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ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

INVESTIGATING THE DEPENDENCE BETWEEN WIND POWER PRODUCTION AND ELECTRICITY SPOT PRICE FOR WIND ONSHORE FARMS IN THE ITALIAN MARKET

ΟΝΟΜΑ ΦΟΙΤΗΤΡΙΑΣ: ΕΥΔΟΚΙΑ ΧΡΙΣΤΙΝΑ ΠΙΕΡΡΟΥ

ΟΝΟΜΑ ΕΠΙΒΛΕΠΟΝΤΑ ΚΑΘΗΓΗΤΗ: ΑΘΑΝΑΣΙΟΣ ΚΑΤΕΒΑΤΗΣ

ΑΘΗΝΑ

ΝΟΕΜΒΡΙΟΣ, 2022

Abstract

In this thesis, the negative dependence between the electricity spot price and the wind onshore power production is examined regarding the Italian market. The mathematical models ARMA-GARCH and LINEAR-GARCH models and Pearson correlation metric are used to examine the dependence. The GARCH model is used to explore the variability of the model errors' variance. Despite the fact that the model development is conducted in a time-period contained the Covid-19 pandemic and Ukraine war, meaning that the spot price time series consists of many extreme events, the negative dependence exists. The model development is used to prove the existence of the negative dependence, rather than for forecasting reasons, since the extreme events of the spot price time series cannot be modeled easily.

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1. Introduction

In 2020 and 2021, 22%[1] of the energy consumption in the European Union was covered from renewable energy sources. The heating sector and solar power, in contrary to wind power which produced less energy due to lower wind speeds, caused the maintaining trend of the energy consumption based on the renewable energy sources. At sectoral level, the renewable energy's share has different percentages in 2021. The share was 23.6% in the heating and cooling sector, the share was 37.7% in power sector, which was mostly driven by solar energy since the wind speed was slow, while the share was 10.2% in the transport sector. The low share in the transport sector was due to the fact that the annual growth of fossil fuels outperformed the share of renewable energy, despite the fact that more renewables were used in transport in 2021.

The power demand in the EU-27+UK was covered by 15% of wind power generation in 2021, which is 1.4% lower than that in 2020. As wind energy is by definition variable, its production was lower in many regions across Europe, especially in Northern Europe in 2021. Despite the fact that Germany, UK, and France are characterized as large wind energy markets, the levels of wind power production were low in 2021 compared to the previous year. While, Spain and Italy, where there were modest new capacity additions, generated more wind power compared to previous years. During the time-period January to March of 2021 the levels of wind generation were mostly low. "The final months of 2021 saw stronger wind generation."(Wind energy in Europe 2021, page 19). In the last quarter of 2021, the electricity demand was covered by 18% by wind generation, and there was an electricity coverage of 19% in October.

The wind power capacity installed in Europe was 236 GW in 2021. The new wind energy capacity installed in Europe was 17.4 GW in 2021, which represents an 18% increase from 2020. 11 GW installed in the EU-27, where 91% constituted onshore wind plants, while the 3.4 GW corresponded to offshore wind plants. The Figure 1.1 shows the trend of the growth of total wind capacity separately by onshore/offshore wind plants for the years 2012-2021.

[1] European Environment Agency, 2022

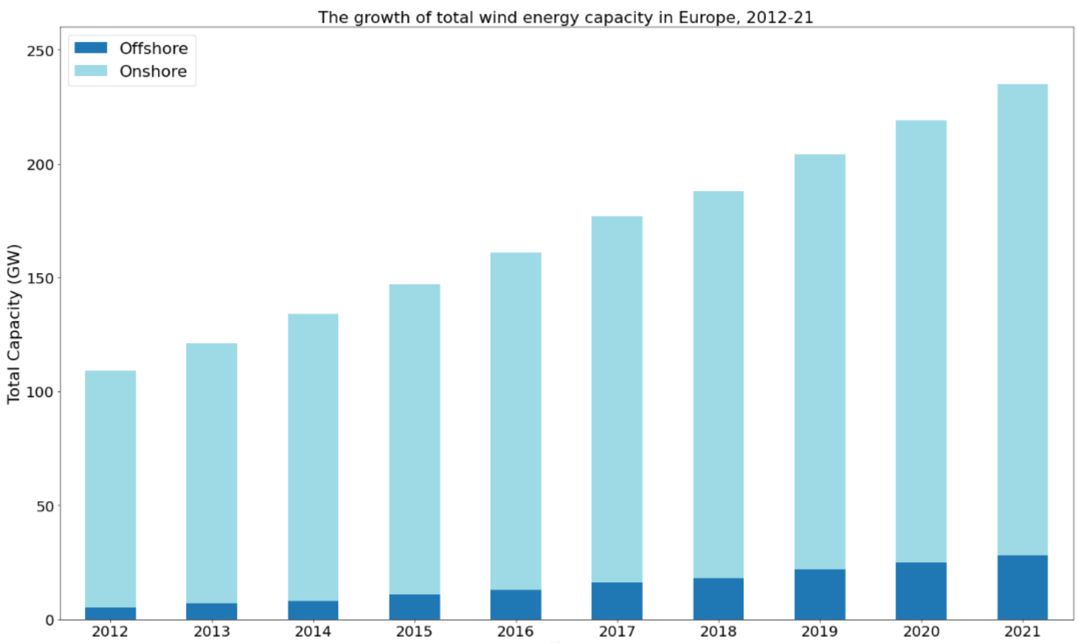

Figure 1.1 Total wind energy capacity in Europe

In Italy, the percentage of average annual electricity demand covered by wind in 2021 was 7% or 11 GW, exclusively produced by onshore wind farms. Based on the Figure 1.2 the top 5 countries with the installed capacity constitute the 64% of all wind power capacity in Europe. Italy is the 6th country with the highest wind power capacity in Europe.

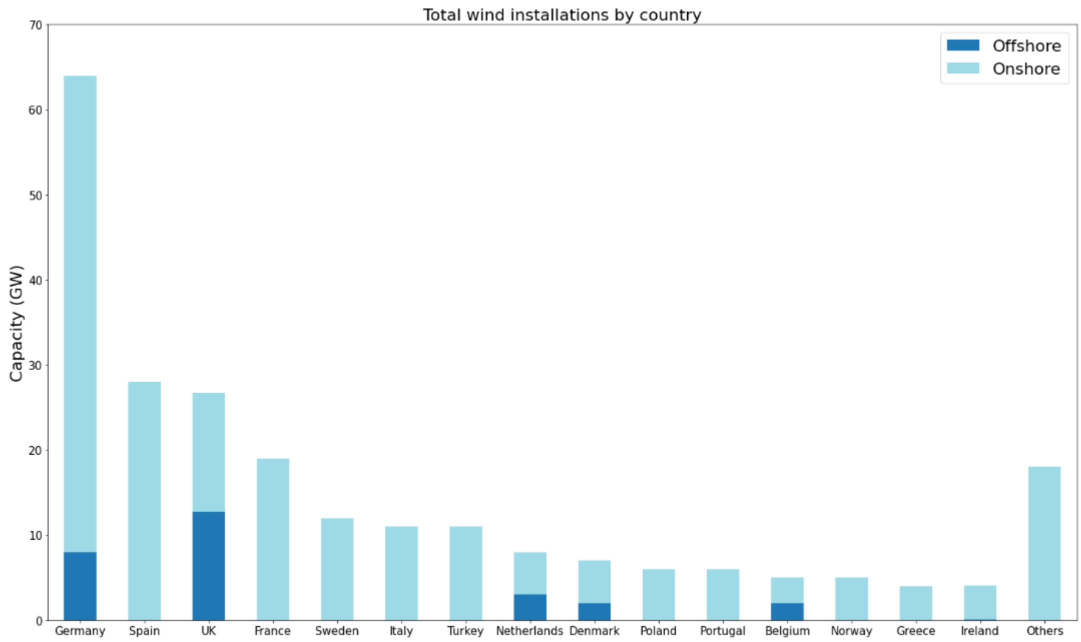

Figure 1.2 Total wind installation by country

The Figure 1.3 illustrates the trend of primary energy consumption based on the energy sources in Italy in the time period starting from 1990 to 2021. There is a downward trend in oil and coal energy sources in contrary to gas where there is an upward trend. The solar, wind, hydro, and other renewables have had a maintaining trend the last 9 years (2013-2021).

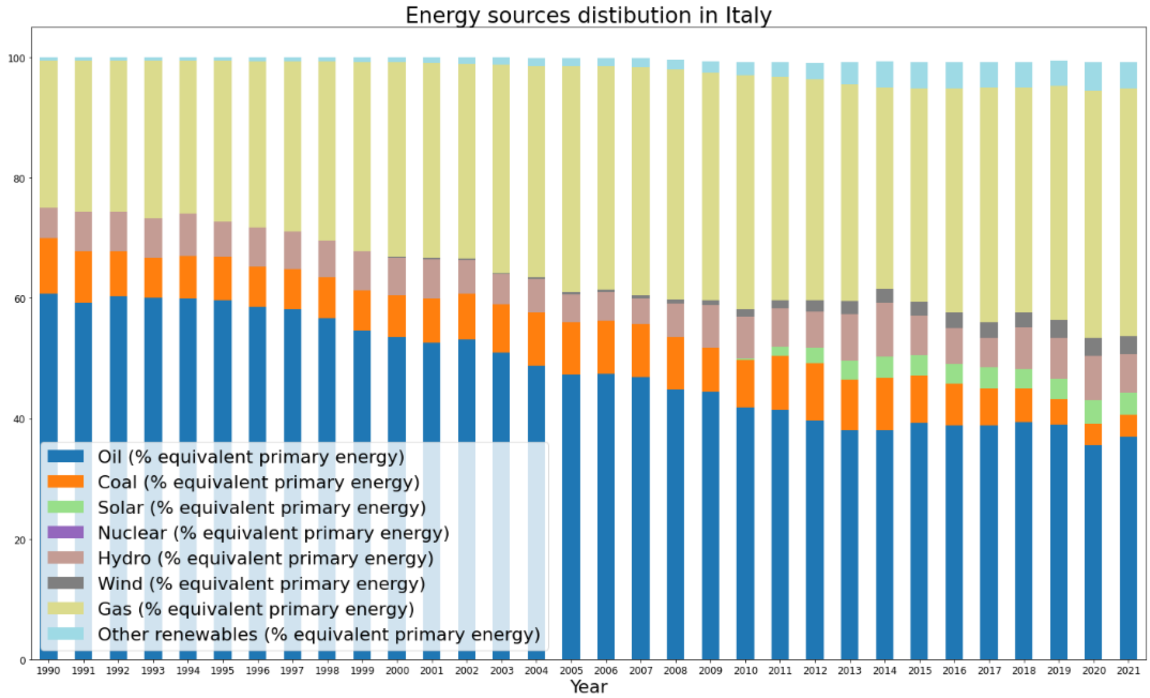

Figure 1.3 Share of energy consumption by source[2]

On the other hand, regarding the milestones to 2050 EU has set, to reduce its domestic CO_2 emissions by 80% compared to 1990 (EU's Roadmap 2050, page 4), the electricity generation is increasingly covered by renewable power generation including wind power. Specifically in Italy, even though it is 6th in terms of wind power capacity in Europe (Wind energy in Europe 2021, page 17), generated more wind power than in previous years – even though new capacity additions were very modest. Wind energy is by definition variable. It is normal to see annual fluctuations in wind capacity factors that will impact the share of demand (Wind energy in Europe 2021, page 19). "The increasing share of variable, non-dispatchable renewable power generation is a structural change to the electricity system and markets compared with the traditional thermal power sources where production can be planned if necessary" (Bo Tranberg et al., 2018).

With reference to the Italy's climate plan for 2030, the objective is the reduction of greenhouse gas emissions by 33%. The plan is based on two pillars: the growth of renewable energy sources and the efficient use of energy consumption. The growth of renewables, built on the electricity sector, will be achieved by the increasing solar capacity and wind. The goal is 187 terawatt-hours (TWh),

[2] Data source: https://ourworldindata.org/energy/country/italy

which constitutes 55% of the total consumption of 340 TWh, to be produced by wind and solar renewables by 2030. “To achieve this ambition goal, solar capacity will increase from 19 to 52 gigawatts (GW) and wind from 10 to 19 GW, mostly onshore.” (Lombardini, 2021, page 2). Along with the growth of energy capacity by renewable sources, the increase capacity of electricity storage by 6000 megawatts (MW) is planned by 2030, and an extra increment of 4000 MW in the future. The second pillar about the efficient use of energy consumption, is planned to be achieved by creating tax incentives for the public in order to renovate their residence. As many houses were built based on the first energy saving law (373/1976), energy efficiency is very low. As a result, the quantity of energy consumption may affect the energy system analogous with extreme weather conditions. Thus, Italy has set a goal to reduce the primary energy consumption by 43% and the final energy consumption by 39.7% by promoting residential renovation measures. Italy does not have an energy and climate plan for 2050, but there are indications that the measures discussed above will lead to a 64% emission reduction by 2050.

Making a retrospective analysis the last three years, two major economic shocks, referring to the Covid-19 and the Ukraine crises have been harmful to the economy, especially the energy European’s economy. As the Covid-19 arrived in Europe in February of 2020, the European Union gradually took economic measures to limit the human and economic impact of the pandemic, such as the prices of the carbon permits were set to zero and the prices of the electricity were decreased because of the reduced energy demand. Also, as consumption based on non-renewable energy sources dropped dramatically due to lower energy demand, the quota energy share of renewable energy sources increased.

Regarding the renewable energy sector, a significant number of projects were put on hold. Government subsidies in the energy sector were reduced in order to be invested mostly in the health industry and to minimize the economic turndown by taking economic measures. Another reason that the renewable energy projects, especially solar power plants, were ceased was due to the supply chain disruptions, as many components originated from Asia, could not be manufactured due to the closed factories. Also the imported components became very expensive since the maritime trade growth was slowed down, as a consequence of the fall in commodity demand in general. In general, China had a huge impact on macroeconomic growth globally.

In the European Union, “the wind-related projects were hit hard, as components for such projects were restricted due to the global pandemic” (Chemical Engineering Technology, 2022, page 564). Natural gas was mostly harnessed for the energy demand, due to lower prices. However, renewable energy generation had sporadic peaks on a weekly basis, during the lockdown. Specifically, in Italy, the energy power production from renewable energy sources increased the first four months of 2020 by 2.3% compared to the previous year. The increased solar energy production by 26.9%, and the increased of hydroelectric and geothermal energy production contributed to this renewable energy increased, while the wind energy production decreased by 14.3% based on the same period in 2019 (CMS,2020, page 2). A substantial number of renewable energy plants which put into operation during 2019 and the priority given to the plants fueled by renewable energy concerning the connection to the electricity grid, are the main reasons for the upward trend of the renewable energy production during the pandemic. However, new renewable energy plants were not created, nor commissioned due to the suspension of the industrial activities and supply chain crisis.

However, in 2021, several reasons contributed to the increased wholesale electricity prices. The gradually increased costs of carbon permits, the increased demand for electricity in the summer due to the high temperatures and high demand for holidays, Gazprom's refusal to deliver enough quantities of natural gas to Europe, the increased demand for liquefied natural gas from Asian countries, and the Ukraine war started on 24/02/2022, are some globally and regional causes of the price developments on the energy European markets.

The Italian market is considered to be the subject of study in this thesis, since this country is almost not referred in any paper for the dependence between spot price and wind power production. The majority of papers found for this study were about Germany, Denmark, and UK which belong to the top 5 countries in EU+UK with the highest energy capacity. Also as Italy is a country that was hit hard by Covid-19 pandemic, the spot electricity price would be interesting to be investigated if it was affected in contrast to the period before Covid-19. Wind and solar power generation made records of shares in Italy’s electricity during a number of months of 2022, so another reason Italy selected as a subject of study here is to investigate if the extreme events of wind power production affect the dependence between wind power production and spot price. Based on these reasons Italy was selected as the subject of study.

Regarding the data, it is observed that the daily average electricity spot price for the time-period 01/01/2020 – 01/05/2021 has few fluctuations with a total average spot price of €45 and maximum value of €82 , while in the time-period 01/05/2021-30/09/2022 the total average spot price is €246 and the maximum spot price €741. However, the Ukraine war should influence more the total average of spot price as the average becomes €351 between 24/02/2022 - 30/09/2022.

Thus, due to the different economic shocks, the dependence between the electricity spot price and wind power production is examined in three time periods, so that the model results are not affected by the different shocks.

2. Literature review

Many studies have been conducted regarding the relationship between electricity spot price and wind power production, as wind power production is a variable and may cause fluctuations in the electricity system and markets.

The study "The market value of variable renewables - The effect of solar and wind power variability on their relative price" (Hirth 2013), was carried out mostly for the German market. In German electricity market has been found that there is a negative dependence between spot price and shares of wind and solar power. As the wind speed and solar radiation are variables, it is inferred that the power production is variable, and this variability affects the market value of the renewable energy generators. Regression models are used in the analysis for various power exchanges. In data preparation, the time-weighted average wholesale day-ahead price is used for the wind power and solar radiation respectively. The yearly installed wind capacity was interpolated to calculate changes during the year and daily solar capacity was used. The market share of wind is calculated as wind power generation over total electricity consumption and respectively for the solar as its power generation over total electricity consumption. In data modeling, the correlation effect and a simple regression model are used. Solar power correlates positively with electricity demand on a daily basis and wind power on a seasonal basis. As the wind market share and solar market share respectively increases, their value factors decline based on the correlation analysis effect. A simple regression model is constructed for wind and solar production separately, in order to investigate how an increase in the market share affects the market value. Based on the regression coefficients, an increase in market share of wind (and respectively of solar radiation) is estimated to reduce the value factor.

The study "On the market impact of wind energy forecasts" (Jonsson et al, 2010), conducted for Denmark market, presented the same effect between electricity spot prices and wind power forecasts. "The spot price is, on average, shown to decrease with increased predicted wind power penetration, while intra-day price variations diminish to some extent" (Jonsson et al, 2010, page 319). Non-parametric regression modeling of electricity prices is developed. In data preparation, the variables "hourly area spot prices", "hourly consumption measurements" and "wind power forecasts (in MW)" are used in the model development, for the time-period from January 4rth 2006 to October 31st of 2007. While the relationship between spot price and wind power generation is not linear in general, it is assumed that the relationship is locally linear, so local estimates are obtained for the spot price. "The average spot price is estimated as a function of both the time of the day and the forecasted wind energy production measured in MWh per hour" (Jonsson et al, 2010, page 316). Based on the modeling results, a large wind power production quantity will on average result in a lower spot price given a specific hour.

The study “The impact of wind power generation on the electricity price in Germany” investigated the relationship between spot price and wind power generation simulated by a non-parametric regression model for Germany. Daily wind electricity generation and prices are used in the analysis. The correlation analysis calculated between spot price and wind power generation, resulted in a negative dependence. A Garch model is developed to explore the effect of wind power generation on the mean and volatility of the electricity price. “The results produced by the Garch model showed that intermitted wind power generation decreases the spot price and increases its volatility” (Ketterer, 2014, page 270).

The study “Join price and volumetric risk in wind power trading: A copula approach” (Pircalabu et al, 2016) explored the dependence between wind power production and electricity prices for the Danish power market. As the dependency between spot prices and wind power production might change through time, time-varying copula models are used for model development. The developed time-varying copula model, which is based on ARMA-Garch models, is interesting to consider if the wind power production has a high penetration ratio in the examined electricity market. The time-series used are the ratio of “total daily wind power production(MWh) divided by the (installed capacity (MW) multiplied by total hours” and the ratio of “daily average of spot electricity prices”. The resulting distribution of prices was explored in accordance with different levels of wind power penetration and the outcome was that when the wind power penetration and production is high (low) the spot price, on average, decreases (increases).

The study “Managing volumetric risk of long-term power purchase agreements” (Bo.Tranberg et al, 2018) investigated the negative dependence between wind power production and spot prices. In contrast with the paper “Join price and volumetric risk in wind power trading: A copula approach”, the paper proposes score-driven model, instead of ARMA-Garch model, for the spot prices as it is more robust to extreme events. The study used the model of Pircalabu et al, (2016) , as a benchmark in order to show that the score-driven model is better than the ARMA-Garch model, based on the same data.

The study “The impact of renewable energy on electricity prices in Netherlands” (Machiel Mulder, 2013) examined whether weather conditions affect the average daily spot price in the Dutch electricity market in the period 2006-2011. An AR model is used with exogenous variables. Economic and climate variables are used in the model. The economic variables are the overall tightness in the market, the intensity of competition, and the marginal costs of production. The climate variables are the speed of wind, both in the Netherlands and Germany, daylight, the intensity of sunshine in the two countries, and the temperature of river water in the Netherlands. The dependent variable is the daily spot price in the Dutch market. Three models are created in the periods 2006-2007, 2008-2009 and 2010-2011 in order to examine if the impact of the economic and climate variables changes over time. Economic variables have an impact on the electricity price. "Both demand and gas price have a positive effect on electricity prices" (Machiel Mulder,2013, page 96). The intensity of competition has a relatively large influence on electricity prices, but its influence decreases when generation capacity increases. The average wind speed in German negatively affects the electricity prices in Netherlands. The remaining climate variables are statistically insignificant, so there is not a change in the impact of these variables.

The study "A combined modeling approach for wind power feed-in and electricity spot prices" (Dogan Keles et al, 2013) explored the impact of wind power generation on electricity prices in Germany. The modeling approach consists of two main model components. Firstly, the wind power feed-in on an hourly basis is modeled based on a stochastic process with an autoregressive component. The simulated wind power feed-in model is used to model the electricity price module. The electricity wholesale prices are impacted by the wind power generation and feed-in especially in hours with high electricity demand. A high wind power feed-in leads to a huge price reduction.

The study "Modeling the impact of wind generation on electricity market prices in Ireland: An econometric versus unit commitment approach" (Eleanor Denny et al, 2016). A multivariate time series regression model and a unit commitment simulation model are used for the analysis of this dependence based on the same data. The variables are on an hourly basis. The explanatory variables are the demand of electricity, wind, gas, oil, coal, carbon, and dummy variables to control public holidays. The unit commitment simulation model is a cost function. The cost function includes different costs, such as start costs, load costs, marginal costs, and reserve costs. The objective is to minimize the costs for all the generating units on the Irish system for every hour, satisfied the demand in each hour. The two models result in the fact that wind generation reduces the marginal price and there is a linear relationship between wind and prices.

The study "The impact of renewable energies on EEX day – ahead electricity prices" (Florentina Paraschiv et al, 2014) analyze the relationship between the renewable energies, wind and photovoltaic, and the day-ahead electricity prices at EEX in Germany. The analysis is conducted for the period between January of 2010 to February of 2013. The granularity of the variables used in the model is on an hourly basis. The explanatory variables used to predict the spot price are categorized into demand and supply side factors. The demand time series is the sum of the vertical net load (or electricity demand in Germany), total wind infeed and total photovoltaic infeed. The demand time series is modeled in order to predict the demand and then use it in the spot price model. An Autoregressive Moving Average model with exogenous regressors is used to forecast the expected electricity demand. On the supply side, the variables are the prices for coal, gas oil, CO_2 emission allowances, and the renewable energies wind and photovoltaic, and the expected power plant availability. A time-varying regression model for each hour is developed with lags variables in order to predict the day-ahead electricity price for each hour. Based on the model results, there is a negative dependence between the infeed from renewable energies and electricity prices.

The study “An ex-post analysis of the effect of renewables and cogeneration on Spanish electricity prices” (Liliana Gelabert et al, 2011) explores the effects the renewable electricity and cogeneration have on the wholesale electricity prices in Spain between 2005 and 2010. The variables used in the model development are calculated on a daily average basis in order to avoid extreme events. The explanatory variables are the daily demand for electricity, and the daily composition of electricity by energy source, that is, the electricity produced from renewables and cogeneration under the special regime, total production by hydro plants, nuclear plants, combined cycle plants and from fuel or natural gas plants. “An extra variable is the difference between total generation and total demand. As a major finding, the paper reports that a marginal increase of 1 GWh of electricity production by renewable energy sources is associated with a reduction of almost 1.9 € in electricity prices (around 4% of the average daily price between 2005 and 2010)” (Liliana Gelabert et al, 2011, page S65)

The study “Spatial dependencies of wind power and interrelations with spot price dynamics” (Christina Elberg et al, 2013) refers to the spatial dependence structure of wind power incorporated into a supply and demand based model for the electricity spot prices in Germany. A stochastic simulation model for electricity spot prices is created based on the market’s aggregated wind power and the residual demand, which is the difference between total demand and aggregated wind power. Secondly, the copula model was created to associate market’s aggregated wind power with the wind power of single turbines in order to quantify their market value and the revenues depending on their specific location. The paper resulted in the significant negative dependence between spatial structure of wind power and spot price, and this effect becomes increasingly important for higher levels of wind power penetration.

The study “Analyzing the impact of renewable electricity support schemes on power prices: The case of wind electricity in Spain” (Gonzalo Saenz de Miera et al, 2008) explores the impact of the increase of renewable energy sources in the electricity prices. The variables used for the analysis are the thermal capacity installed, thermal production, wind power generation, the price of gas in the UK and the CO_2 allowance price in the EEX (European Energy Exchange). Regression simulations are used to investigate the relationship between the merit order effect and the electricity prices based on two scenarios: considering or not the absence of wind power generation. Regarding wind power generation, the result of the simulation is that electricity prices reduction is greater than the increase of the costs generated from the establishment of new wind energy plants.

The study “The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany” (Frank Sensfuß et al, 2008) investigates the relationship between renewable electricity generation and spot market prices. “In the energy only market, the merit order effect describes the lowering of power prices at the electricity exchange due to an increased supply of renewable energies” (Journalism for the energy transition). The calibrated PowerACE model is used to simulate electricity market prices. The electricity demand is traded based on simulated spot market prices (on an hourly level for an entire year). The results generated by the model platform indicate that the volume of the merit-order effect is higher than the cost payments for renewable energy production, which is positive from a consumer point of view.

The study “Renewable energy and electricity prices: indirect empirical evidence from hydro power” (Ronald Huisman et al, 2013) explores how the spot market prices are influenced by the increasing of marginal costs of hydro power energy plants. The modeling process consists of a regression model that quantifies this relationship. The study results in the fact that an increase in renewable energy production will decrease the market price of power.

The negative dependence between the spot price and wind production had been resulted in all the above studies. However, the model developments of these studies were conducted in a time-period without a Covid-19 pandemic neither a Ukraine war. Thus, the performance of all models referred in the studies above, should be examined in the time period including Covid-19 pandemic and Ukraine War, as the majority of the spot prices in this time-period are characterized as extreme events.

3. Empirical analysis

Methodology

The methodology applied for the analysis, using the Python programming language, is consisted of the following elements:

1. The variables used are the "Daily average purchase electricity prices" and the "Daily average of wind onshore production in MWh"
2. The examined time-period begins from 1st January of 2020 until 30 September of 2022.
3. Anova and Tukey statistical methods are used to ensure that the variable "Daily average purchase electricity prices" is statistically differentiated based on the three time-periods referred in the Introduction.
4. Stationarity analysis is applied using the Augmented Dickey Fuller test in order to investigate if the variables referred to in bullet (1) have a unit root. Necessary transformations are applied in order to have stationary variables.
5. The investigation of the relationship between the two variables is done by using ARMA and linear models and the Pearson correlation metric.
6. The order of auto-regressive (AR) and moving average (MA) terms are explored by using the ACF (autocorrelation function) and PACF (partial autocorrelation function) plots.
7. The volatility of the errors of the developed model is investigated by using a Garch model.

Data Preparation

Two data sources were used for the analysis: the historical purchase electricity prices for end customers[3] and the actual wind power generation[4] from onshore plants, regarding the Italian market. The granularity level of the two datasets is based on hour and date. The columns used in the dataset of the purchase electricity prices are the [Data/Date, Ora/Hour, PUN]. The column "PUN" is defined as the "Purchase price for end customers" based on the sheet "Legenda". The columns used in the dataset of the actual wind power generation are the [Area, MTU, Wind Onshore-Actual Aggregated MW]. The column "Area" refers to the country, which is "Italy' in our case, the column "MTU" refers to the date-time interval, for example "01.01.2020 00:00 - 01.01.2020 01:00", and the column

[3] https://www.mercatoelettrico.org/En/Download/DatiStorici.aspx
[4] https://transparency.entsoe.eu/dashboard/show

“Wind Onshore-Actual Aggregated MW” is the actual wind power production based on onshore plants.

The granularity of the two datasets is transformed in order to have daily aggregations. So, the calculated new fields are the “daily average wind power production in MWh” and the “daily average purchase electricity prices”. The date range of the datasets is between January 2020 and September of 2022. The number of observations is 992.

Descriptive Statistics

Based on the analysis made in the Introduction section, a variable is created to separate three significant date ranges considering the fluctuations of the daily average purchase electricity prices: the time interval between [January of 2020 and April of 2021] where there are few fluctuations in the daily average prices, the time interval between [May of 2021 and 23 February of 2022] where there are high fluctuations until the start of the Ukraine war and the time interval between [24 February of 2022 and September of 2022] where there is the Ukraine war period.

Daily average purchase electricity prices

The Figure 3.1 illustrates the time series of the daily average purchase electricity prices for the Italian market. The Covid-19 period [January of 2020 and April of 2021], where we had low energy prices and their volatility, after the Covid-19 until the Ukraine war period [May of 2021 and 23 February of 2022] the high energy prices with increasing price volatility that followed the strong recovery in demand, and the period of the Ukraine war until now [24 February of 2022 and September of 2022], that causes the fallout of the extremely high energy prices and theirs volatility, all the above advocate that there is high price volatility.

Statistically wise, a one-way analysis of variance (ANOVA) is conducted in order to examine if there are any statistical differences between the means of the three groups, i.e. time periods of few fluctuations, high fluctuations, and Ukraine war.

Figure 3.1: Daily average electricity spot prices

The Figure 3.2 illustrates three box plots of the variable daily average spot prices for each time-period. The ranges of the variable are differentiated among these time-periods. The statistical significance between the three groups of the variable is proved using the ANOVA tests and Tukey test.

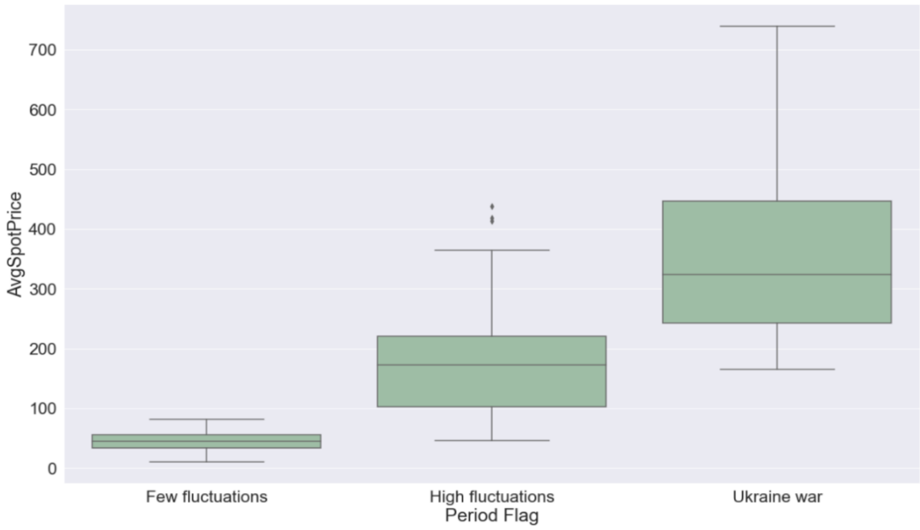

Figure 3.2: Box plot of daily average electricity spot prices for each time-period

The Table 3.1 presents the results of the ANOVA test between the variable and the time-periods. Since the p-value is lower than 0.05, there is significant evidence that there is at least one pair of groups which are differentiated between them.

ANOVA test statistic	pvalue
1324.1379898438206	6.804530590167079e-292

Table 3.1: ANOVA test for the daily average spot prices

The Table 3.2 presents the results of the Tukey test between the variable and the time-periods. Since the p-adj are below 0.05 for each pair of groups, there is significant evidence that all the pairs of groups are differentiated between them.

Multiple Comparison of means – Tukey HSD, FWER = 0.05						
Group1	Group2	Meandiff	P-adj	Lower	Upper	Reject
Few fluctuations	High fluctuations	122.9121	0.0	110.0997	135.7245	True
Few fluctuations	Ukraine War	306.2717	0.0	292.0957	320.4477	True
High fluctuations	Ukraine War	183.3596	0.0	167.9231	198.7961	True

Table 3.2: Tukey test for the daily average spot prices

So, the assumption of creating the three time – periods: few fluctuations, high fluctuations, and the Ukraine war, is valid statistically wise, based on the statistical tests ANOVA and Tukey test.

Stationarity analysis

In this part of the analysis, the statistical properties, i.e. average, variance and covariance, of the variable "daily average purchase electricity prices" are examined if they do not change over time. The Augmented Dickey-Fuller unit root test is conducted, where the null hypothesis is the existence of a unit root, i.e. the time series is not stationary. In short, if a time series is stationary, its mean, variance and autocovariance (at various lags) remain the same no matter at what time we measure them (Basic econometrics, Gujarati, page 713). The p-value of the Augmented Dickey-Fuller is 0.786592, which is greater than 0.05, thus the variable is not stationary. The analytical results are presented in the Table 3.3. The technical name of the variable "daily average purchase electricity prices" is the "AvgSpotPrice".

Results of Dickey-Fuller Test: AvgSpotPrice	
Test Statistic	-0.904181
p-value	0.786592
#Lags Used	21.00000
Number of Observations Used	971.00000
Critical Value (1%)	-3.437102
Critical Value (5%)	-2.864521
Critical Value (10%)	-2568357

Table 3.3: ADF test of daily average spot prices

Since forecasting methods will be used to predict the energy prices, the stationarity assumption of the time series needs to be considered. Thus, the variable "daily average purchase electricity prices" needs to be transformed into a stationary time series. The variable is transformed into the "return of the daily average purchase electricity prices". The technical name of the variable is "Return_AvgSpotPrice". The Figure 3.3 illustrates the time series of the transformed variable.

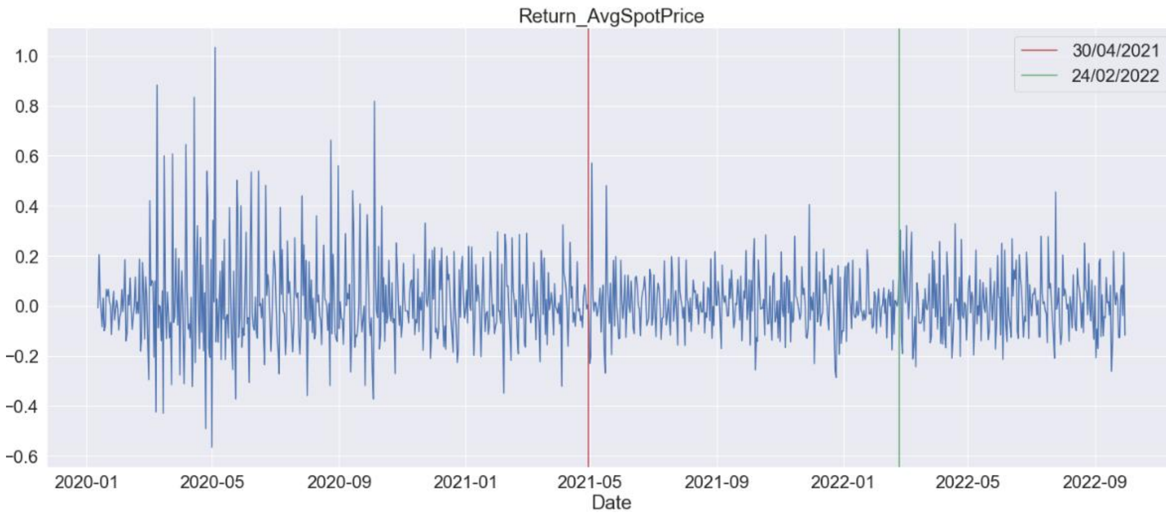

Figure 3.3: Return of daily average purchase electricity prices

The p-value of the Augmented Dickey-Fuller test is almost zero, which is less than 0.05, thus the variable is stationary. The analytical results are presented in the Table 3.4.

Results of Dickey-Fuller Test: Return_AvgSpotPrice	
Test Statistic	-6.505998e+00
p-value	1.130822e-08
#Lags Used	2.100000e+01
Number of Observations Used	9.710000e+02
Critical Value (1%)	-3.437102e+00
Critical Value (5%)	-2.864521e+00
Critical Value (10%)	-2.568357e+00

Table 3.4: ADF test of return of daily average spot prices

ACF-PACF Plots

The next step of the forecasting process is to identify the parameters of ARMA process. The graphs ACF (autocorrelation function) and PACF (partial autocorrelation function) are the tools identification of this process.

Since the variable "return of daily average spot prices" is stationary, the ACF and PACF plots can be used to find the ARMA pattern of this variable. The Figure 3.4 illustrates the ACF and PACF, and it can be observed that there is a trend pattern every 7 lags in the ACF plot.

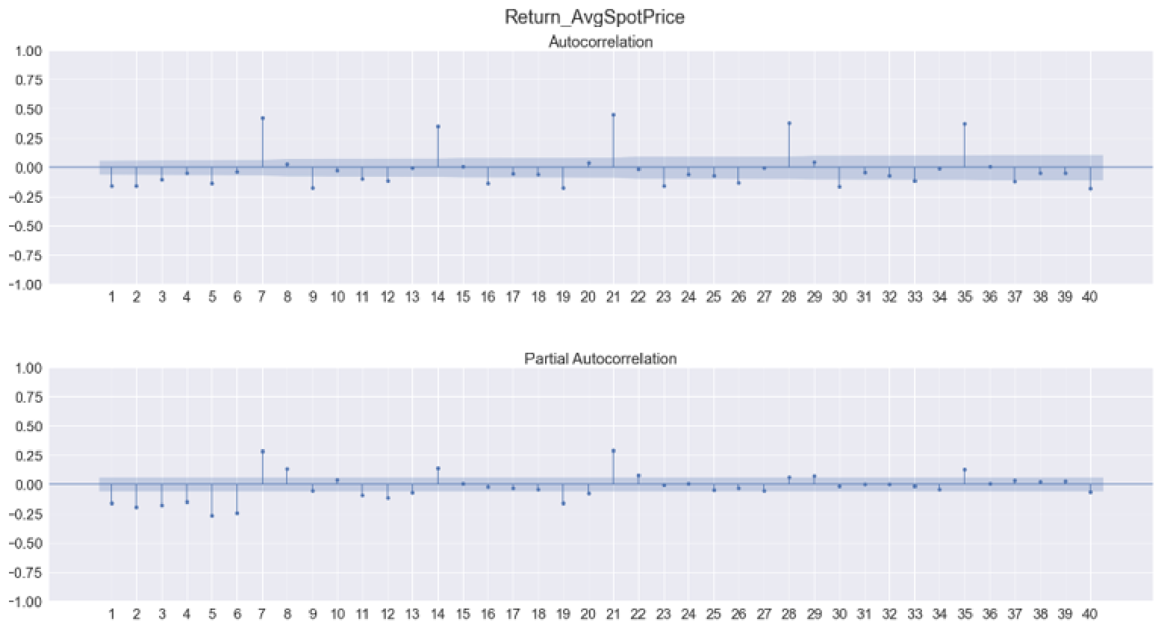

Figure 3.4: ACF PACF plots of Return of daily average purchase electricity prices

Since the "return of daily average spot prices" seems to have a seasonality effect, the variable is transformed into a moving average based on 7 days. The technical name of the transformed variable is "Return_AvgSpotPrice_MA7". The Figure 3.5 illustrates the transformed variable, which is smoother than the variable presented in the Figure 3.3 (the range of the y-axis in the Figure 3.5 is smaller than the scale of the Figure 3.3).

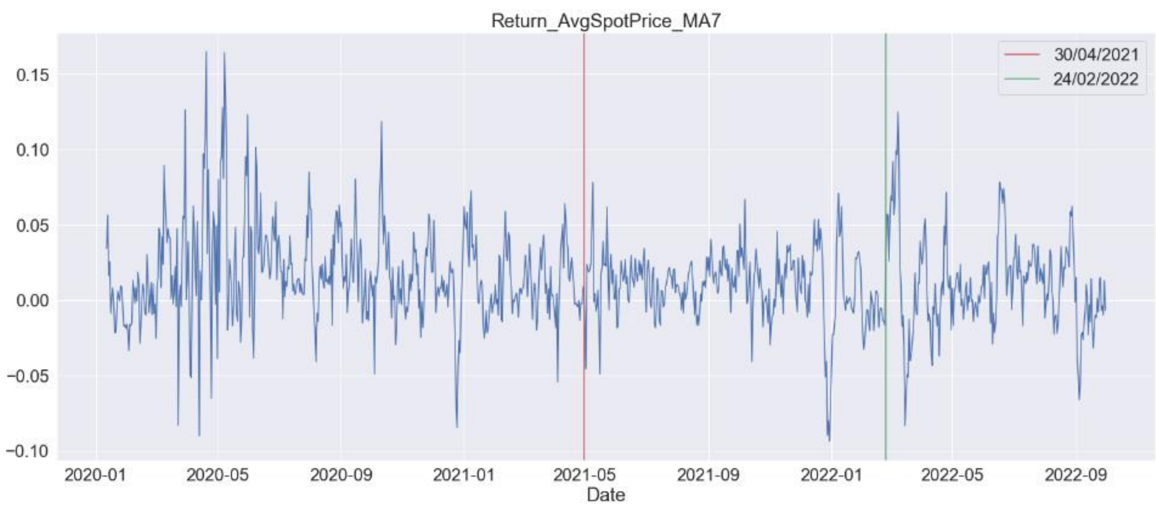

Figure 3.5: Moving average 7-days of Return of daily average purchase electricity prices

The Figure 3.6 illustrates the ACF – PACF plots of the transformed variable. The ACF plot decays almost exponentially. If the typical pattern of the PACF had significant spikes through lags p, the type of the model would be AR(p), or, if the typical pattern of the PACF was exponential decay, then the type of the model would be ARMA(p,q). In our case, the statistically significant partial correlation coefficients are outside of the blue region for many different lags. Thus, there are concerns if the AR model can be used for the analysis.

Figure 3.6: ACF PACF plots of moving average (7 days) of return of daily average purchase electricity prices

Daily average of wind onshore production in MWh

The Figure 3.7 illustrates the time series of the daily average wind onshore production in MWh for the Italian market. Extreme volatility is observed, which is reasonable in general, since there is a production uncertainty associated with wind power generation. Thus, wind power production cannot be predicted, so it cannot be planned and controlled since there is a dependency on weather conditions, such as wind speed and air density. Furthermore, the variable "daily average of wind onshore production in MWh" is used in the model as an exogenous regressor since the price can be affected theoretically upwards or downwards based on the wind power production quantity. Because wind power has a very low marginal cost, a high production for a given hour will, other things being equal, pull the market clearing price downwards and similarly, if wind power production is low for a given hour, demand will have to be met by either import or turning on more costly generating plants pulling the market clearing price upwards (Pircalabu et al, 2016, page 1).

The technical name of the variable is “AvgWindProduction[MWh]”.

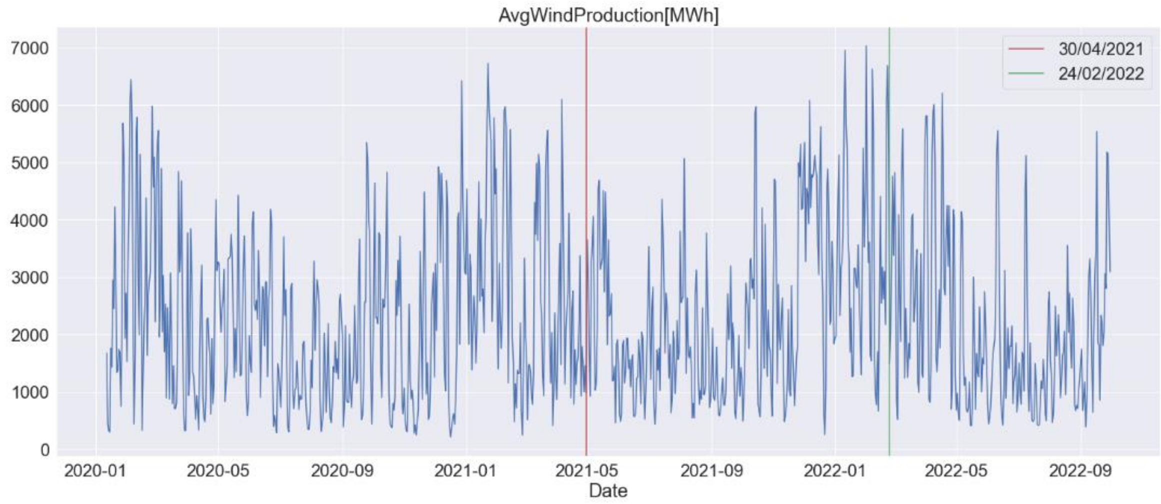

Figure 3.7: Daily average wind onshore power production in MWh

As the variable “daily average wind onshore power production in MWh” is used as exogenous variable in the AR(1) process to predict the “Moving average 7-days of Return of daily average purchase electricity prices”, it is transformed into the variable “Moving average 7-days of daily average wind onshore power production in MWh” for consistency reasons. The technical name of the variable is “AvgWindProduction_MA7”. Also, its stationarity is examined based on the test Augmented Dickey-Fuller. The p-value of the statistical test is 0.00147 which is lower than 0.05, thus the variable is stationary. The results of the test are presented in the Table 3.5 below.

Results of Dickey-Fuller Test: AvgWindProduction_MA7	
Test Statistic	-3.988801
p-value	0.001470
#Lags Used	22.000000
Number of Observations Used	959. 000000
Critical Value (1%)	-3.437187
Critical Value (5%)	-2.864559
Critical Value (10%)	-2.568377

Table 3.5: ADF test of 7-days moving average of daily average wind onshore power production in MWh

Pearson correlation analysis

The dependence between the variables “7 days moving average of wind power production’ and “7 days moving average of spot prices” is examined first using the Pearson correlation metric. A 30-day moving correlation is calculated in order to examine the evolution of this metric. The Figure 3.8 illustrates the 30-days moving correlation through the time.

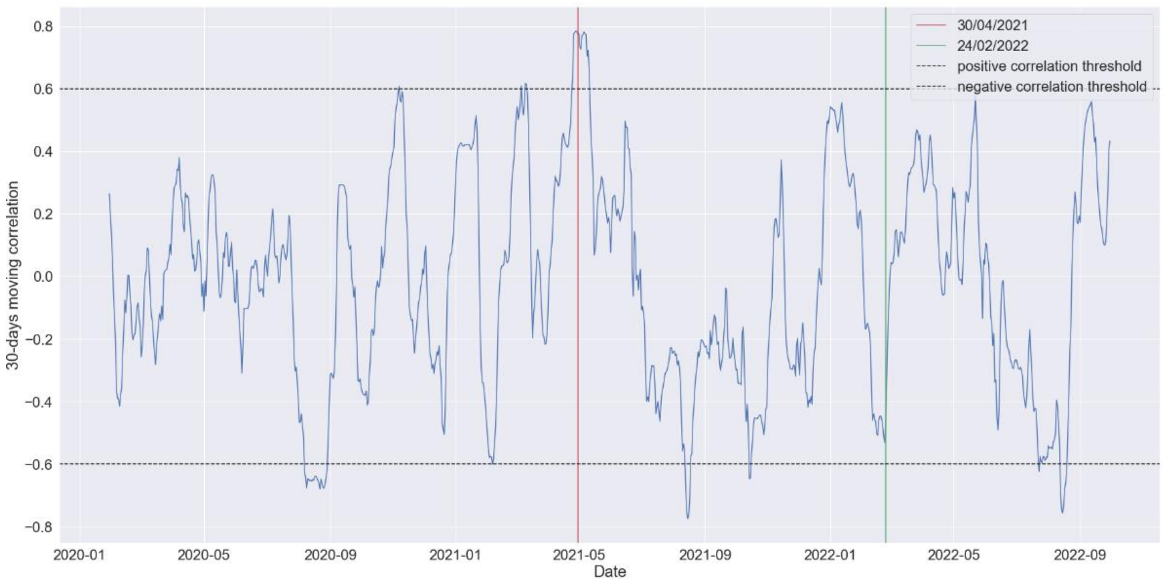

Figure 3.8: 30-days moving correlation

The variable 30-days moving correlation is categorized in order to examine the distribution of the positive and negative correlations under the assumption that the threshold is 60%, i.e. considering we have negative correlation if the 30-days moving correlation is lower or equal to -60% , and respectively the positive correlation if the 30-days moving correlation is higher or equal to +60%. The Table 3.6 presents the distribution of the variable 30-days moving correlation. In general, the correlation between the two variables is not strong, since the value of the 30-day moving correlations fluctuates between -60% and 60%. The spot prices are not depending strongly on the changes of the wind power production considering the time-period January of 2020 and September of 2022.

Category	Number of rows
Negative Correlation (<= -60%)	39
Positive Correlation (>=60%)	21
Other	893

Table 3.6: Categorization of 30-days moving correlation

Furthermore, the correlation metric is calculated separately in three time periods: Covid period (01/01/2020- 30/04/2021), after Covid period (30/04/2021-24/02/2022) and Ukraine period (24/02/2022-30/09/2022). The Table 3.7 presents that the dependence between the two variables is low, so wind power generation does not influence enough the electricity spot prices for the specific time periods.

Period	Value of correlation coefficient
Covid period (few fluctuations)	-5%
After Covid period (high fluctuations)	-10%
Ukraine war	6%

Table 3.7: Correlation coefficient results

Autoregressive model with exogenous regressor

Three autoregressive models are created with exogenous regressor for each time-period (Covid period, After Covid period and Ukraine war), in order to investigate how the wind power production along with the lag1 of the return of electricity spot prices are associated with the return of electricity spot prices.

The dependent variable of the model is the "Moving average 7-days of Return of daily average purchase electricity prices" (technical name: "Return_AvgSpotPrice_MA7") and the predictor variables are the first lag of the "Moving average 7-days of Return of daily average purchase electricity prices" (technical name: "Return_AvgSpotPrice_MA7_lag1") and the "Moving average 7-days of daily average wind onshore power production in MWh" (technical name: "AvgWindProduction_MA7"). Hereinafter, the technical names of the variables will be used. The Table 3.8 presents the results for each model. The model that is created in the time-period "After Covid period (high fluctuations)" is better than the other ones based on the AIC metric.

Model period	AIC
Covid period (few fluctuations)	12.051
After Covid period (high fluctuations)	-424
Ukraine war	45.183

Table 3.8: AR(1) model results

The Table 3.9 presents the coefficient values and their confidence intervals for each model. Based on the confidence intervals, the predictor variables of the models "Covid period (few fluctuations)" and "Ukraine war" seems to have no relation with the dependent variable, since the confidence intervals of their coefficients contain the value zero (0). Thus, the predictor variables do not have anything to do with the dependent variable. Only the model created in the “After covid period (high fluctuations)” seems to create an important association between the dependent variable and the predictors, based on the non-existence of the zero value in their predictors’ coefficients confidence intervals. However, the coefficient of the variable “Return_AvgSpotPrice_MA7_lag1” of the model “After Covid period (high fluctuations)” is not in the range (-1,+1) so neither this model can be used for the analysis.

Model	Variable	Coefficient	95% Confidence Interval
Covid period (few fluctuations)	Constant	-0,0141	[-6.209e+02,6.208e+02]
Covid period (few fluctuations)	Lag 1 of moving average 7-days of Return of daily average purchase electricity prices	0,0549	[-2.092e+03,2.092e+03]
Covid period (few fluctuations)	Moving average 7-days of daily average wind onshore power production in MWh	-0,0015293	[-0.228, 0.225]
After Covid period (high fluctuations)	Constant	-0,1707	[-0.199, -0.143]
After Covid period (high fluctuations)	Lag 1 of moving average 7-days of Return of daily average purchase electricity prices	3,2355	[2.641, 3.830]
After Covid period (high fluctuations)	Moving average 7-days of daily average wind onshore power production in MWh	0,00011231	[9.457e-05,1.300e-04]
Ukraine war	Constant	0,0419	[-3.552e+03,3.552e+03]
Ukraine war	Lag 1 of moving average 7-days of Return of daily average purchase electricity prices	1,185	[-1.039e+04,1.039e+04]
Ukraine war	Moving average 7-days of daily average wind onshore power production in MWh	0,0014075	[-1.465, 1.468]

Table 3.9: AR(1) model coefficients

Linear regression model

A linear regression model is used to associate the variables “Return_AvgSpotPrice_MA7” and “AvgWindProduction_MA7”. The Table 3.10 presents the results of the AIC metrics for each model period. The model created in the “After Covid period (high fluctuations)” has the lowest AIC metric against the other models, thus it is the most appropriate model to be used.

Model period	AIC
Covid period (few fluctuations)	324
After Covid period (high fluctuations)	-29
Ukraine war	2.129

Table 3.10: Linear model results

The Table 3.11 presents the model results for each time-period. Only the model created in the "After covid period (high fluctuations)" seems to create an important association between the dependent variable and the predictor, based on the non-existence of the zero value in the predictor's coefficient confidence intervals. The coefficient of the Constant is not statistically significant as its confidence interval contains zero value.

Model	Variable	Coefficient	95% Confidence Interval
Covid period (few fluctuations)	Constant	0,0079921	[-0.145, 0.161]
Covid period (few fluctuations)	AvgWindProduction_MA7	-0,00012437	[-2.132e-04,-3.557e-05]
After Covid period (high fluctuations)	Constant	0,0752	[-7.086e-02, 0.221]
After Covid period (high fluctuations)	AvgWindProduction_MA7	-0,00012427	[-1.800e-04,-6.850e-05]
Ukraine war	Constant	-0,1301	[-0.131, -0.130]
Ukraine war	AvgWindProduction_MA7	0,000058226	[5.822e-05,5.823e-05]

Table 3.11: Linear model coefficients

Thus, the model type is the following:

$$\text{Return\_AvgSpotPrice\_MA7} = \text{Constant} + \text{AvgWindProduction\_MA7} * \text{Coefficient}$$

$$\Leftrightarrow$$

$$\text{Return\_AvgSpotPrice\_MA7} = 0{,}0752 - \text{AvgWindProduction\_MA7} * 0{,}00012427 \qquad (1)$$

According to the formula (1), the Return_AvgSpotPrice_MA7 has slightly a negative dependence from the AvgWindProduction_MA7, i.e. the Return_AvgSpotPrice_MA7 will decrease by 0.012% if the AvgWindProduction_MA7 increases by 1 MWh. Furthermore, in conjunction with the correlation results presented in the Table 3.7, it must be said that there is some evidence of a negative dependence between the variables Return_AvgSpotPrice_MA7 and AvgWindProduction_MA7.

The Figure 3.9 illustrates the calculated Return_AvgSpotPrice_MA7 based on the formula (1), and the observed Return_AvgSpotPrice_MA7 based on the raw dataset. The model fit is not good as the Return_AvgSpotPrice_MA7 depends on multiple various factors which are not considered in the model predictors. The linear model is constructed in order to investigate if there is a negative dependence between the Return_AvgSpotPrice_MA7 and AvgWindProduction_MA7.

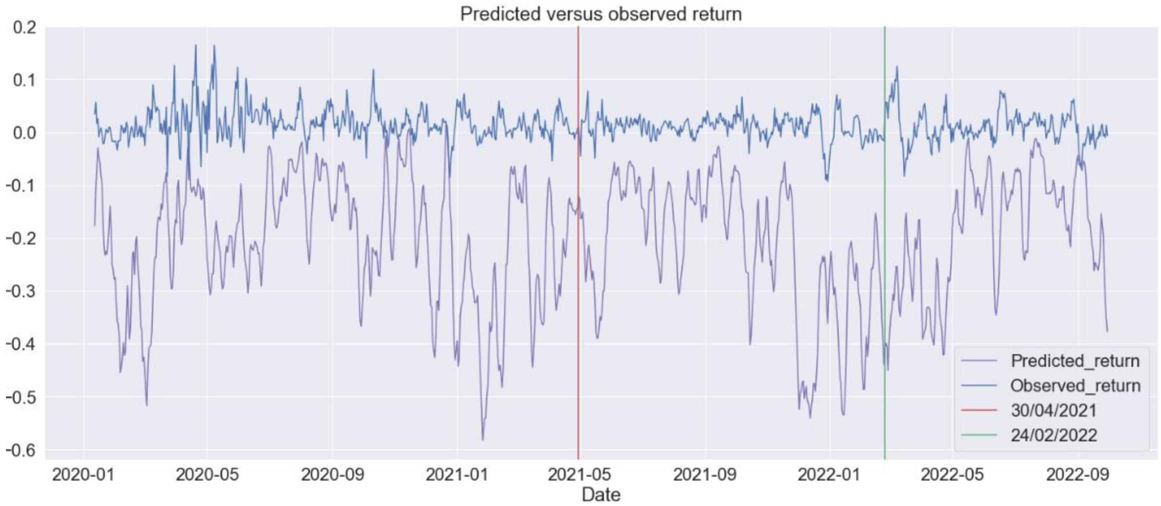

Figure 3.9: Predicted versus observed return of spot price

Garch model

Another model created is the Garch model in order to capture if the errors of the linear model (1) are variable. The variability of the linear model errors can very well be due to volatility in markets, sensitive as they are to rumors and political upheavals. Thus, the variance of the linear model errors should be investigated if it is not constant but varies from period to period.

A Garch(1,1) model is developed in order to investigate the linear errors' variability. The Table 3.12 presents the coefficients and their confidence internals. Based on the Table 3.12, only the coefficient omega is not statistically significant, as its confidence interval contains the zero value. Based on the Table 3.12 and equation (2), the variance depends on the time, something that has been seen from the Figure 3.5.

Model	Variable	Coefficient	95% Confidence Interval
After Covid period (high fluctuations)	omega	0,000010444	[-6.616e-04,6.825e-04]
After Covid period (high fluctuations)	alpha	0,2002	[4.041e-02, 0.360]
After Covid period (high fluctuations)	beta	0,7798	[0.610, 0.950]

Table 3.12: Garch(1,1) coefficients

The form of the Garch(1,1) model is the following:

$$\sigma_t^2 = \omega + \alpha * \varepsilon_{t-1}^2 + \beta * \sigma_{t-1}^2$$

$$\Leftrightarrow$$

$$\sigma_t^2 = 0{,}000010444 + 0{,}2002 * \varepsilon_{t-1}^2 + 0{,}7798 * \sigma_{t-1}^2 \qquad (2)$$

Where ε_t is the error term of the model (1) and the error term follows a normal distribution.

4. Conclusion

Our findings suggest that there is a negative dependence between the moving average of return of spot price and moving average of wind power production. The negative dependence is proved based on the statistically significant coefficient produced by the linear model developed in the Empirical analysis section. An increase of 1MWh in the moving average of wind power production results in a decrease of 0.01% in the moving average of return of spot price. The result of the negative dependence is quite in line with all the studies referred in the

Literature review section, despite the fact that the model development across all papers and this thesis was conducted in different time periods, countries amidst to significant economic and political scenes.

The performance of the model created in this thesis, is low as the only explanatory variable used is the wind power production, and the time period of the model development consists of the Ukraine war and Covid-19 pandemic. Thus the spot price time series has many extreme events as a consequence of these two major crises, and the modeling of such a time series constitutes a difficult task. Moreover, all the models referred to in this thesis should be recalculated in the same data the linear model was created here in order to investigate if their model performance and conclusions are aligned with my conclusion.

Based on the climate target for the 2030 Italy has to achieve, in the Introduction section is referred that along with the goal of the growth of energy capacity by renewable sources, there is a plan to increase capacity of electricity storage by 6000 megawatts (MW) and an extra increment of 4000 MW in the future. The increased capacity of electricity storage intended to save the electricity produced by wind power plants (or in general renewable energy sources) may disrupt all the conclusions made for the negative dependence between spot price and wind power production. Electricity storage is potentially a new explanatory variable that needs to be investigated along with the other variables that have already been used in the models developed to describe this dependence. So further research into this explanatory variable is required to come, since wind power production acquired further characteristics and cannot be said that it is only variable and affected by the weather conditions. The opportunity to store wind power production, contributes to the variable to have less volatility.

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