wholesale electricity market, Clò et al. (2015) found an increase in price volatility due to the penetration of wind and solar power. The results of Figueiredo and da Silva (2019) for the market of the Iberian Peninsula are similar, albeit without separating the effect for each type of renewable technology on variability. Sapio (2019) using a quantile regression model examined the relationship between wholesale prices and the power generation from wind and photovoltaic units in the Italian electricity market from 2006 to 2015. His work confirms the merit-order effect which is stronger in market conditions with relatively lower price levels, also indicating an increase in price volatility which, however, was limited by the interconnection of the Italian mainland system with Sardinia.

Maciejowska (2020) using a quantile regression model examined the impact of wind and solar power on price level and volatility of the German wholesale electricity market over January 2015 to January 2018. By measuring variability as the inter-quantile range (IQR), the results indicate that the effect of the two renewables technologies on variability is different. Wind power can either increase the volatility of wholesale electricity prices when the demand is low, or decrease it when the demand is high. On the other hand, solar power stabilizes price volatility for moderate levels of demand.

Motivated by the above-mentioned studies, we investigate the relationship of average daily wholesale electricity prices with total electricity demand and forecasted output from each type of renewables in Greece. Furthermore, we examine the effect on price volatility in peak hours (high demand) and off-peak hours (low demand) in order to identify any differences in the impact stemming from the substitution of conventional power plants located in different segments of the electricity supply curve.

4. Context and data

4.1. The wholesale electricity market in Greece

The Greek wholesale electricity market since its inception in 2005 and until November 2020, was organized as a mandatory pool, in which each power plant submits an injection offer (quantity and price of energy) for each hour of the next day (dispatch period) with an obligation for physical delivery of energy (Simoglou et al., 2014). The offer is a combination of energy and price values in ten steps and should not exceed the administratively set maximum bid price which was 150 euros per MWh until July 15, 2016, when it increased to 300 euros per MWh. Moreover, offers must not be lower than the minimum variable cost per unit. Producers can only operate if they are selected by the System Operator according to their day-ahead market offers. Renewables are dispatched with priority and they are compensated with feed-in tariffs or from 1/1/2016 with feed-in premiums for the energy they inject into the system.

LAGIE, the Market Operator (Energy Exchange from mid-2018) was solving on a daily basis a unit commitment problem, which was called Day-Ahead Scheduling (DAS) and referred to the simultaneous co-optimization of energy needs and reserves for each hour of the next day under a number of constraints for the power plants and the system. The solution of DAS was leading to the system's marginal price (SMP) for each hour of the next day, which represented the offer of the most expensive unit included in the dispatch for each hour of the day. SMP is the wholesale electricity price at which all transactions were settled for the declared quantities of energy. However, the energy imbalances are settled ex-post by the System Operator at the imbalances price, which was calculated by solving the DAS using the actual load during each day.

Regulatory mechanisms that influence producers' bidding strategies can have a significant impact on wholesale electricity price formation. Such a mechanism in the Greek wholesale electricity market allowed thermal units to offer up to 30% of energy at prices below their minimum average variable cost ("30% rule"). This rule was accompanied by the Variable Cost Recovery Mechanism (CRM), which allowed thermal units that did not cover their variable costs by the SMP to recover with certainty from the wholesale market their variable costs, increased by 10%. With this arrangement, the more expensive (at that time) gas units offered low or zero prices for 30% of their power and they were in effect getting priority in the dispatch, displacing other, more economical baseload thermal units, such as the lignite plants. As a result, SMP was determined by the cheapest among the lignite plants for most hours of the day, and as gas prices were higher, prices had higher intraday volatility, since during peak-load hours the SMP was determined by the higher variable cost gas units.

The Greek Regulatory Authority for Energy (RAE) having identified the market distortions arising from the systematic use of these mechanisms, had proceeded to eliminate them. The "30% rule" was abolished on 1.1.2014 (RAE Decision no. 338/2013) and also the CRM rule on 1.7.2014 (RAE Decision no. 339/2013). The interest in these regulatory mechanisms lies in the fact that the period considered in this paper also includes a sub-period during which the wholesale electricity market operated with these mechanisms in force. For this reason, in the empirical part of this study we consider their effect on price volatility.

The Greek wholesale electricity market design has recently converged to the European "target model" through its evolution in November 2020 into an energy exchange with the establishment of four distinct markets (forward, day-ahead, intraday, balancing) in a structure that also allows for the existence of bilateral contracts between producers and suppliers or directly between producers and final consumers (Ioannides et al., 2019).

4.2. Data and variables

In our analysis we use hourly data of the Greek wholesale electricity market received from the Transmission System Operator (ADMIE). The data which cover the period from 1st August 2012 to 31st December 2018, were transformed to daily frequencies compiling a total of 2344 observations for each variable. The sample variables include the wholesale price of electricity (SMP) as settled in the day-ahead market, calculated as a simple arithmetic mean of the 24 hourly values of each day, as well as forecasts of the daily system's load[2] and wind and solar photovoltaic generation, which are used by the Market Operator as inputs to DAS. Similarly to Ketterer (2014), but in contrast to other studies (Kyritsis et al., 2017; Nicolosi, 2010) in which data on forecasts were lacking, we use the forecasts of wind and solar output and system load, and not the actual values, as these forecasts determine the wholesale prices for each hour of the next day. For the above variables, a further separation of prices for peak and off-peak hours was made to identify any differences in wholesale electricity price dynamics and volatility (Kyritsis et al., 2017). We consider that peak hours include 08:00 a.m. to 23:00 p.m., while off-peak hours include 24:00 p.m. and 01:00 a.m. to 07:00 a.m. without seasonal differentiation throughout the period under examination.[3] This is reasonable taking into account that peak hours cover most hours of the day when residential, industrial and commercial electricity consumption needs in Greece are higher during all months of the year. On the other hand, off-peak hours cover mainly the nighttime hours, during which electricity demand is systematically lower throughout the year.

4.3. Descriptive statistics

In the period under consideration electricity supply in Greece is characterized by a) the dramatic reduction of electricity output from lignite power plants, resulting from the gradual phase-out of lignite units and the increase in the prices of CO_2 emission allowances and b) the large increase in renewables output (Table 1). The share of output of natural gas units, following a decline in 2014 and 2015 due to the abolition of CRM and the "30% rule", has shown significant increase from 2016 onwards. The share of hydroelectric power has fluctuated without a clear trend, due to the hydrological conditions that prevail each year. Overall, the power system in Greece is in a decarbonization path, but it is still substantially dependent on fossil fuels.

Wholesale prices in the Greek electricity market have shown high volatility as shown in Fig. 2. More specifically, prices have shown volatility clustering, mean reversion and a few instances of spikes mainly associated with events that have created supply constraints. Furthermore, price volatility has been less intense since 2014 when the "30% rule" and the CRM were abolished.

Table 2 presents the summary statistics of wholesale electricity prices, (forecasted) electricity output from wind and solar photovoltaic units, load of the system as well as the ratio of wind and solar photovoltaic output in total electricity load. It also presents summary statistics for peak and off-peak hours.

The hypothesis of normality of the wholesale price distribution is rejected, as suggested by the Jarque-Bera statistic. The distribution of daily wholesale electricity prices shows positive skewness and it is leptokurtic. This suggests that values above average are observed more often than expected under the normal distribution, posing difficulties in price risk management in electricity markets. In addition, the comparison of prices for the different periods of the day shows that the prices during peak hours are higher and have greater standard deviation compared to off-peak hours.

Electricity demand, as approximated by the load forecast in the day-ahead market, is one of the fundamental determinants of wholesale electricity prices. According to Fig. 3, electricity load in Greece presents obvious seasonality during the year. Peak loads are observed in the summer when the cooling needs are particularly high, but as they coincide with the highest solar output, the impact on the level of electricity prices is rather limited. Higher demand is also observed in the winter when the heating needs of the population increase. The average load is obviously higher at peak hours and shows relatively greater variability compared to off-peak hours.

Fig. 4 depicts the evolution of wind and solar output and their share in daily electricity load. The forecasted daily wind output has a large range and has followed an upward trend as new wind power capacity has been installed into the system. Wind output has covered on average about 8% of daily demand, having reached up to 31% of the electricity load during the examined period. In general, wind power generation is highly volatile due to changes in wind availability and has a seasonal pattern since it is higher in the winter, which is a positive feature from the point of view of power system adequacy and flexibility given the low output of photovoltaic units in the winter. Solar power generation has shown a clearer and more predictable seasonal pattern. The average solar output has been relative stable after 2012, as since then almost no new photovoltaic units were installed into the system and has covered on average about 7% of electricity load.

Tables 3 and 4 present the distribution of the wholesale electricity price conditional on the share of wind and solar output in daily electricity load. As it is evident, with the increase in the share of wind and solar output in electricity load, the average wholesale price tends to decrease, providing an indication of the existence of the merit-order effect in the Greek wholesale market. In addition, the standard deviation of wholesale price decreases with the increasing wind and solar output penetration, indicating a reducing impact on price volatility.

However, in the case of wind power the standard deviation of wholesale electricity price is decreasing for penetration levels of up to 20%, but thereafter is increasing again. As the penetration of wind and solar power increases, the price distribution changes. The values of skewness decrease, but remain positive. Furthermore, for higher levels of wind output penetration there is a reduction in the value of kurtosis that indicates a lower probability of occurrence of very high wholesale electricity prices at high levels of wind power penetration. In contrast,

[2] The hourly system load is increased by the forecasted electricity generated by photovoltaics in the medium voltage distribution network.

[3] In other studies, such as in Kyritsis et al. (2017), the separation between peak and off-peak hours is based on average price indicators in energy exchanges, which did not exist in the Greek market during the examined period.

Table 1
Distribution of electricity generation in the Greek interconnected power system.

	2012	2013	2014	2015	2016	2017	2018
Lignite	53.7	47.5	56.0	47.7	36.0	36.6	33.6
Natural Gas	27.5	24.8	15.6	17.9	30.2	34.4	31.8
Hydroelectric	7.6	11.5	9.6	13.3	11.7	7.7	11.4
Renewables	10.8	15.9	18.4	20.7	21.6	20.9	22.8
Wind	*6.2*	*6.9*	*7.4*	*9.5*	*10.5*	*10.7*	*12.6*
Small Hydro	*1.3*	*1.6*	*1.7*	*1.7*	*1.7*	*1.3*	*1.6*
Biogas-Biomass	*0.4*	*0.4*	*0.5*	*0.5*	*0.6*	*0.6*	*0.7*
Solar photovoltaics (PV)	*2.4*	*6.0*	*7.6*	*7.8*	*7.7*	*7.2*	*6.9*
Rooftop PV	*0.5*	*0.9*	*1.2*	*1.1*	*1.1*	*1.1*	*1.0*
CHP	0.3	0.2	0.4	0.5	0.4	0.4	0.4
Oil	0.2	0.0	0.0	0.0	0.0	0.0	0.0
Total Output	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Source: TSO (ADMIE), authors' calculations. **Note**: The Greek interconnected power system serves the needs of the mainland and some connected islands and accounts for the bulk of power generation capacity in Greece (89.2% in 2019).

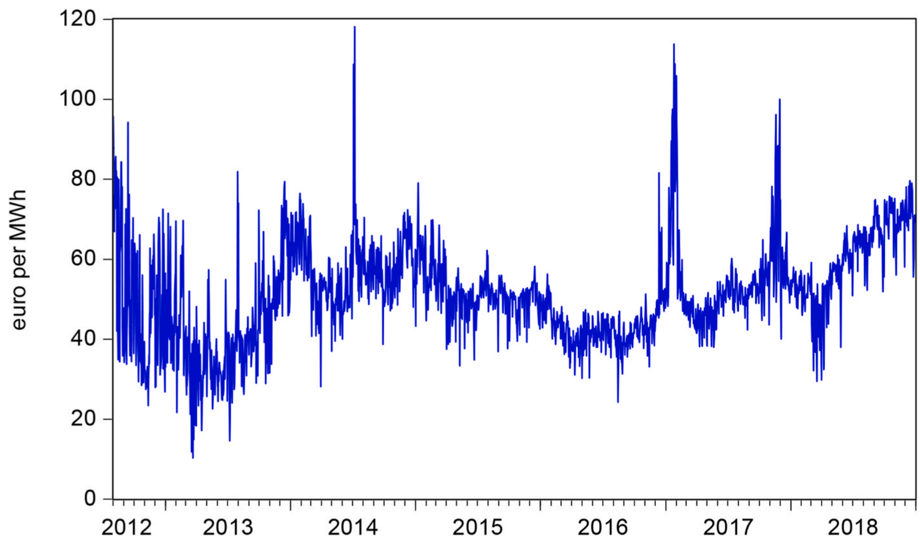

Fig. 2. All-hours wholesale electricity prices.

the price distribution shows a slightly higher kurtosis for higher penetration of solar power, indicating that the probability of observing high wholesale electricity prices in the conditional price distribution does not change significantly. The above results are in line with Jónsson et al. (2010) and Kyritsis et al. (2017) which showed a similar change in the conditional distribution of electricity prices and argued that wind and solar output should be included as fundamental factors in forecasting models of electricity price formation.

5. Modelling

5.1. Justifying the use of GARCH models

The observed price behavior in liberalized wholesale electricity markets, with the appearance of characteristics such as mean reversion, volatility clustering and price spikes, renders GARCH models particularly useful for the empirical investigation of the factors affecting the level and volatility of electricity prices. These models have their roots in the work of Bollerslev (1986) and have been used with various extensions to model time series and price and volatility forecasts of financial assets and commodities (Narayan and Narayan, 2007). Applications of GARCH models in electricity have been presented by Knittel and Roberts (2005), Escribano et al. (2011) and Efimova and Serletis (2014), among others.

Ketterer (2014) and Kyritsis et al. (2017) have extended the GARCH univariate applications to examine the effect of intermittent renewables on electricity price volatility, as the inclusion of load and output from them helps to better understand the dynamics of wholesale electricity prices. In this context, GARCH models are suitable for describing electricity price behavior provided that no extreme values are observed (Karakatsani and Bunn, 2010). This seems to be the case for the Greek wholesale electricity market, where negative prices are not allowed and the price-cap is relatively low.

To investigate the impact of wind and solar power on the Greek wholesale electricity market we use a univariable GARCH-in-Mean model (Engle et al., 1987) which is similar to that of Kyritsis et al. (2017) and Ketterer (2014). Additionally, this model allows us to examine the impact of certain changes in regulatory parameters on electricity price formation, such as the change of the price-cap and the abolition of the "30% rule" and the CRM which might have affected both the level and volatility of prices in the Greek wholesale electricity market. Specifically, our empirical approach consists in the application of GARCH (1,1) models to the daily prices of the Greek wholesale electricity market.

According to Hansen and Lunde (2005), GARCH (1,1) models have been found to perform better than other autoregressive lag specifications, provide accurate predictions, converge faster on maximum likelihood estimates, and allow the inclusion of a significant number of additional parameters. The specification of the basic mean equation is based on the minimization of the Bayesian information criterion or Schwarz information criterion, which indicates that the mean equation must include seven lags. The number of lags reflects the weekly

Table 2
Summary statistics.

	P	Load	Wind	PV	Wind/Load	PV/Load
Panel A. All hours						
Mean	51.34	140,880.80	10,873.12	9305.92	0.08	0.07
Median	50.8	137,890.00	9050.00	9595.00	0.07	0.07
Max	118.15	198,423.00	40,070.00	20,965.00	0.31	0.14
Min	10.24	97,575.00	1260.00	584	0.01	0
Standard Deviation	12.25	16,685.07	7014.12	3934.17	0.05	0.03
Skewness	0.54	0.46	1.12	−0.27	1.21	−0.2
Kurtosis	4.57	2.7	3.89	1.86	4.38	1.99
J-B normality	357.12	91.04	564.78	154.57	760.9	116.3
Observations	2344	2344	2344	2344	2344	2344
Panel B. Off-peak hours (01am-07am;24pm)						
Mean	46.63	39,090.20	3586.86	13.84	0.09	0
Median	47.47	38,196.50	2920.00	0	0.08	0
Max	123.91	56,422.00	13,140.00	170	0.38	0
Min	0	29,717.00	450	0	0.01	0
Standard Deviation	11.51	4541.69	2372.95	25.26	0.06	0
Skewness	−0.07	0.81	1.16	2.39	1.24	2.36
Kurtosis	5.29	3.26	3.96	8.99	4.41	8.86
J-B normality	514.88	261.7	615.65	5729.52	793.7	5539.70
Observations	2344	2344	2344	2344	2344	2344
Panel C. Peak hours (8am-23pm)						
Mean	54.17	101,785.20	7286.27	9289.89	0.07	0.09
Median	52.43	99,885.00	5940.00	9579.00	0.06	0.1
Max	147.09	142,647.00	26,930.00	20,927.00	0.29	0.2
Min	13.96	65,336.00	780	357	0.01	0
Standard Deviation	14.36	12,533.96	4840.34	3931.59	0.05	0.04
Skewness	1.04	0.35	1.11	−0.27	1.2	−0.18
Kurtosis	6.29	2.64	3.83	1.86	4.29	1.99
J-B normality	1484.29	61.26	553.26	154.7	730.29	111.56
Observations	2344	2344	2344	2344	2344	2344

Note: P is the wholesale electricity price (System Marginal Price) in €/MWh. Wind is the daily sum of the forecasted hourly output from wind units in MWh. PV is the daily sum of the forecasted output of solar photovoltaic units in MWh, Load is the daily sum of the forecasted hourly system load including the forecasted PV output from the medium voltage distribution network, in MWh. The data cover the period from August 1, 2012 to December 31, 2018. Panel A provides summary statistics of the variables for all hours of the day, Panel B for off-peak hours (from 24:00 p.m. and 01:00 a.m. to 07:00 a.m.) and Panel C for peak hours (from 08:00 a.m. until 23:00 p.m.).

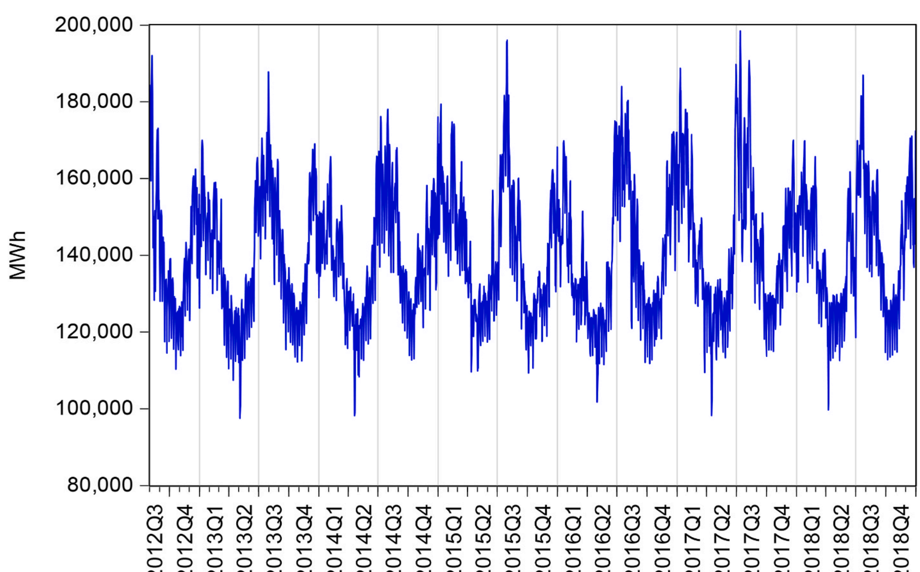

Fig. 3. Electricity load.

seasonality and has been found in other studies (Escribano et al., 2011; Ketterer, 2014; Kyritsis et al., 2017).

5.2. Model

Our basic model is applied: a) for the total forecasted daily output of intermittent renewables, b) separately for wind and solar output during all-hours, off-peak hours and peak hours, in order to catch any differ-

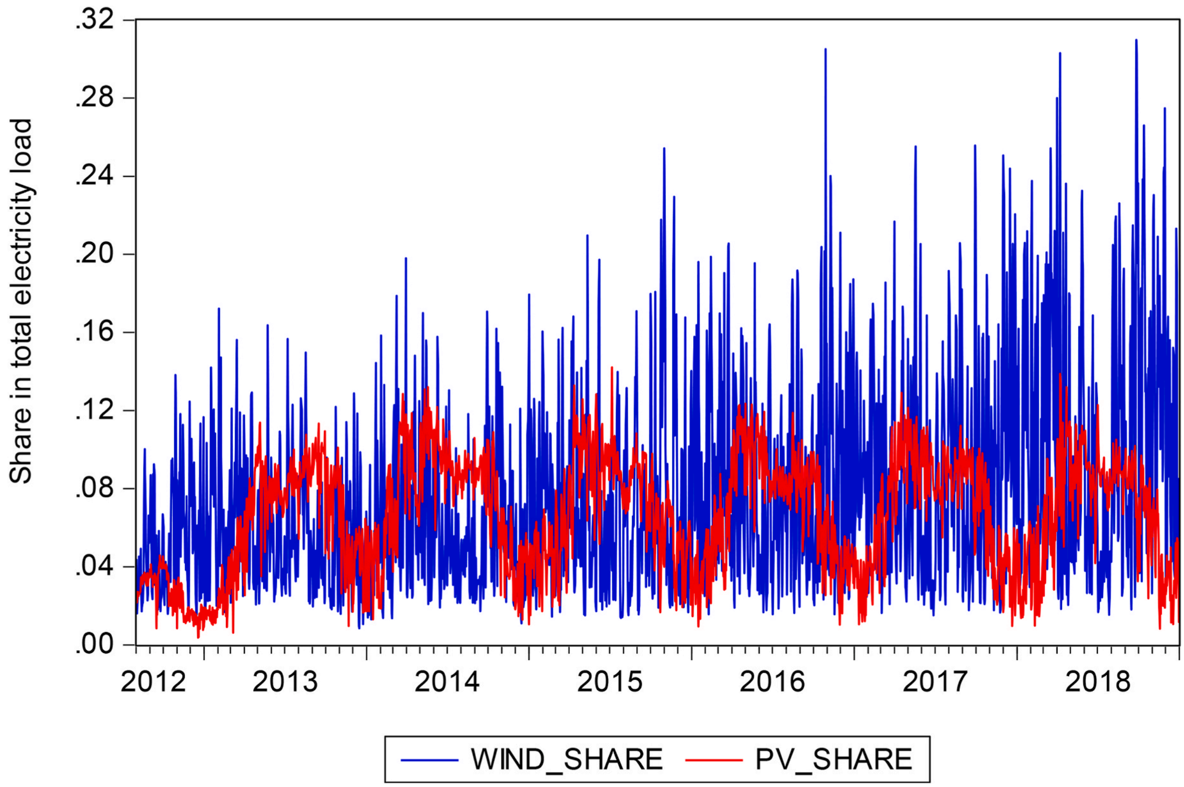

Fig. 4. Share of wind and solar power output to total electricity load.

Table 3
Wholesale price distribution properties for different wind power penetration levels.

Wind Share	Mean	Median	Max	Min	St. Dev	Skewness	Kurtosis	Observations
[0, 0.05)	53.29	52.38	118.15	11.78	12.41	0.40	4.16	864
[0.05, 0.1)	50.65	50.23	113.78	23.16	12.36	0.81	5.29	853
[0.1, 0.15)	49.43	49.43	108.71	10.24	11.52	0.39	5.09	388
[0.15, 0.2)	49.50	48.75	81.24	14.56	11.16	0.17	3.47	174
[0.2, 0.25)	51.33	49.04	75.20	29.41	11.96	0.30	1.96	50
[0.25, 0.3)	50.79	48.97	74.67	29.82	15.41	0.02	1.65	11
[0.3, 0.35)	45.36	44.82	58.15	33.63	11.58	0.08	1.26	4
Total (100%)	51.34	50.80	118.15	10.24	12.25	0.54	4.57	2344

Table 4
Wholesale price distribution properties for different solar power penetration levels.

PV Share	Mean	Median	Max	Min	St. Dev	Skewness	Kurtosis	Observations
[0, 0.05)	54.30	52.90	113.78	10.24	14.54	0.47	3.71	748
[0.05, 0.1)	50.65	50.75	118.15	11.78	11.19	0.23	4.46	1301
[0.1, 0.15)	46.92	47.59	82.45	24.21	7.85	0.18	4.28	295
Total (100%)	51.34	50.80	118.15	10.24	12.25	0.54	4.57	2344

ences on price volatility that are related to each type of renewables or to the level of electricity load[4] and c) for the share of wind and solar output in total electricity load. Finally, in contrast to other studies (Ketterer, 2014; Kyritsis et al., 2017), no price smoothing or outliers filtering takes place, as the price-caps applied in the Greek wholesale electricity market limit the occurrence of such observations. The mean equations are described by the following relations (1) to (3):

$$P_t = a + \beta_1 \sqrt{h} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 RES_t + \beta_{10} Load_t + \varepsilon_t \tag{1}$$

$$P_t = a + \beta_1 \sqrt{h} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 Wind_t + \beta_{10} PV_t + \beta_{11} Load_t + \varepsilon_t \tag{2}$$

$$\begin{aligned} P_{off-peak,\ t} = a + \beta_1 \sqrt{h} + \sum_{i=1}^{7} \beta_{1+i} p_{off-peak,\ t-i} + \beta_9 Wind_{off-peak,\ t} \\ + \beta_{10} PV_{off-peak,\ t} + \beta_{11} Load_{off-peak,\ t} + \varepsilon_t \end{aligned} \tag{2a}$$

[4] The impact of renewables on the volatility of wholesale electricity prices depends not only on the existence of peak and off-peak periods of demand but mainly on the particular characteristics of power systems, as well as on the profile of wind and photovoltaic generation in relation to demand (i.e. the climatic conditions and wind and solar resources in different regions).

$$P_{peak,\ t} = a + \beta_1 \sqrt{h} + \sum_{i=1}^{7} \beta_{1+i} p_{peak,\ t-i} + \beta_9 Wind_{peak,\ t} + \beta_{10} PV_{peak,\ t} + \beta_{11} Load_{peak,\ t} + \varepsilon_t \quad (2b)$$

$$P_t = a + \beta_1 \sqrt{h_t} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 Wind\_Share_t + \beta_{10} PV\_Share_t + \varepsilon_t \quad (3)$$

where α is the constant term, P_t is the average daily wholesale electricity price in the day-ahead market in €/MWh, $\sqrt{h_t}$ is the conditional standard deviation (GARCH-in-Mean effect), RES_t is the day-ahead forecast of wind and solar power output in GWh, $Wind_t$ is the day-ahead forecast of wind power output in GWh, PV_t is the day-ahead forecast of solar power output in GWh, $Load_t$ is the day-ahead forecast for the daily system load in GWh, $Wind\_Share_t$ and PV_Share_t are the ratios of wind and solar power output to total electricity load, ε_t is the error term and β_i (for i = 1 to 11) the coefficients of independent variables. The peak and off-peak indices denote that the respective variables refer to peak and off-peak hours.

The variance equation h_t is given by relation (4):

$$h_t = \omega + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + \gamma \boldsymbol{X}_t \quad (4)$$

where h_t is the conditional variance, ω is the constant term that represents the long-run variance, ε_{t-1}^2 are the squared residuals, $\boldsymbol{X}_t$ is the vector of independent variables (Wind, PV, Load, Wind_Share, PV_Share) which correspond to the above models (1) to (3) and γ is the vector of coefficients of independent variables. For the model to be stationary it must hold that $a_1 + b_1 < 1$, with $a_1, b_1 > 0$, where α_1 and b_1 the coefficients of squared residuals and conditional variance respectively.

In addition to examining the impact of intermittent renewables output on the level and volatility of prices in the Greek wholesale electricity market, another objective of this study is to investigate the impact of the increase in price-cap in a market environment that presents increased penetration of intermittent renewables. For this reason, the above models (1) to (4) (mean and variance equations) are extended to include the control variable *Price_Cap*, which takes the value 1 after the change of the price-cap (July 15th, 2016). Moreover, as it is possible that the CRM and the "30% rule" have affected the level and volatility of prices, we introduce an additional control variable (*CRM*), which takes the value of 1 from 1 August 2012 to 31 December 2013 and of zero thereafter when these regulatory mechanisms were abolished.

5.3. Stationarity tests

Before proceeding to the empirical analysis we carry out the necessary stationarity tests in each of the employed series. In particular, we use the Augmented Dickey Fuller (ADF) test to identify the existence of a unit root in series level with and without a stochastic trend, which tests the null hypothesis that the series has a unit root against the alternative of stationarity. The determination of the optimal lag in the control model is based on the Schwarz information criterion. We also use the Phillips-Perron unit root test with and without a stochastic trend, which is robust in the presence of non-specified autocorrelation and heteroscedasticity in the residuals. For all variables the null hypothesis of a unit root is rejected at the statistical significance level of 1% so the series are stationary. Results are shown in Table 5.

For models (1)–(3) of mean equations we also assume that all independent variables are exogenously determined. This assumption is reasonable, at least in the short run, since wind and solar power output depend on weather conditions and are not affected by the level of wholesale prices. This problem could exist in the long-run in the event of large curtailments of renewables output (e.g. for maintaining the stability of the system) which has not been observed in Greece. In addition, the absence of demand response to changes in wholesale prices does not indicate the existence of endogeneity problems and there is no sign of severe multicollinearity in the independent variables.

Table 5
Unit roots and stationarity tests.

Variable	ADF levels	ADF Levels with linear trend	PP Levels	PP Levels with linear trend
P	−4.0794	−6.3549	−24.9576	−26.5954
Wind	−13.7638	−21.9277	−23.1727	−23.2061
PV	−3.9078	−3.8809	−11.5590	−12.1213
Load	−5.6552	−5.6928	−14.4509	−14.4728
$P_{off\text{-}peak}$	−5.7073	−7.3611	−27.3421	−32.6361
$Wind_{off\text{-}peak}$	−12.4295	−26.9533	−25.4373	−25.7001
$PV_{off\text{-}peak}$	−4.1785	−4.3360	−8.5557	−9.0298
$Load_{off\text{-}peak}$	−5.7133	−5.7427	−7.1515	−7.1724
P_{peak}	−4.6178	−4.8343	−28.4750	−29.0245
$Wind_{peak}$	−14.0037	−27.0864	−26.2736	−26.4004
PV_{peak}	−3.9062	−3.8806	−11.6072	−12.1830
$Load_{peak}$	−5.4087	−5.4481	−19.7697	−19.7981

Note: ADF is the Augmented Dickey Fuller unit root test. PP is the Phillips-Perron unit root test. The critical values of ADF and PP tests according to MacKinnon (1996) for statistical significance levels 1%, 5% and 10% are (a) **-3, 430**, −2861 και −2567 respectively for series levels and (b) **-3,958**, −3410 and −3127 respectively for series levels with linear trend.

6. Results and discussion

This section presents the empirical findings regarding the impact of wind and solar power generation on the level and volatility of wholesale electricity prices in Greece, taking into account the impact of changes in regulatory parameters and mechanisms.

6.1. Basic models

Table 6 summarizes the estimation results of the three specifications of the GARCH model (1,1) for wholesale electricity prices, as described by equations (1)–(3) and equation (4). Column A presents the results of the first specification which includes the total wind and solar power generation and the electricity load as explanatory variables. All autoregressive coefficients are statistically significant at the 1% level (with the exception of the fifth term which is significant at the 3% level). Their sum is less than one, indicating that shocks on the conditional variance tend to have a temporary effect (Ketterer, 2014).

The GARCH-in-Mean effects are negative and statistically significant at the 1% level, which implies that volatility tends to have a reducing impact on electricity prices. Overall, wind and solar power generation negatively affects the wholesale electricity price level, implying the existence of the merit-order effect in the Greek wholesale electricity market. In addition, based on the estimated coefficient, each GWh produced by wind and photovoltaic units reduces the wholesale price of electricity by 0.20 euros per MWh on average. Electricity load, as expected, has a positive impact on the level of wholesale electricity prices.

The variance equation shows that the GARCH term (h_{t-1}) which reflects the persistence of past shocks in price variance is high, while the ARCH term (ε_{t-1}^2), which reflects the impact of new shocks is considerably lower. The impact of wind and solar power generation on the volatility of electricity prices is not statistically significant, while the electricity load has a positive and statistically significant impact on volatility.

Column B of Table 6 presents the results of the second model specification (eq. (2)) which includes the wind and solar power generation separate from each other and the electricity load as explanatory variables. All autoregressive coefficients of the mean equation are

Table 6
Results of AR(7)-GARCH(1,1) model with additional explanatory variables.

	A. Model (1)		B. Model (2)		C. Model (3)	
Mean equation						
	Coeff.	*p-values*	*Coeff.*	*p-values*	*Coeff.*	*p-values*
Constant	−0.639	(0.459)	−1.460	(0.104)	5.896	(0.000)
$\sqrt{h_t}$	−0.146	(0.008)	−0.083	(0.138)	−0.091	(0.107)
P_{t-1}	0.376	(0.000)	0.377	(0.000)	0.392	(0.000)
P_{t-2}	0.097	(0.000)	0.100	(0.000)	0.095	(0.000)
P_{t-3}	0.072	(0.001)	0.069	(0.002)	0.071	(0.002)
P_{t-4}	0.076	(0.001)	0.077	(0.001)	0.078	(0.001)
P_{t-5}	0.024	(0.030)	0.025	(0.291)	0.020	(0.385)
P_{t-6}	0.090	(0.000)	0.089	(0.000)	0.092	(0.000)
P_{t-7}	0.200	(0.000)	0.201	(0.000)	0.220	(0.000)
RES_t	−0.200	(0.000)				
$Wind_t$			−0.207	(0.000)		
PV_t			−0.116	(0.000)		
$Wind\_share_t$					−29.702	(0.000)
PV_share_t					−20.159	(0.000)
$Load_t$	0.064	(0.000)	0.060	(0.000)		
Variance equation						
Constant	−0.997	(0.092)	−0.840	(0.135)	1.530	(0.000)
ε^2_{t-1}	0.153	(0.000)	0.153	(0.000)	0.151	(0.000)
h_{t-1}	0.835	(0.000)	0.836	(0.000)	0.837	(0.000)
RES_t	−0.020	(0.116)				
$Wind_t$			0.011	(0.490)		
PV_t			−0.065	(0.000)		
$Wind\_share_t$					2.401	(0.267)
PV_share_t					−12.366	(0.000)
$Load_t$	0.016	(0.000)	0.015	(0.000)		
Adj. R^2	0.712		0.710		0.704	
Standardized residual diagnostics						
Q(30) p-value	0.000		0.000		0.000	
Q^2(30) p-value	0.787		0.910		0.931	

statistically significant at the 1% level (with the exception of the fifth term) and have a sum of less than one. The GARCH effect in the mean equation is not statistically significant, while electricity load has a positive impact on the level of wholesale electricity price. The estimates confirm the merit-order effect for both types of renewables, which is higher in the case of wind power. In the variance equation, the coefficients of the load, h_{t-1} and ε^2_{t-1} are similar to equation (1). However, these estimates reveal that the effect of each type of renewables on price volatility differs, as it is statistically insignificant for wind power and negative and statistically significant for solar power.

It is interesting, however, to consider whether the results of equation (2) differ during the day, when renewables and load exhibit different characteristics. Table 7 presents the results of the estimates of equations (2a) and (2b) for off-peak and peak hours in order to identify possible differences in the impact on volatility.[5] The merit-order effects are strong and do not change for the two types of renewables during the day. The coefficient of solar power in off-peak hours is very high, but in practice its effect on prices is negligible, as during these hours solar output is very low. Moreover, the positive effect of the load is maintained throughout the day and seems to be stronger during peak hours.

However, substantial differences are observed in the variance equation, where in off-peak hours wind power generation tends to increase the volatility of prices as opposed to peak hours at which it reduces the price volatility. Solar power generation increases the volatility during off-peak hours and reduces it during peak hours. Electricity load, in contrast to the results for the whole day, reduces price volatility in both sub-periods of the day. In addition, the persistence of past shocks in

Table 7
Results of AR(7)-GARCH(1,1) model with additional explanatory variables for off-peak hours and peak hours.

	Model (2)		Model (2a) Off-peak		Model (2b) Peak	
Mean equation						
	Coeff.	*p-values*	*Coeff.*	*p-values*	*Coeff.*	*p-values*
Constant	−1.460	(0.104)	−2.000	(0.028)	−4.619	(0.020)
$\sqrt{h_t}$	−0.083	(0.138)	0.297	(0.138)	−0.166	(0.075)
P_{t-1}	0.377	(0.000)	0.367	(0.000)	0.364	(0.000)
P_{t-2}	0.100	(0.000)	0.102	(0.000)	0.114	(0.000)
P_{t-3}	0.069	(0.002)	0.119	(0.000)	0.062	(0.005)
P_{t-4}	0.077	(0.001)	0.083	(0.000)	0.102	(0.001)
P_{t-5}	0.025	(0.291)	0.055	(0.022)	−0.042	(0.087)
P_{t-6}	0.089	(0.000)	0.112	(0.000)	0.104	(0.000)
P_{t-7}	0.201	(0.000)	0.134	(0.000)	0.206	(0.000)
$Wind_t$	−0.207	(0.000)	−0.720	(0.000)	−0.338	(0.000)
PV_t	−0.116	(0.000)	−13.817	(0.002)	−0.291	(0.000)
$Load_t$	0.060	(0.000)	0.120	(0.000)	0.157	(0.000)
Variance equation						
Constant	−0.840	(0.135)	0.710	(0.085)	55.414	(0.000)
ε^2_{t-1}	0.153	(0.000)	0.116	(0.000)	0.269	(0.000)
h_{t-1}	0.836	(0.000)	0.869	(0.000)	0.442	(0.000)
$Wind_t$	0.011	(0.490)	0.343	(0.000)	−1.467	(0.000)
PV_t	−0.065	(0.000)	12.104	(0.000)	−1.193	(0.000)
$Load_t$	0.015	(0.000)	−0.034	(0.000)	−0.102	(0.004)
Adj. R^2	0.710		0.678		0.681	
Standardized residual diagnostics						
Q(30) p-value	0.000		0.000		0.000	
Q^2(30) p-value	0.910		0.612		0.000	

prices is much lower during peak hours. These results are consistent with the assumption that when renewables power generation is positively correlated with demand, a reduction in price volatility is expected.

Column C of Table 6 presents the results of the third specification (eq. (3)) which includes as explanatory variables the ratio of wind and solar output to total electricity load. These results reinforce the previous findings in mean equations, as the coefficients for wind and solar are negative and statistically significant, with a stronger impact from wind power. The coefficients are higher compared to the previous specifications because the variables are expressed as shares of the total load.[6] In the variance equation, the coefficients have the same signs as in equation (2), also revealing the statistically insignificant effect of wind power on price volatility and the negative and statistically significant impact of solar power generation.

Tables 6 and 7 also present the values of the Ljung-Box Q test for residual autocorrelation. Although autocorrelation in the residuals cannot be rejected for all equations, an overview of autocorrelation plots shows very little autocorrelation with no particular pattern.[7] In addition, the Q^2 statistics for squared residuals indicate that, in almost all equations, no other ARCH effects remain in the residuals. Overall, similarly to Kyritsis et al. (2017) we conclude that the GARCH models have been correctly specified.

6.2. *The impact of changes in regulatory parameters and mechanisms*

Table 8 presents the results of the models (1)–(3) and (4) with the inclusion of control variables for the changes in the regulatory mechanisms and the price-cap in the Greek wholesale electricity market. The

[5] The results of equation (2) are also presented to facilitate comparisons.

[6] This implies that an increase of one percentage point of the share of wind or solar power generation corresponds to a rather large increase in electricity generation in terms of GWh (Ketterer, 2014).

[7] Autocorrelation plots are not shown here for space limitations but are available upon request.

Table 8
Results of AR (7)-GARCH (1,1) model with additional explanatory variables and control variables for changes in regulatory parameters and mechanisms.

	Model (1)		Model (2)		Model (3)	
Mean equation						
	Coeff.	*p-values*	*Coeff.*	*p-values*	*Coeff.*	*p-values*
Constant	−0.575	(0.486)	−1.311	(0.114)	6.007	(0.000)
$\sqrt{h_t}$	0.131	(0.057)	0.219	(0.004)	0.242	(0.002)
P_{t-1}	0.369	(0.000)	0.375	(0.000)	0.392	(0.000)
P_{t-2}	0.079	(0.001)	0.085	(0.001)	0.083	(0.001)
P_{t-3}	0.081	(0.000)	0.078	(0.000)	0.079	(0.000)
P_{t-4}	0.071	(0.001)	0.067	(0.001)	0.067	(0.002)
P_{t-5}	0.023	(0.316)	0.016	(0.494)	0.010	(0.678)
P_{t-6}	0.098	(0.000)	0.097	(0.000)	0.098	(0.000)
P_{t-7}	0.188	(0.000)	0.198	(0.000)	0.208	(0.000)
RES_t	−0.222	(0.000)				
$Wind_t$			−0.229	(0.000)		
PV_t			−0.129	(0.000)		
$Wind\_share_t$					−32.906	(0.000)
PV_share_t					−20.875	(0.000)
$Load_t$	0.063	(0.000)	0.058	(0.000)		
Price_CAP	1.206	(0.000)	1.117	(0.000)	1.098	(0.000)
CRM	−0.947	(0.055)	−1.290	(0.000)	−1.525	(0.000)
Variance equation						
Constant	−0.676	(0.462)	−0.109	(0.893)	1.787	(0.000)
ε^2_{t-1}	0.223	(0.000)	0.182	(0.000)	0.178	(0.000)
h_{t-1}	0.724	(0.000)	0.741	(0.000)	0.736	(0.000)
RES_t	−0.058	(0.005)				
$Wind_t$			0.127	(0.000)		
PV_t			−0.087	(0.004)		
$Wind\_share_t$					17.840	(0.000)
PV_share_t					−17.388	(0.000)
$Load_t$	0.006	(0.292)	0.010	(0.045)		
Price_CAP	−0.369	(0.082)	−0.598	(0,001)	−0,548	(0,000)
CRM	6.060	(0.000)	6.159	(0,000)	6.553	(0.004)
Adj. R^2	0.707		0.707		0.701	
Standardized residual diagnostics						
Q(30) p-value	0.000		0.000		0.000	
$Q^2(30)$ p-value	0.014		0.231		0.189	

estimates of the mean equations show in all cases the negative and statistically significant impact of wind and solar power generation on the electricity price level.

Regarding the impact of the changes in regulatory parameters and mechanisms it is worth mentioning that firstly, the increase in the price-cap had a positive impact on the price level and secondly, that the "30% rule" and the CRM had a negative impact on the price level at the 5.5% level of significance, as might be expected, given that these mechanisms allowed bids at zero prices for the 30% of the energy offers of each power plant.

The variance equations show that overall wind and solar power generation have reduced price volatility (eq. (1)). Yet, there is a difference between these types of renewables, since wind output tends to increase while solar output tends to reduce the price volatility (eq. (2) and eq. (3)). Therefore, compared to the specifications of the basic model, the main difference lies in the statistical significance of both total renewables output and wind output. Moreover, the increase in the price-cap, according to all specifications has led to a reduction in price volatility, as opposed to the "30% rule and the CRM, which have intensified the volatility of wholesale electricity prices.

The above results are not incompatible with those of Tashpulatov (2013) who has found that the introduction of a price-cap regulation in the England and Wales wholesale electricity market succeeded in reducing the price level, but led to greater price volatility. However, our results go even further. The increase in the price-cap allows higher price offers during periods of scarcity, so that the power plants that serve intermediate and peak loads can recover their fixed costs. This policy is more likely to intensify the volatility of prices. Apart from the installed renewables capacity, that at least in the short-term limits the frequency of supply constraints, it is quite likely that the structure of the Greek electricity market and the behavior of the market participants have contributed to these results. Specifically, the price offers from hydro-electric plants (exclusively owned by the dominant electricity producer in Greece) at a level slightly above the offers of natural gas combined-cycle units, has operated as an effective price-cap for most hours of the year (Capros, 2014). This was happening because the dominant producer, being also the dominant supplier of electricity in Greece, had an interest in keeping wholesale electricity prices as low as possible. As a result, the increase in the price-cap in the Greek wholesale electricity market did not have the expected impact on price volatility, as the price-cap has constituted a real constraint on the offers of conventional power plants only for a few hours during the year.

7. Conclusions and policy implications

With the increasing penetration of intermittent renewables in electricity generation, there is a concern that the inherent variability of their output can be transmitted to electricity prices. This implies an increase in the risk of investors, producers and suppliers from their activity in the electricity market, additional costs for final consumers and possible under-investment that can undermine the adequacy and reliability of the power system as well as the path towards decarbonization. In this context, we have examined the impact of wind and solar power generation on the level and volatility of wholesale electricity prices in Greece. Furthermore, in a market environment in which intermittent renewables play an increasingly important role, we also investigated the impact of a change in the wholesale market price-cap on the price level and volatility.

Our empirical results have confirmed the existence of the merit-order effect, both for the intermittent renewables as a whole and separately for wind and solar power generation, which was stronger in the case of wind power. The penetration of intermittent renewables also has an impact on price volatility. Furthermore, accounting for the regulatory mechanisms that may affect price volatility, we found that, overall, intermittent renewables have reduced price volatility, contrary to the prevailing view in the literature that price volatility is increased. Yet, wind and solar power generation have a different impact on volatility. In particular, when controlling for regulatory mechanisms, wind power generation tends to increase, while solar power generation tends to decrease the volatility of wholesale electricity prices. Depending on the mixture of wind and solar capacity, these opposite effects may offset each other leading to no impact on price volatility, increase it if wind power is the dominant technology or decrease it if solar technology dominates. In any case, the balanced development of renewables is particularly useful from the perspective of the impact they may have on price volatility and system flexibility needs, and this should be considered in energy policy considerations to support and integrate different types of renewables into the power system.

Price volatility during the day is being affected differently by wind and solar electricity generation. Our empirical findings suggest that wind power generation during low demand hours tends to increase price volatility, as opposed to higher demand hours during which it decreases price volatility. These results are in line with those of Maciejowska (2020) who found a similar effect of wind power on price volatility. In addition, generation from solar power has reduced price volatility during hours of high demand, at which almost all of their output is concentrated. This result confirms the hypothesis that when the output of intermittent renewables is positively correlated with electricity demand, at high segments of the supply curve, a smaller impact or even a reduction in price volatility is expected. It must be noted, however, that these results should be considered with caution. Recent changes in the Greek electricity market design and structure, its integration with neighboring European markets, additions in the capacity of renewables as well as higher fossil fuel and emission allowances prices may have an impact on the direction and intensity of the above results. In this context, a promising area for further research is the analysis of the impact of intermittent renewables on price level and volatility in different electricity market environments, using alternative econometric methods, such as quantile regression and the examination of the inter-quantile range, which reflects the differentiation in price volatility for different levels of demand.

Finally, the design of wholesale electricity markets and especially regulations that directly affect wholesale electricity prices should also be considered when assessing the impact of the integration of intermittent renewables into the power systems. Our results show that the increase in the price-cap in the Greek wholesale electricity market is associated with an increase in the level and a decrease in the volatility of wholesale electricity prices. This result highlights the importance of the composition of the portfolio of power plants and the degree of vertical integration of participants in liberalized electricity markets, which determines their behavior in the market and has a potential impact on the volatility of electricity prices.

Funding source

The research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Georgios I. Maniatis: Data curation, Software, Methodology, Writing – original draft. **Nikolaos T. Milonas:** Conceptualization, Visualization, Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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