L'impact de la production d'énergie éolienne sur le prix de l'électricité: données de l'État de New York

Yousef Nasseri [1]

Abstract

Avec la croissance de la production éolienne, la compréhension de son impact sur les prix de marché de l'électricité et sur leur volatilité devient de plus en plus pertinente. En tirant parti de la base de données du New York Independent System Operator (NY ISO), disponible au public pour l'année 2019, nous montrons que la part croissante de l'énergie éolienne dans l'État de New York peut non seulement entraîner une baisse des prix de l'électricité, mais qu'elle peut provoquer également une augmentation substantielle de la volatilité. De plus, en analysant l'effet prix dans les zones de production éolienne, nous montrons que l'étendue de cet effet dépend de la quantité de production éolienne dans la zone. La principale contribution de cette thèse est de modéliser le comportement de la volatilité dynamique des prix de l'électricité tout en prenant explicitement en compte les variations de la production éolienne zonale. Nos résultats ont deux implications majeures: premièrement, la pression à la baisse croissante sur les prix de l'électricité due à la part croissante de la production éolienne peut remettre en question la viabilité financière des marchés de l'électricité à long terme. Ce défi souligne la nécessité de procéder à une réforme qui garantist le recouvrement des coûts fixes. Deuxièmement, la volatilité induite des prix implique que l'utilisation efficace des stratégies de couverture du risque de prix doit être envisagée par tous les acteurs des marchés de l'électricité.

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The Impact of Wind Power Generation on the Electricity Price: Evidence from the State of New York[☆]

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Abstract

With the growing share of wind production, understanding its impact on electricity spot prices and on price volatility behavior becomes increasingly relevant. Taking advantage of the publicly available New York Independent System Operator (NY ISO) database for the year 2019, we show that the growing share of wind in the state of New York can not only lead to a decline in electricity prices, but that it can also cause a substantial rise in the spot prices volatility. Moreover, by analyzing the price effect in wind producing zones, we provide evidence that the extent of this effect depends on the amount of wind generation within the zone. The main contribution of this thesis is to model the dynamic volatility behavior of electricity prices while explicitly taking into account the variations in zonal wind output. Our findings have two major implications: First, the increasing downward pressure on electricity prices due to the growing share of wind generation can challenge the financial sustainability of the electricity markets in the long run. The mentioned challenge, highlights the need to proceed towards an effective market structure which ensures the recovery of utilities fixed costs. Second, the induced price volatility, implies that effective use of price risk hedging strategies should be considered by all actors in the power markets.

Keywords: Wind Generation, Electricity Price, Price Volatility

JEL Classification Codes: C32; Q42; Q48

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1. Introduction

Climate change and environmental concerns have come to dominate the debate over development of electricity markets. Energy policy makers across the world have implemented policies to encourage large-scale integration of hydro, wind and solar into the power grid as traditional power plants play a detrimental role in rising the greenhouse gas emissions. The integration of renewable energies is expanding rapidly across the world not only because they are sustainable, safe, widely available and clean but because they are proven to be economically viable in many parts of the world (Jacobson et al., 2015).

In the United States (U.S.), Federal and State governments try to promote investment in renewable energies through various incentive programs and financing options such as production and investment tax credits. In 2019, renewable energy sources accounted for about 17.5 percent of total electricity generation across the U.S. [1], while the share of renewable energies in the total electricity generation within the state of New York was 28 percent for the same year (NY ISO load and capacity report-2020)[2]. Since 2004 and the implementation of its first Renewable Portfolio Standard (RPS), New York has always been known as an environmental policy leader in fighting climate change by adopting ambitious legislation and policies. In 2019, the state of New York passed the Climate Leadership and Community Protection Act (CLCPA) and signed it into law. The CLCPA sets the goal of a Carbon free electricity system by 2040 while setting new standards to achieve the goal of cutting greenhouse gas emissions by 85 percent by 2050 (New York State Energy Research and Development Authority Strategic Outlook, 2020.[3]). Currently, New York State relies mostly on conventional hydroelectric power plants to meet its renewable energy goals and wind generation forms only 3 percent of the state's electricity production. However, in an attempt to meet the targets of the state's clean energy and carbon reduction mandate, New York has

[1] see: https://www.eia.gov/tools/faqs/faq.php?id=427t=3.
[2] See: https://www.nyiso.com/documents/20142/2226333/2020-Gold-Book-Final-Public.pdf/.
[3] Seehttps://www.nyserda.ny.gov/About/Publications/.

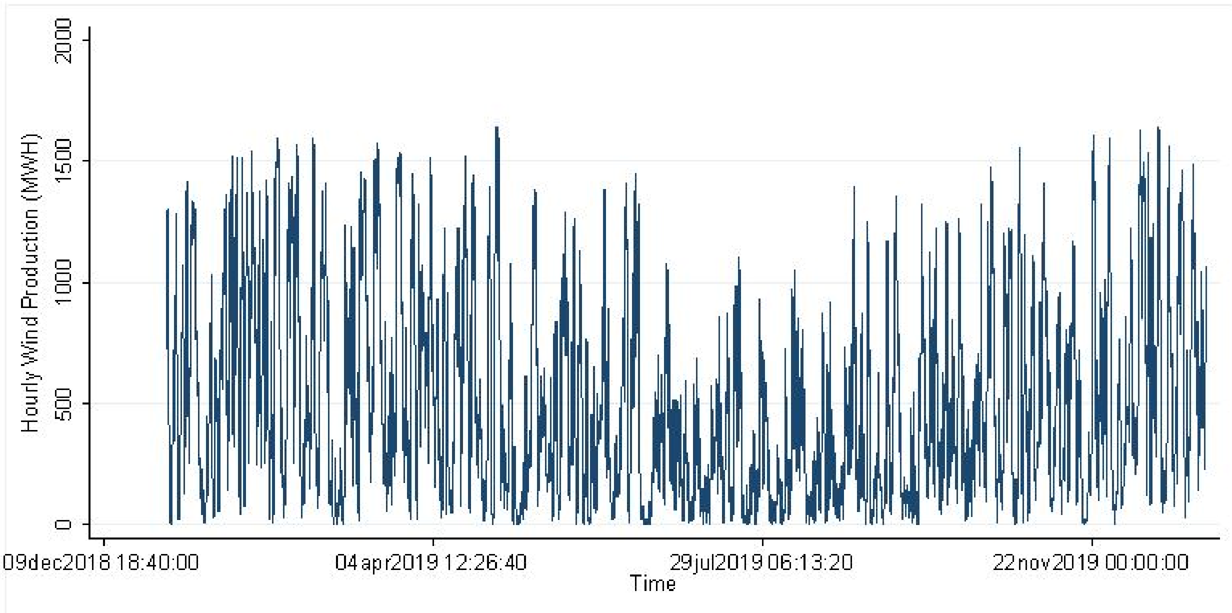
signed two new offshore wind contracts with a combined capacity of 1,700 MW while 9,000 MW of offshore wind production is targeted for 2050.

While the environmental benefits of using wind energy to fuel electricity production are undeniable, system and market operators face new challenges when an intermittent energy source like wind is fed into the system. Wind turbines have close to zero operational costs and whenever wind power allows enough electricity production to push the electricity supply curve to the right, the available low price electricity places a downward pressure on the wholesale electricity prices. This dampening effect of the prices is defined in the literature as the merit order effect (Cludius et al., 2013). However, electricity generated by wind farms is intermittent and not adjustable to variations in demand. Therefore, when enough wind power is not available to meet the demand, reserve capacity has to be fed into the system at a higher cost which will lead to an upward price adjustment.

The dampening effect of wind production on electricity prices has already been observed in several studies which are reviewed in detail in the next section. However, very few studies focused on the impact of feeding wind power into the system on volatility of the prices. Understanding the impact of wind generation over the fluctuations in spot prices is particularly important in implementing risk management strategies for power markets participants and policy makers. Moreover, the growing share of wind generation implies that market participants will experience lower prices with higher volatility. With the current market structure, which was primarily designed to adapt a generation fuel mix with a small share of intermittent renewable generation (Pollitt and Anaya, 2016), a persistent low price with high volatility as a result of rising trend in wind energy integration will challenge the financial sustainability of the electricity markets as the generated revenues will be insufficient to cover the utilities fixed cost. Therefore, a major policy implication of this study is to contribute to the understanding of the need for a structural market reform to smooth the transition towards a 100 percent renewable generation fuel mix, while ensuring the financial sustainability of power markets.

Figure 1, illustrates hourly wind generation within the NY ISO control area for the year 2019. As evident in the figure, hourly wind generation is subject to strong fluctuations which can in turn impact the volatility of hourly electricity prices.

Figure 1: Hourly Wind in-feed



Despite being one of the largest markets in the U.S., the NYISO market has not received much attentions from researchers in recent years. Hadsell and Shawky (2006) and Hadsell and Shawky (2009) are among the few studies which examined the impact of market deregulation over electricity spot prices in the NYISO's control area. Nevertheless, the price effect of integrating renewable energies in the generation fuel mix of the state remains completely unattended in the literature. Given the projects of the state to increase offshore and onshore wind production to achieve a carbon-free power grid, in this study, we employ the NYISO's public database to estimate the impact of hourly wind generation on hourly electricity prices and on the prices volatility using an AR-GARCH model. The choice of the model is based on two facts: first, GARCH models lend themselves well to capture the volatility behavior of electricity price, second, using a GARCH model gives us the freedom to explicitly test the impact of other influencing factors, such as wind output and electricity demand, by defining additional explanatory variables in the mean and variance equation of a multivariate GARCH model.

In sum, we offer four important contributions to the current literature on energy policy and energy economics. First of all, most studies on the volatility behavior of electricity price in the presence of large amount of wind generation is performed using day-ahead daily prices. This study is among the first to empirically examine the impact of wind-generated electricity into the power grid on the volatility of the electricity spot prices while benefiting from the hourly data and actual wind generation. Such dataset enables us to exploit most of the important characteristics of high-frequency data such as leptokurtosis (non-normality), autocorrelation between measurements, presence of intraday volatility, and clustering (Chavez-Demoulin and McGill, 2012). Second, to the best of our knowledge, this study is the first to explicitly take into account the extent of wind generation in each of the interconnected load zones within an independent system operator's control area and examine how the variations in wind production across the mentioned zones affects the dynamic volatility behavior of the electricity spot prices. Previous studies, including Woo et al. (2011) and Quint and Dahlke (2019) to name a few, ignored the effect of variations in wind outputs across the inter-connected load zones of their control area. Third, we analyze the response of electricity spot prices to an increase in the share of wind with respect to total demand by explicitly testing the effect of the Wind/Load ratio (the percentage of demand covered by wind energy in the state of New York) over the electricity spot prices. Finally, we capture the mean reverting behavior of the electricity prices and examine the impact of feeding wind-generated electricity to the system on the mean reverting behavior of electricity prices. To the best of the authors' knowledge, this is the first study which provides evidence that all zonal prices take almost the same amount of time to revert back to their equilibrium level regardless of the amount of wind generation within the zone.

The rest of the thesis is structured as follows: Section 2 provides a detailed review of the literature on the impact of wind generation on electricity prices. Section 3 explains the data and provides a summary of their descriptive statistics. Section 4 first provides a brief history on the development of electricity price modeling and then describes and discusses the employed model. Section 5 presents and interprets the results and finally, Section 6 contains concluding remarks.

2. Literature Review

This section provides an overview of previous studies on the impact of wind generation on electricity prices. Different approaches have been employed to assess the impact of large-scale wind generation on hourly electricity prices which can be divided into two main categories:

1. Simulation-based approach which is mainly used to investigate the effect of hypothetical scenarios which are different from the actual condition as they allow system redispatch to explore scenarios which are different from the actual conditions(Martinez-Anido et al., 2016).

2. Empirical analysis, also known as accounting approach, which is mainly based on actual historical data and is generally performed through econometric models (Würzburg et al., 2013).

Therefore, we separate this section into two subsections: Section 2.1, reviews the articles which employed simulation-based methods and Section 2.2, presents a brief overview of the researches which performed empirical analysis on the impact of wind on hourly electricity prices.

2.1. Simulation-Based Studies

There is a sizeable literature which relies on simulation based modeling to assess the impact of renewable energy generation on electricity prices. Holttinen et al. (2001) were among the first to employ a simulation method to examine the effect of wind generation on electricity prices in the Nord pool area. Their analysis predicted a 2 Euro/MWh drop in prices for each 10 TWH increase in wind generation in the Nord pool region. Sensfuß et al. (2008), analyzed the impact of renewable energy generation on Germany's spot prices by employing an agent-based simulation model to simulate various scenarios, with and without feeding renewable generation. Their main findings suggest that the anticipated growth in renewable production in Germany can dampen the average electricity prices by 1.7 to 7.8 Euro/MWh. In an extensive report on the impact of renewable generation over the United Kingdom (U.K) power markets, Poyry Management Consulting (2011) [4], used a wholesale electricity model which is based on a mixed integer linear programming platform to simulate the impact of renewable production on electricity prices in a longtime horizon of two decades. They anticipated a sharp decline in the wholesale electricity prices by 2030 in the U.K as a result of the merit order effect. In another approach Green and Vasilakos (2010), used a market equilibrium model to simulate the effect of implementing intermittent wind into the U.K power system. They found that once the industry reaches a long-term equilibrium large scale wind production leads to a downward adjustment of the prices. Using a long term generation expansion model, Pereira and Saraiva (2013), modeled the impact of wind power on electricity prices in Spain and Portugal. They estimated that a 25 percent increase in the wind generating capacity can cut the wholesale electricity prices by approximately 4 Euro/MWh. In the U.S., Fagan et al. (2012), simulated the impact of changes in the generation fuel mix, as a result of an increase in wind generation, on the electricity prices in the Midwest ISO region. They found that an increase in wind production indeed has an impact on reducing wholesale electricity prices but the extent of this simulated effect varies based on assumptions regarding installation costs and market response. Martinez-Anido et al. (2016), simulated various scenarios in terms of wind generation and penetration in order to assess the influence of wind production over prices within the Independent System Operator of New England (ISO NE) control area. Their findings indicate that wind production lowers the electricity prices within the ISO NE area but increases the prices volatility. However,

[4]See: https://www.slideshare.net/garyswandells/the-challenges-of-intermittency-in-north-west-european-

they did not account for the variations in zonal wind outputs.

The results generated through employing simulation-based approaches vary based on the models' assumptions and calibration methods. Moreover, redispatching the power system as a result of changes in wind generation is unlikely in the short run (Amor et al., 2014). Therefore, a considerable part of the literature is dedicated to using historical generation data to assess the actual impact of wind production on electricity prices. Section 2.2 provides a review of the empirical studies on the impact of wind over electricity prices.

2.2. Empirical Studies

Different econometric approaches have been employed in the literature to evaluate the impact of large scale intermittent wind generation on electricity prices while benefiting from ex-post data. Woo et al. (2011), used ERCOT power market high frequency data to estimate the impact of wind generation on Texas hourly electricity prices through an AR (1) model. Their results indicate that, while dampening the price, wind generation increases the spot price variance. Cutler et al. (2011) (2011) used data analysis techniques to investigate the relationship between wind production and electricity prices in Australia and found a strong inverse relationship. Amor et al. (2014) analyzed the impact of wind on hourly electricity prices in Ontario using panel regression analysis. Their main contribution to the literature is to account for grid congestion and they found that the effect of wind in reducing electricity prices varies between congested and uncongested hours. In an econometric analysis on the impact of wind production on the electricity prices in Ireland, O'Flaherty et al. (2014) found that the growth in wind generation in the U.K did not lead to meaningful changes of electricity prices. In a new approach, Unger et al. (2018), employed a multinomial logit model to estimate the impact of wind energy on electricity prices in the Nord pool market. Their results suggest large price effect as a result of cross-border wind generated electricity flow between Denmark, Norway and Sweden. Finally, in a recent study over the Midcontinent System Operator (MISO) energy market, Quint and Dahlke (2019) used an AR(1) model while including additional variables to control for potential sources of bias in the model.

They estimated the impact of 100 MWh increase in wind production to be a 0.14 to 0.34 USD decline in the spot prices.

Overall, despite employing different approaches, the articles reviewed in sections 2.1 and 2.2 indicate a consensus in the literature on the downward adjustment of the electricity prices as a result of increasing wind production.

Although, the price effect of wind generation has been observed in the aforementioned studies, little attention is paid to the impact of integrating wind power on volatility behavior of electricity prices. Moreover, very few studies (Amor et al., 2014, Woo et al., 2011) have assessed the extent of influence of wind generation over the electricity prices in inter-connected load zones with different wind generating capacities. Given the importance of understanding volatility behavior of electricity prices, this study is dedicated to empirically analyze the price effect of wind generation with a particular focus on electricity price volatility behavior in the presence of intermittent wind generation. Moreover, price effect in different zones with various wind generating capacities is assessed which provides useful insights for policy makers to ensure supply security and financial sustainability of the markets with increasing share of renewables in the generation fuel mix.

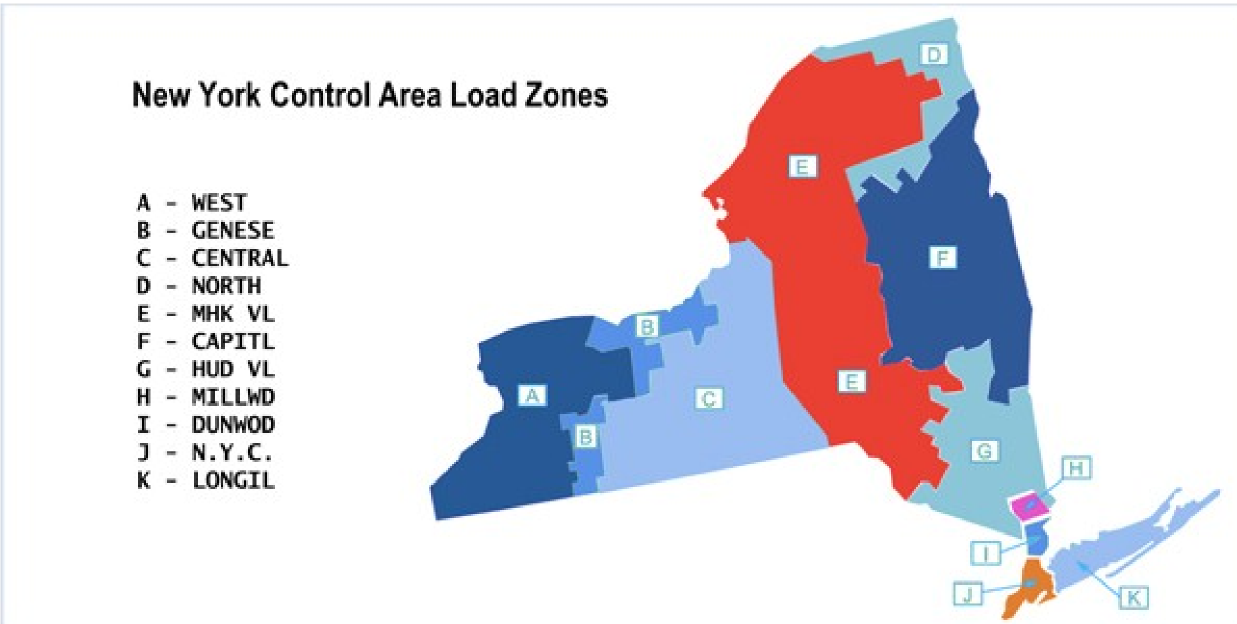
3. Data

This section provides an overview of the data used in the thesis followed by addressing the time series properties of the data.

3.1. Overview of the Data

The state of New York is divided into 11 inter-connected load zones as well as 4 neighboring control areas, namely Hydro Quebec, ISO-New England, Independent Electricity System Operator (IESO) and PJM. The price of electricity for each zone is determined through a day-ahead auction where suppliers are provided with an anticipated electricity demand for the following day. However, real-time auctions are also employed to true up the differences between actual demand and the previous day's forecast. Figure 2, illustrates NY ISO control area load zones.

Figure 2: NY ISO Zone Map



Source: NY ISO

For the purpose of this analysis, we use hourly locational based marginal prices for each specific zone from NY ISO website for the period 1st January 2019 to 31st December 2019. To account for the impact of zonal demand on electricity prices, we obtain hourly load data, which reflects the demand for electricity, for each specific zone from the same website and for the same period. The main challenge in analyzing the impact of wind generation on hourly electricity prices is that NY ISO does not maintain record on hourly wind generation data for each specific zone but only provides hourly aggregate wind generation data within the state of New York. However, to achieve an estimate of the hourly zonal wind generations, we use annual wind generation for each specific zone, published in NY ISO's annual load and capacity report, to allocate each zone its share of wind from the aggregate hourly wind generation. Table 1 shows the annual wind generation and wind generation capability for each zone for the year 2019.

Table 1: Annual Wind Energy Generation (GWh) and Wind Generation Capability (MW) by Zone

Variable	West	Genesee	Central	North	Mohawk Valley	Capital	Hudson Valley	Millwood	Dunwoodie	N.Y.C	Long Island	Total
Annual wind generation	508.8	3.0	1259.0	1444.3	1238.6	0.0	0.0	0.0	0.0	0.0	0.0	4453.6
Percentage share	11.4	0.06	28.27	32.43	27.81	0.0	0.0	0.0	0.0	0.0	0.0	100
Installed Summer Capability	100.5	0.0	518.4	678.4	441.9	0.0	0.0	0.0	0.0	0.0	0.0	1739.2
Installed Winter Capability	100.5	0.0	518.4	678.4	441.9	0.0	0.0	0.0	0.0	0.0	0.0	1739.2
Percentage share	5.7	0.0	29.8	39.00	25.4	0.0	0.0	0.0	0.0	0.0	0.0	100

As shown in the table, out of the 11 zones in NY ISO, only 4 have considerable wind generation. Therefore, we perform two distinct analyses: first we assess the impact of the aggregate wind generation on the average hourly NY ISO electricity prices, second and to assess how the prices in wind producing zones are affected by wind generation, we analyze the impact of wind output of each specific zone on its hourly zonal prices.

Table 2, presents the basic statistics of the data. As shown in the table, the data on hourly electricity prices reveals excess skewness and kurtosis. This result is in line with the observations of Mugele et al. (2005) and Bierbrauer et al. (2007) which according to them can be due to a number of extreme outliers as a result of market anomalies or autocorrelation in the data. We remove the outliers which are defined as values that exceed three times the standard deviation of the original price series (Clewlow and Strickland, 2000). We then replace the outliers in each specific weekday by the median of all prices which have the same weekday and month as the outlier[5]. Moreover, electricity price is highly dependent upon cyclical demand which is largely influenced by economic and business activities and weather conditions. This dependency has made the seasonal component in electricity price more pronounced than any other commodity and several different seasonal patterns are observable in the electricity price series during the course of a day, week and year. Thus, we capture the seasonal behavior in the electricity price series.[6]

[5]In an alternative approach, the value of three times the standard deviation for the respective weekday is used to replace outliers. This does not lead to remarkable changes in the nature of the results or any of the findings of this article.

[6]In Appendix A, we provide a detailed explanation regarding the deseasonalization of electricity price series.

Table 2: Summary Statistics of the Data

Zone	Variables	Min	Mean	Median	Max	SD	Skew	Kurt	Correlation		
									Price	Load	Wind
All	Average Price	-50.74	23.5	21.77	162.57	11.68	1.889	11.998	1	0.457***	-0.006***
	Total Load	12,289	17,787	17,425	30,397	3,203.09	0.814	4.07	0.457***	1	-0.093***
	Wind Output	0.0	500.59	386	1648	412.27	0.786	2.58	-0.006***	-0.093***	1
West	Zonal Price	-22.08	23.55	20.28	616.5	19.18	5.734	17.330	1	0.352***	-0.137***
	Zonal Load	724	1,697	1,683	2,620	227.2	0.462	3.716	0.352***	1	-0.012***
	Wind Output	0	57.07	44.004	187.9	47	0.786	2.578	-0.137***	-0.012***	1
Central	Zonal Price	-126.6	20.64	20.05	106.7	11.11	1.027	12.45	1	0.550***	-0.126***
	Zonal Load	924	1,804	1,783	2,711	279.2	0.263	2.846	0.550***	1	0.071***
	Wind Output	0	141.7	109.23	466.4	116.7	0.786	2.578	-0.126***	0.071***	1
North	Zonal Price	-90.68	18.18	18.11	235	12.62	1.942	23.79	1	0.395***	-0.204***
	Zonal Load	396	550.3	536	774	68.55	0.397	2.789	0.395***	1	0.217***
	Wind Output	0	162.3	125.17	534.4	133.7	0.786	2.578	-0.204***	0.217***	1
Mohawk Valley	Zonal Price	-38.21	20.75	20.08	129.3	11.26	1.426	10.78	1	0.536***	-0.122***
	Zonal Load	741	897.7	887	1,418	164.2	0.134	2.613	0.536***	1	0.138***
	Wind Output	0	139.2	107.34	458.3	114.7	0.786	2.578	-0.122***	0.138***	1

***: indicates 1% significance level. Number of observation for each variable: 8760. Min, Max, SD, Skew, and Kurt are abbreviations for minimum, maximum, standard deviation, skewness, and kurtosis, respectively. All price are in terms of USD and load and wind outputs are in terms of MWh.

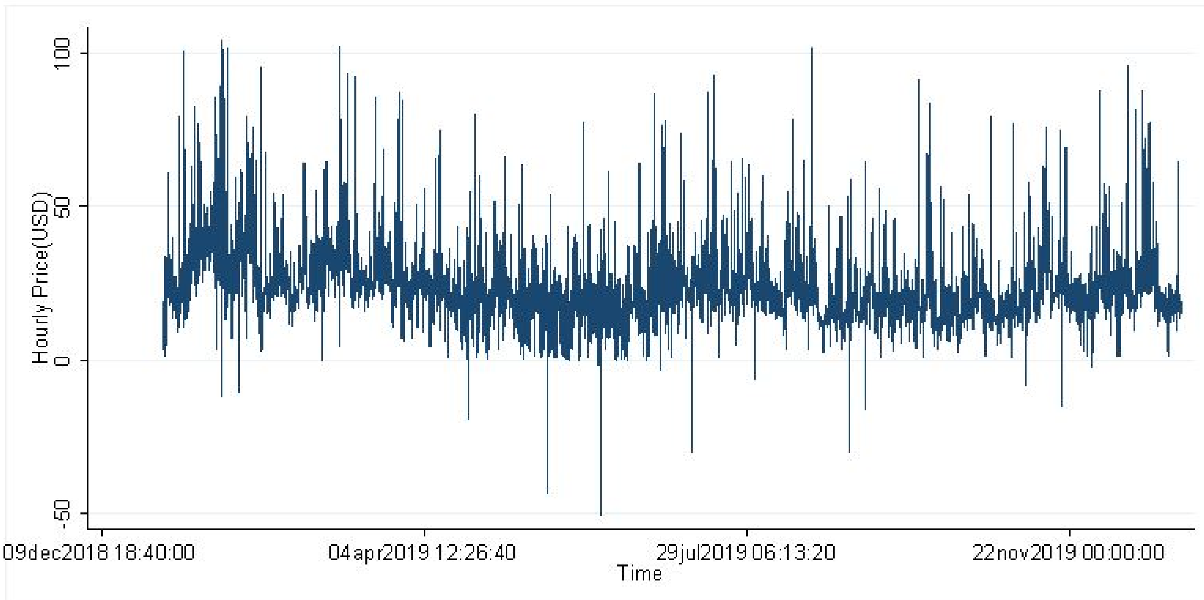
Figure 3 shows the development of average hourly NY ISO prices after outliers have been removed and seasonal trend is subtracted. Given the high skewness of the price series, logarithm transformations of hourly prices are employed as dependent variable to perform the statistical analysis. Moreover, using the logarithm transformation makes interpreting the coefficients more convenient.[7] The main explanatory variable employed in the mean and variance equation of the AR-GARCH model is the hourly wind generation. However, electricity price is indeed affected by the total load and to capture the impact of total load on electricity prices, we also include hourly load as the second explanatory variable.

Another parameter which can explain the impact of wind generation on electricity price behavior is the ratio between wind and load which is defined in the literature as wind penetration (Jónsson et al., 2010). The share of wind is particularly important since the same amount of wind generation will have different impact on prices during periods of high and low demand. Therefore, we perform a second estimate of the model by including the Wind/Load ratio as the main explanatory variable. Detailed explanation of the GARCH

[7]Negative prices, which constitute less than 0.5 percent of the sample, are replaced by the previous hour's value.

model can be found in the methodology section.

Figure 3: Electricity Price Development



3.2. Time Series Properties of the Data

Before proceeding with the data, it is necessary to test for stationarity properties of the electricity price series. Therefore, after removing the outliers and performing the seasonal adjustment, we perform the ADF (Dickey and Fuller, 1979) and Phillips-Perron (Phillips and Perron, 1988) unit-root tests. We also perform a Ljung-Box-Q test[8] to account for serial correlation patterns and an ARCH-LM test on the residuals of an auxiliary OLS regression to control for potential heteroskedasticity in the residuals.

[8]Following Tsay (2010), we choose the optimal value for number of lags (H) in the Ljung-Box-Q test using $H \approx \ln T$, where T is the time series' length.

The results, presented in Table 3, indicate that the null hypothesis of the unit-root tests is rejected with highly significant test statistics which implies that all price series are stationary and thus eliminating the possibility of spurious regressions. The value of the Ljung-Box-Q test statistic indicates the presence of serial correlation. The null hypothesis of no ARCH effect in the residuals is also rejected with highly significant test statistics for all price series, supporting a GARCH modeling approach.

Table 3: Unit-Root and Diagnostic Tests

Price Variables	Average Price	West	Central	North	Mohawk Valley
Unit-Root Test Statistics					
ADF	-49.388***	-56.182***	-53.408***	-53.539***	-52.711***
Phillips-Perron	-56.455***	-63.11***	-60.209***	-58.99***	-59.89***
Diagnostic Tests Statistics					
Ljung-Box-Q	6833.64***	3342.31***	5032.95***	3508.35***	5262.21***
ARCH-LM	685.365***	617.69***	468.616***	321.52***	259.094***

***: indicates 1% significance level.

4. Method

Since the deregulation of power markets, electricity trading has been transformed from a technical business, to one in which the product is treated the same way as any other commodity (Dragana, 1997). However, electricity has unique features that makes it different from any other commodity. Electricity is yet not economically storable, therefore, price is very sensitive to variations in supply and demand: changes in load or generation can lead to large price changes within hours and sometimes minutes. Electricity price can show strong mean reversion which can be explained by cyclical mean reverting nature of demand and the market fundamentals: an increase in demand due to cyclical changes leads to using technologies with higher marginal cost which will in turn push the prices higher. However, once demand returns to normal levels, more expensive conventional power plants such as coal and petroleum will be turned off and prices will decline. Another unique characteristic of electricity price is unusually high volatility which changes across time based on generation, demand and regulatory interferences. Understanding volatility behavior of electricity price is particularly important to price volatility risk in electricity markets.

During the past two decades, a considerable amount of studies emphasized on the fact that unique characteristics of electricity price, namely seasonality, mean reversion and pronounced volatility, should be considered in choosing an empirical price model. To capture these features Huisman and Mahieu (2003) used regime switching models which model price spikes to analyze electricity price dynamics in Germany, Netherlands and the U.S. electricity markets. They concluded that regime switching models perform better in specifying the amount of mean reversion in the electricity price series than classical stochastic jump processes. Zhang and Tan (2013) used Wavelet Transform (wavelets with limited duration), time series prediction using Chaotic Least Squares Support Vector Machine and Exponential GARCH (EGARCH), to forecast the day ahead electricity price for the Spanish market. Chan and Gray (2006) used EGARCH model to account for serial autocorrelation, seasonality and heteroscedasticity of the electricity price series in order to assess the Value at Risk (VaR) in multiple electricity markets. Liu and Shi (2013) examined the effectiveness of ten different models in forecasting day ahead electricity price volatility in California electricity market. They concluded that Autoregressive Moving Average-GARCH-M (ARMA-GARCH-M) model is an effective tool for modeling and forecasting the mean and volatility of electricity prices. In a study on electricity spot prices in the U.S., Nowotarski et al. (2014) provided evidence that Ordinary Least Squares (OLS) and Bayesian Model Averaging (BMA) methods are not suitable for predicting day ahead electricity prices. Ziel et al. (2015) examined the effectiveness of a periodic Vector Autoregressive-Threshold Autoregressive Conditional Heteroscedasticity (VAR-TARCH) model for the hourly electricity price of the European Power Exchange for Germany and Austria. Their results suggest that their model outperforms models with the assumption of homoscedasticity.

Overall, empirical researches suggest that homoscedastic models are not able to capture volatility behavior of electricity price as they assume constant one-period forecast variance which is not realistic in the case of electricity, a commodity with considerable price fluctuations across time.

Although the specific characteristics of electricity price pose a real challenge in choosing an econometric model, GARCH models lend themselves well to properly understand price dynamics as they allow volatility shocks to cluster and persist over time and to revert to normal level (Worthington et al., 2005). Moreover, using a GARCH model allows us to explicitly test the effect of demand and generation variations by including these variables in an extension of the mean and variance equations. Ketterer (2014) used an AR-GARCH model to assess the impact of wind generation and load on day ahead electricity prices in Germany. Similarly, Benhmad and Percebois (2017) employed GARCH model to understand the effect of wind and Photovoltaic feed-in on electricity spot price level in the German power system.

In light of the mentioned studies, we assess the impact of wind generation on New York's hourly electricity prices using an AR-GARCH model. ARCH family models are particularly suitable for the purpose of our analysis as they make it possible to model volatility clustering which is likely to be observed in high frequency data.

Autoregressive Conditional Heteroscedasticity (ARCH) model was first introduced by Engle (1982) in an attempt to describe the temporal evolution of the conditional variance of the variable of interest. The ARCH(q) process is composed of two main equations, a conditional mean equation and a conditional variance equation. Suppose that we denote the variable of interest by Y_t, we can then write the ARCH(q) mean process as:

$$Y_t = E[Y_t|I_t] + \varepsilon_t \quad , \quad \varepsilon_t \sim (0, h_t) \tag{1}$$

Where h_t is the temporal variance of the variable of interest conditional on the past and I_t stands for information available at time t. The key assumption of the ARCH model is that the conditional variance is not constant and can exhibit different behavior across time which is a function of the previous periods error terms. Therefore, the conditional variance of the variable of interest can be explained by the following specification:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{2}$$

Bollerslev (1986) introduced an extension of the ARCH model which allows past conditional variances in the current conditional variance equation. The so called GARCH model provides a better fit for modelling time series data in the presence of heteroscedasticity and volatility clustering. The conditional variance equation for the GARCH(p,q) model is defined as:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{3}$$

In the ARCH/GARCH models, the two equations form a system and should be estimated simultaneously using Maximum Likelihood. In specifying the GARCH system of equations, it is crucial to define the mean process in a way that it can capture the dynamics of the series correctly otherwise a misspecified mean equation will affect the variance equation's explanatory power.

In specifying the mean equation of a GARCH model which is used to capture the behavior of electricity price series, mean reverting characteristic of the electricity price should be taken into account. To capture mean reversion, a classical Vasicek (1977) process has been used in several studies on electricity markets (Schwartz, 1997; Bierbrauer et al., 2007; and Ketterer, 2014). Let X_t represents the log of price after removing the seasonal trend, μ represents a constant and the coefficient of the autoregressive parameter is shown by α. According to Bierbrauer et al. (2007), the Vasicek process for deseasonalized log of electricity price in discrete time can be written as a Gaussian AR (1) process:

$$X_t = C + \phi X_{t-1} + \varepsilon_t \quad , \quad t = 2, 3, .. \quad , \quad \varepsilon_t \sim NID(0, \sigma^2) \tag{4}$$

Where C=$\alpha\mu$ and $\phi = 1 - \alpha$. In this setting, the speed of mean reversion can be found from the coefficient of the autoregressive parameter. Therefore, in order to capture the mean reverting nature of electricity price we specify the mean equation of the AR-GARCH model by including a mean reverting parameter as follows:

$$X_t = \mu + \sum_{i=1}^{l} \phi_i X_{t-i} + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t} Z_t \quad , \quad Z_t \sim NID(0,1) \tag{5}$$

Where X_t is the log hourly electricity price after removing the outliers and the seasonal trend and μ is the mean of electricity price series. The AR-GARCH(q,p) model variance equation will be defined as:

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \quad , \quad \alpha_i, \beta_j > 0 \tag{6}$$

Where h_t is the conditional variance and ω is the long-run variance. The necessary condition for the process to be stationary is that: $\alpha_i + \beta_j < 1$.

An advantage of using the mentioned AR-GARCH model is that it allows to explicitly assess the impact of other influencing factors by including additional explanatory variables in the mean and variance equations. Let W_t denote the log hourly wind generation and L_t represent log hourly load, we can test the impact of hourly wind generation and hourly load on log hourly electricity price by extending the AR-GARCH mean and variance equations as follows:

$$X_t = \mu + \sum_{i=1}^{l} \Phi_i X_{t-i} + \sum_{j=1}^{m} \varphi_j W_{t-j} + \sum_{k=1}^{n} \zeta_k L_{t-k} + \varepsilon_t \tag{7}$$

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{k=1}^{m} \gamma_k W_{t-k} + \sum_{l=1}^{n} \psi_l L_{t-k} \tag{8}$$

It is necessary to contain load data, which reflect the demand for electricity, in order to put the wind data into context since the same amount of wind will have a different impact on prices during the periods of high and low demand. Given that the demand is independent of the wind generation, it can be considered an appropriate choice to avoid endogeneity problems. We estimate Equations 7 and 8 under two different specifications: First, we estimate by including only one autoregressive parameter. Second and to account for serial correlation in the price series, we include different number of lags and choose the one which minimizes the Bayesian Information Criterion (BIC). However, the results show that the coefficients vary only slightly.

5. Results

5.1. Impact of the Aggregate Wind Generation on Average Hourly Electricity Prices

In this section we use the aggregate hourly wind generation and hourly total load as explanatory variables in the mean and variance equations of an AR-GARCH model in order to assess the impact of the mentioned variables on the average hourly electricity prices in New York. Table 4 presents the maximum likelihood estimates of the AR-GARCH model specification by including only one autoregressive parameter. All estimated coefficients are statistically significant, robust standard errors are reported which are all positive and their sum is smaller than 1. The first column of the table shows the baseline AR (1)-GARCH (1,1) specification for the log level of electricity price. The estimated size of the coefficient β (=0.476) indicates the estimated autoregressive persistence of the conditional variance for the examined price series. The GARCH term α (= 0.346), mirrors the effect of previous periods' shocks on the conditional variance which is transmitted through the error term ε_t. Given that $\alpha + \beta < 1$ and α, $\beta > 0$, the model is stationary which implies that the conditional variance is reverting to its conditional mean and the effect of shocks on volatility is transient. Finally, the estimated autoregressive coefficient, $\phi = 0.662$, reflects the mean reversion characteristics of the price series and shows that in the long run, price returns back to its mean. In this setting, 1/1-ϕ reflects the speed of adjustment and the estimated coefficient for ϕ indicates that price reverts back to its equilibrium level within approximately 3 hours, implying a rapid adjustment of prices which is in line with the findings of Woo et al.

(2011) in their study on Texas high frequency data.

In the first column of Table 5, we estimate the same benchmark GARCH specification after including additional autoregressive parameters which minimizes the Bayesian Information Criterion to better capture serial correlation in the data. Estimated size of the coefficient β (=0.610) after including 7 additional lags, shows an increase compared to the specification of the GARCH model with including only one autoregressive parameter which implies that the estimation under the first specification was biased. On the other hand, the GARCH term α shows a decline, which implies that accounting for serial autocorrelation leads to a reduction in the estimated effect of new shocks on conditional variance. The second columns of Tables 4 & 5 reports the result of estimating the GARCH model by including additional explanatory variables, logarithm of wind and logarithm of load, in the mean and variance equation of the GARCH model. In the mean equation, the coefficient for the wind variable is negative and statistically significant which shows that wind generation indeed has an effect on reducing the electricity price. More precisely, a one percent increase in the hourly wind generation reduces hourly electricity prices by approximately 0.012 percent. The coefficient for load variable in the mean equation of the model is positive and statistically significant under both specifications of the model, which implies that an increase in load is associated with a rise in hourly prices. The results imply that the effect of hourly demand on electricity prices is much more pronounced than the effect of wind generation: increasing the load by just one percent leads to an increase of approximately 0.35 percent in hourly prices which implies that load has a greater influence in determining the prices. In the variance equation of the model the coefficient for the variable wind is positive and statistically significant under both specifications, which implies that when intermittent wind generation is fed into the system it causes an increase in the volatility of the electricity prices since the conditional variance of the price shows a 0.12 percent increase for each one percent rise in the wind generation. The coefficient for the variable load in the variance equation of the electricity price is negative and statistically significant under both specifications of the model which implies that an increase in demand decreases the volatility of electricity prices which can be as a result of higher liquidity in the electricity market (Ketterer, 2014). Finally, the third column of the tables is presenting the results of estimating the GARCH model after including the variable Wind/Load which accounts for the share of wind relative to total load. As evident in Tables 4 & 5 the estimated coefficient for the mean equation is negative and statistically significant under both specifications of the GARCH model which implies that increasing the share of wind in the grid mix leads to a decline in electricity prices. More precisely a one percentage point increase in the share of wind reduces the prices between 2.46 percent to 2.65 percent. Here, the estimated coefficient is greater than before because for wind share percentage to rise, wind production needs to increase significantly, which can in turn reduce the prices substantially. The wind share effect is more pronounced in the estimated coefficients for the variance equation of the GARCH model. The estimated coefficient for Wind/Load variable in the variance equations of the both specifications indicates that a strong wind in-feed leads to a substantial increase in price volatility.

5.2. Impact of Wind Generation on Zonal Electricity Prices

In this section, we assess the impact of wind production in each of the four wind producing zones on the hourly prices of the same zone. For this purpose, we introduce hourly wind generation and hourly demand of each zone as additional explanatory variables in the mean and variance equations of the AR-GARCH model. To avoid making the main text of the thesis too long, we only present the most salient results of our econometric analysis for all

Table 4: Results of the AR (1)-GARCH (1,1) Models with Additional Explanatory Variables

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
	Mean Equation		
Constant	3.113***	-0.698**	3.18***
	(0.006)	(0.348)	(0.008)
ϕ_1	0.662***	0.654***	0.654***
	(0.007)	(0.007)	(0.007)
Log(Wind)		-0.012***	
		(0.003)	
Log(Load)		0.397***	
		(0.035)	
Wind/Load			-2.65***
			(0.262)
	Variance Equation		
ω	0.025***	3.993***	-3.73***
	(0.0005)	(0.644)	(0.022)
α	0.346***	0.364***	0.359***
	(0.011)	(0.010)	(0.011)
β	0.476***	0.427***	0.425***
	(0.010)	(0.009)	(0.10)
Log(Wind)		0.128***	
		(0.007)	
Log(Load)		-0.029***	
		(0.644)	
Wind/Load			6.855***
			(0.353)
	Information Criteria		
Wald χ^2	8011.14***	7565.39***	7896.65***
Log Likelihood	-1918.341	-1859.35	-1860.586
AIC	3846.68	3736.707	3735.172
BIC	3882.05	3800.325	3784.689
	Diagnostic Tests		
Ljung-Box-Q^2	0.100	0.051	0.031
	[0.751]	[0.820]	[0.859]
ARCH-LM	0.067	0.083	0.066
	[0.795]	[0.773]	[0.797]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 5: Results of the AR (8)-GARCH (1,1) Model with Additional Explanatory Variables

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
		Mean Equation	
Constant	3.10***	0.289***	3.169***
	(0.011)	(0.352)	(0.0131)
ϕ_1	0.446***	0.445***	0.445***
	(0.012)	(0.012)	(0.012)
ϕ_2	0.155***	0.153***	0.153***
	(0.014)	(0.013)	(0.0139)
ϕ_3	0.067***	0.073***	0.070***
	(0.012)	(0.011)	(0.012)
ϕ_4	0.048	0.052***	0.046***
	(0.011)	(0.011)	(0.011)
ϕ_5	0.024***	0.014	0.015
	(0.010)	(0.009)	(0.009)
ϕ_6	0.004	0.002	0.006
	(0.010)	(0.010)	(0.010)
ϕ_7	0.035	0.030***	0.031***
	(0.009)	(0.008)	(0.008)
ϕ_8	0.023**	0.019**	0.024***
	(0.008)	(0.008)	(0.008)
Log(Wind)		-0.011***	
		(0.004)	
Log(Load)		0.295***	
		(0.355)	
Wind/Load			-2.463***
			(0.303)
		Variance Equation	
ω	0.018***	3.364***	-3.96***
	(0.0005)	(0.638)	(0.028)
α	0.238***	0.277***	0.267***
	(0.008)	(0.009)	(0.008)
β	0.610***	0.534***	0.537***
	(0.009)	(0.010)	(0.010)
Log(Wind)		0.121***	
		(0.007)	
Log(Load)		-0.114***	
		(0.065)	
Wind/Load			6.28***
			(0.363)
		Information Criteria	
Wald χ^2	10065.40***	9641.14***	10061.89***
Log Likelihood	-1675.86	-1638.108	-1682.453
AIC	3375.723	3308.21	3296.69
BIC	3460.612	3421.315	3395.731
		Diagnostic Tests	
Ljung-Box-Q^2	0.213	0.005	0.002
	[0.644]	[0.939]	[0.956]
ARCH-LM	0.057	0.078	0.064
	[0.811]	[0.780]	[0.8000]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

zones in table 6.[9]

Table 6 presents the maximum likelihood estimates of the AR-GARCH model for each of the four wind producing zones. All estimated coefficients are statistically significant, robust standard errors are reported in the parenthesizes which are all positive and their sum is smaller than 1. The estimated coefficients for the GARCH terms, α and β, are positive and their sum is smaller than one for all zones which implies that the estimated models are all stationary. The estimated autoregressive coefficient, ϕ, does not change considerably for zonal prices compared to the case of average prices which suggests that the speed of mean reversion is almost the same for all zones. The coefficient for hourly wind generation variable in the mean equation is negative for all zones and shows an upward adjustment in all cases when compared to the estimation results by using average prices. This is an important observation: zonal prices in wind producing zones tend to be much more influenced by fluctuations in wind productions than the average NY ISO prices. One percent increase in wind production leads to 0.0558 percent decline in zone West prices, 0.0595 percent decline in zone Central prices, 0.0843 percent decline in zone North prices and 0.0673 percent decline in zone Mohawk Valley prices, while, as discussed in the previous section, the drop in average prices for the same rise in wind production is only 0.012 percent.

The coefficient for load variable in the mean equation of the model is positive and statistically significant for all zones and under both specifications of the model which indicates that increasing the load leads to a rise in hourly prices. The estimated coefficients for the variable load are almost in line with the findings in the analysis on average prices. In the variance equation of the model the coefficient for the variable wind is positive for all zones which suggests that when intermittent wind generation is fed into the system it causes an increase in the volatility of the zonal electricity prices. Once again, wind generation shows

[9] The detailed presentation of the regression results is provided in the Appendix B, where we contain all the estimated variables for each specific zone under two different specifications of the model: by including only one autoregressive parameter and by including additional autoregressive parameters which minimizes the BIC and AIC.

Table 6: Results of AR-GARCH Model for Prices in Wind Producing Zones

Variable	Average Price	West	Central	North	Mohawk Valley
Mean Equation when including Log(Wind) and Log(Load) as additional explanatory variables					
Log(Wind)	-0.012***	-0.0558***	-0.0595***	-0.0843***	-0.0673***
	(0.003)	(0.00432)	(0.003)	(0.00431)	(0.00450)
Log(Load)	0.397***	0.197***	0.464***	0.467***	0.358***
	(0.035)	(0.561)	(0.034)	(0.0600)	(0.0409)
Variance Equation when including Log(Wind) and Log(Load) as additional explanatory variables					
Log(Wind)	0.128***	0.252***	0.437***	0.603***	0.430***
	(0.007)	(0.0121)	(0.010)	(0.0103)	(0.00619)
Log(Load)	-0.029***	-0.0925***	-1.703***	-2.726***	-0.762***
	(0.644)	(0.103)	(0.073)	(0.0708)	(0.0469)
Mean Equation when including Wind/Load as additional explanatory variables					
Wind/Load	-2.65***	-4.527***	-2.74***	-0.922***	-1.521***
	(0.262)	(0.242)	(0.262)	(0.0455)	(0.0771)
Variance Equation when including Wind/Load as additional explanatory variables					
Wind/Load	6.855***	9.586***	7.015***	2.484***	3.947***
	(0.353)	(0.400)	(0.141)	(0.0438)	(0.0633)

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses.

more impact over the volatility of zonal prices in wind producing zones compared to the case of average prices. The coefficient for the variable load in the variance equation of AR-GARCH model is negative under both specifications of the model for all zones which implies that an increase in demand decreases the volatility of zonal electricity prices. As expected, the impact of zonal load on the volatility of zonal prices is more pronounced than the effect of total load on average prices.

The second part of the Table 6 presents the results of estimating the AR-GARCH model after including the variable Wind/Load which accounts for the share of wind production in the zone relative to the zonal load. As evident in the table, the estimated coefficient for the mean equation is negative and statistically significant for all zones which implies that increasing the share of wind in the grid mix leads to a decline in zonal electricity prices. However, the estimated coefficient is smaller than the case of average prices since wind production has to increase considerably to rise the Total-Wind/Total-Load ratio while increasing the Zonal-Wind/Zonal-Load ratio is possible with a smaller growth in wind generation, especially because wind producing zones are among the zones with lowest demands within the state of New York. The same pattern is observable in the estimated coefficients for variables Zonal-Wind/Zonal-Load in the variance equation of the model: increasing the share of wind indeed increases the volatility of zonal prices but this effect is weaker than the case of average prices.

5.3. Post-Estimation Tests

To evaluate the fit of the employed models, we perform standard diagnostic tests on the residuals of all the estimated models and the results are presented in the last two rows of each table.

The Ljung-Box-Q^2 test is performed for each model to control the models for remaining linear dependencies in the residuals. The p-values associated with the Ljung-Box-Q^2 test statistics for all the estimated models indicate that the remaining autocorrelation in the residuals is very small, thus non of the estimated models show a lack of fit. The ARCH-LM test is also performed for the squared residuals of all the estimated models, to control for the remaining ARCH effects. The p-values associated with all the ARCH-LM test statistics implies that the null hypothesis of no ARCH effects can not be rejected for any of the estimated models. Therefore, we conclude that the estimated residuals have no remaining ARCH effects. Overall, the tests' results suggest that the specified mean and variance processes fit the data as they successfully capture heteroscedasticity and volatility clustering, identified in section 3.2.

6. Conclusion

The share of wind generation as an environmentally friendly alternative for conventional power plants is growing across the world. Being known as a leading state in the fight against climate change, the state of New York is relying on wind generated electricity to produce 3 percent of its annual electricity production while planning to increase its wind generated electricity production by more than 200 percent by the year 2050. However, the price of electricity is not independent of the intermittent electricity generation by wind power and with the growing share of wind in the electricity generation fuel mix, understanding the extent of its impact over electricity spot prices and on the prices volatility becomes increasingly important. In this research, we analyze this impact in the state of New York, by including hourly wind generation in the mean and variance equation of an AR-GARCH model of electricity prices. The main contribution of this study is to assess the impact of wind generation both on electricity prices and on the prices volatility while comparing this effect on the average state prices with the effect on wind producing zones. The results of our statistical analysis suggest that wind production is associated with a decline in electricity spot prices while increasing their volatility. However, this price effect is not equal across the state: wind generation shows more influence over prices in wind producing zones than the average NY ISO prices. Moreover, the impact of wind over the prices in wind producing zones is proportional to the quantity of their generation: the same percentage of increase in wind production leads to a greater fall in prices in the zones with higher share of wind generated electricity than in zones with lower wind generation.

Our results imply that with the growing share of wind production within the state of New York, the existing market structure might be insufficient to guarantee the financial sustainability of the electricity market. In the presence of persistent low prices as a result of further increase in wind output, electric utilities will face challenges to achieve a full fixed costs recovery. Therefore, an important policy implication of this research is to highlight the need for a structural reform in power markets' design which allows electric utilities to sustain after integrating large amount of renewable generation. Providing such support is particularly important to ensure the financial sustainability of the wind farm owners as the limitations they are facing to dispatch 100 percent of their capacity, prevents them from considerably benefiting from capacity payments.

Moreover, the increased price variance as a result of relying on intermittent wind output implies a rise in price risk which can bring new challenges to policy makers as well as system and market operators. The results of this study suggest that it is necessary for all market participants to rely more on risk management techniques to hedge against these extreme price volatilities. Being aware of the price risk raised from relying on intermittent wind output enables policy makers to arrange better policies to support wind producers and grid operators. Taking steps to hedge against this risk will make the move towards a reliable power grid with zero GHG emissions easier and more economical for all market participants.

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Appendix A Deseasonalization of the Electricity Price Series

We remove the seasonality of the price series by dividing the observed price P_t into a seasonal component S_t and a stochastic part X_t:

$$P_t = X_t + S_t \tag{9}$$

In line with the literature (Nowotarski et al., 2014), we calculate the cyclical component by including dummies for months (M_j), weekdays (D_i), and hours of the day (H_r), in the following function:

$$S_t = C + \sum_{r=1}^{l} \theta_r H_r + \sum_{i=1}^{m} \tau_i D_i + \sum_{j=1}^{n} \nu_j M_j \tag{10}$$

The results are presented in Table 7. The estimated coefficient for hourly dummies shows the daily seasonality of hourly electricity price: price exhibits a seasonal trend across the day which mostly arises from the changes in the end users' demand as well as the grid congestion. The coefficients for weekly dummies are not all statistically significant but overall show that the price reaches its pick on Wednesday while declines from Friday onwards, reaching its minimum on Sunday. The coefficients for monthly dummies are all negative and statistically significant which implies that prices are the highest in January with a considerable decline in May and October. Finally, the seasonal component is subtracted from the original price series to remove the seasonal trend.

Table 7: Seasonal Trends

Variables	Average Price	West	Central	North	Mohawk Valley
H1	-0.953	-1.324	-1.236*	-1.069	-1.177
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H2	-2.352***	-2.079	-1.992***	-1.396*	-2.067***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H3	-2.684***	-3.430**	-2.746***	-2.347***	-2.684***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H4	-3.358***	-3.424**	-3.130***	-2.914***	-3.110***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)

H5	-2.788***	-3.381**	-2.770***	-2.401***	-2.913***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H6	-1.072	-1.066	-0.697	-0.156	-0.503
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H7	1.364*	3.178**	2.295***	2.876***	2.295***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H8	1.935***	4.624***	2.750***	2.760***	2.741***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H9	3.316***	9.686***	3.983***	3.429***	3.838***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H10	3.265***	7.561***	4.283***	4.182***	4.031***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H11	3.792***	9.358***	4.805***	4.004***	4.647***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H12	3.543***	11.10***	4.634***	4.052***	4.420***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H13	4.073***	9.657***	4.416***	3.922***	4.172***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H14	3.832***	9.620***	3.904***	3.466***	3.762***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H15	4.805***	9.368***	4.455***	4.069***	4.314***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H16	4.492***	6.094***	3.853***	3.336***	4.293***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H17	6.595***	8.942***	6.344***	6.001***	6.389***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H18	7.560***	9.562***	7.393***	7.006***	7.904***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H19	7.740***	9.838***	7.762***	7.438***	7.832***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H20	7.845***	9.357***	7.398***	6.837***	7.564***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H21	4.467***	7.253***	4.972***	4.638***	5.106***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H22	2.770***	5.782***	2.774***	2.450***	2.634***
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
H23	0.417	2.204*	1.190*	1.426*	1.216*
	(0.736)	(1.339)	(0.720)	(0.843)	(0.721)
Tue	-0.144	1.120	0.295	0.0632	0.0645
	(0.396)	(0.721)	(0.388)	(0.454)	(0.388)
Wed	0.808**	-0.879	0.0933	0.119	0.227

	(0.398)	(0.725)	(0.390)	(0.456)	(0.390)
Thu	0.202	0.00458	0.0409	-0.0923	0.0861
	(0.398)	(0.725)	(0.390)	(0.457)	(0.390)
Fri	-1.300***	-3.094***	-1.156***	-1.692***	-1.218***
	(0.398)	(0.725)	(0.390)	(0.457)	(0.390)
Sat	-1.537***	-2.452***	-1.200***	-0.419	-0.882**
	(0.398)	(0.725)	(0.390)	(0.457)	(0.390)
Sun	-2.354***	-5.326***	-2.853***	-2.065***	-2.726***
	(0.398)	(0.725)	(0.390)	(0.456)	(0.390)
Feb	-6.858***	-5.969***	-3.204***	-3.604***	-3.747***
	(0.529)	(0.963)	(0.518)	(0.606)	(0.518)
Mar	-5.061***	-3.031***	-0.863*	-1.586***	-1.385***
	(0.516)	(0.939)	(0.505)	(0.591)	(0.505)
Apr	-12.32***	-8.626***	-8.350***	-8.661***	-9.209***
	(0.520)	(0.946)	(0.509)	(0.596)	(0.509)
May	-16.11***	-10.98***	-11.42***	-12.18***	-12.89***
	(0.515)	(0.938)	(0.505)	(0.591)	(0.505)
Jun	-14.99***	-4.981***	-12.63***	-13.52***	-14.00***
	(0.520)	(0.947)	(0.509)	(0.596)	(0.510)
July	-8.634***	-2.530***	-4.988***	-5.114***	-5.678***
	(0.515)	(0.938)	(0.505)	(0.591)	(0.505)
Aug	-13.00***	-9.193***	-8.265***	-8.113***	-8.863***
	(0.516)	(0.939)	(0.505)	(0.591)	(0.505)
Sep	-15.89***	-9.610***	-11.58***	-12.61***	-12.82***
	(0.520)	(0.947)	(0.509)	(0.596)	(0.510)
Oct	-16.50***	-10.73***	-11.95***	-13.77***	-12.91***
	(0.515)	(0.938)	(0.504)	(0.591)	(0.505)
Nov	-10.65***	-6.695***	-7.775***	-10.85***	-9.122***
	(0.520)	(0.947)	(0.509)	(0.596)	(0.510)
Dec	-9.822***	-10.79***	-8.349***	-8.644***	-8.945***
	(0.516)	(0.939)	(0.505)	(0.591)	(0.505)
Constant	32.48***	27.05***	26.09***	24.42***	26.99***
	(0.680)	(1.238)	(0.666)	(0.779)	(0.666)
Observations	8,760	8,760	8,760	8,760	8,760
R-squared	0.268	0.115	0.237	0.189	0.255

*, ** and ***: indicate 10%, 5% and 1% significance levels, respectively. Hour 00:00, Monday and January are used as reference variables.

Appendix B Detailed Presentation of the AR-GARCH Model Results for the Wind Producing Zones

In this appendix, we provide a detailed presentation of the results of our empirical analysis for the wind producing zones. The AR(1)-GARCH(1,1) model is estimated under three different specifications and the results are contained in separate columns. However to account for serial correlation in the price series, we perform a second estimate of all the three models' specifications after including optimal number of autoregressive parameters, to minimize the BIC, in the mean equation. Therefore, two separate tables are dedicated to each zone. The results provide evidence that all the specified processes are stationary as $\alpha + \beta < 1$ for all the models. Moreover, the post-estimation diagnostic tests, reported in the last two rows of each table, support the fact that the specified models do not show a lack of fit as they successfully capture the time series properties of the data.

Table 8: Results of the AR (1)-GARCH (1,1) Models with Additional Explanatory Variables for the Zone West

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
		Mean Equation	
Constant	3.052***	1.792***	3.201***
	(0.0068)	(0.419)	(0.0099)
ϕ_1	0.555***	0.544***	0.537***
	(0.0095)	(0.00892)	(0.0088)
Log(Wind)		-0.0558***	
		(0.00432)	
Log(Load)		0.197***	
		(0.0561)	
Wind/Load			-4.527***
			(0.242)
		Variance Equation	
ω	0.0524**	3.267***	-3.388***
	(0.00089)	(0.753)	(0.0255)
α	0.440***	0.465***	0.465***
	(0.00881)	(0.00913)	(0.00880)
β	0.520***	0.524***	0.524***
	(0.00603)	(0.00552)	(0.00513)
Log(Wind)		0.252***	
		(0.0121)	
Log(Load)		-0.0925 ***	
		(0.103)	
Wind/Load			9.586***
			(0.400)
		Information Criteria	
Wald χ^2	3396.08***	3760.00***	3671.77***
Log Likelihood	-6579.70	-6475.39	-6453.23
AIC	13169.41	12968.78	12920.46
BIC	13204.71	13032.27	12969.88
		Diagnostic Tests	
Ljung-Box-$Q^2(8)$	0.396	0.688	0.64
	[0.528]	[0.406]	[0.421]
ARCH-LM	0.016	0.033	0.040
	[0.899]	[0.856]	[0.842]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 9: Results of the AR (8)-GARCH (1,1) Model with Additional Explanatory Variables for the Zone West

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
	Mean Equation		
Constant	3.053***	2.876***	3.212***
	(0.00963)	(0.437)	(0.0120)
ϕ_1	0.378***	0.375***	0.372***
	(0.0129)	(0.0128)	(0.0127)
ϕ_2	0.175***	0.174***	0.169***
	(0.0123)	(0.0119)	(0.0119)
ϕ_3	0.0421***	0.0399***	0.0410***
	(0.0100)	(0.00999)	(0.00998)
ϕ_4	0.0531***	0.0487***	0.0508***
	(0.00997)	(0.0105)	(0.0110)
ϕ_5	0.00061	-0.00536	0.000147
	(0.00815)	(0.00830)	(0.00862)
ϕ_6	0.0228***	0.0168**	0.0116
	(0.00746)	(0.00771)	(0.00753)
ϕ_7	0.0218***	0.0211***	0.0191**
	(0.00818)	(0.00803)	(0.00831)
ϕ_8	0.00662	0.0117	0.00957*
	(0.00756)	(0.00752)	(0.00761)
Log(Wind)		-0.0520***	
		(0.00486)	
Log(Load)		0.0503***	
		(0.0581)	
Wind/Load			-4.571***
			(0.271)
	Variance Equation		
ω	0.0511***	2.906***	-3.433***
	(0.00091)	(0.747)	(0.0281)
α	0.421***	0.458***	0.437***
	(0.0088)	(0.00968)	(0.00883)
β	0.529***	0.526***	0.542***
	(0.0061)	(0.00602)	(0.00548)
Log(Wind)		0.245***	
		(0.0121)	
Log(Load)		-0.139***	
		(0.101)	
Wind/Load			9.391***
			(0.409)
	Information Criteria		
Wald χ^2	5439.79***	5982.40***	5754.65***
Log Likelihood	-6401.66	-6312.34	-6291.98
AIC	12827.33	12656.68	12611.97
BIC	12912.05	12769.55	12710.8
	Diagnostic Tests		
Ljung-Box-Q^2	0.547	0.953	0.795
	[0.459]	[0.328]	[0.372]
ARCH-LM	0.019	0.037	0.042
	[0.889]	[0.848]	[0.837]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 10: Results of AR (1)-GARCH (1,1) Models with Additional Explanatory Variables for the Zone Central

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
	Mean Equation		
Constant	2.983***	-0.232***	3.16***
	(0.0059)	(0.261)	(0.008)
ϕ_1	0.599***	0.591***	0.599***
	(0.0076)	(0.007)	(0.007)
Log(Wind)		-0.0595***	
		(0.003)	
Log(Load)		0.464***	
		(0.034)	
Wind/Load			-2.74***
			(0.262)
	Variance Equation		
ω	0.0155***	7.164***	-3.723***
	(0.00035)	(0.512)	(0.017)
α	0.190***	0.289***	0.608***
	(0.0055)	(0.0073)	(0.011)
β	0.762***	0.619***	0.207***
	(0.0045)	(0.0043)	(0.008)
Log(Wind)		0.437***	
		(0.010)	
Log(Load)		-1.703***	
		(0.073)	
Wind/Load			7.015***
			(0.141)
	Information Criteria		
Wald χ^2	6081.04***	6070.16***	10136.54***
Log Likelihood	-4427.59	-4154.32	-4057.12
AIC	8865.18	8326.64	8128.24
BIC	8900.518	8390.189	8177.70
	Diagnostic Tests		
Ljung-Box-Q^2	0.365	0.017	0.893
	[0.545]	[0.894]	[0.344]
ARCH-LM	0.005	0.006	0.010
	[0.941]	[0.939]	[0.922]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 11: Results of AR (8)-GARCH (1,1) Model with Additional Explanatory Variables for the Zone Central

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
		Mean Equation	
Constant	2.933***	0.684***	3.145***
	(0.011)	(0.272)	(0.0096)
ϕ_1	0.409***	0.410***	0.402***
	(0.011)	(0.012)	(0.011)
ϕ_2	0.166***	0.155***	0.137***
	(0.013)	(0.013)	(0.013)
ϕ_3	0.0317***	0.0424***	0.0434***
	(0.011)	(0.012)	(0.009)
ϕ_4	0.080***2	0.0669***	0.0524***
	(0.011)	(0.012)	(0.008)
ϕ_5	0.0218***	0.00543	0.00532
	(0.011)	(0.010)	(0.006)
ϕ_6	-0.002	0.007	0.010
	(0.010)	(0.010)	(0.007)
ϕ_7	0.0358***	0.0333***	0.0326***
	(0.011)	(0.009)	(0.008)
ϕ_8	0.0242**	0.0235**	-0.00215
	(0.011)	(0.009)	(0.007)
ϕ_9	0.0455***	0.0352***	0.0624***
	(0.008)	(0.006)	(0.002)
Log(Wind)		-0.0445***	
		(0.004)	
Log(Load)		0.331***	
		(0.036)	
Wind/Load			-2.585***
			(0.111)
		Variance Equation	
ω	0.0144***	8.108***	-3.303***
	(0.0003)	(0.540)	(0.0199)
α	0.184***	0.271***	0.642***
	(0.005)	(0.007)	(0.0132)
β	0.768***	0.640***	0.215***
	(0.004)	(0.004)	(0.009)
Log(Wind)		0.434***	
		(0.011)	
Log(Load)		-1.842***	
		(0.0773)	
Wind/Load			6.788***
			(0.145)
		Information Criteria	
Wald χ^2	8965.19***	9220***	16543.61***
Log Likelihood	-4181.12	-3954.22	-3871.89
AIC	8388.241	7942.45	7773.79
BIC	8480.10	8062.49	7879.79
		Diagnostic Tests	
Ljung-Box-Q^2	0.062	0.020	1.48
	[0.802]	[0.887]	[0.232]
ARCH-LM	0.005	0.007	0.009
	[0.941]	[0.933]	[0.924]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 12: Results of AR (1)-GARCH (1,1) Models with Additional Explanatory Variables for the Zone North

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
	Mean Equation		
Constant	2.829***	0.296	3.089***
	(0.00984)	(0.374)	(0.0108)
ϕ_1	0.698***	0.659***	0.631***
	(0.00910)	(0.00939)	(0.00902)
Log(Wind)		-0.0843***	
		(0.00431)	
Log(Load)		0.467***	
		(0.0600)	
Wind/Load			-0.922***
			(0.0455)
	Variance Equation		
ω	0.0476***	11.36***	-3.328***
	(0.0007)	(0.415)	(0.0147)
α	0.505***	0.513***	0.517***
	(0.013)	(0.0119)	(0.0149)
β	0.494***	0.457***	0.322***
	(0.006)	(0.00481)	(0.00598)
Log(Wind)		0.603***	
		(0.0103)	
Log(Load)		-2.726***	
		(0.0708)	
Wind/Load			2.484***
			(0.0438)
	Information Criteria		
Wald χ^2	5874.00***	5037.00***	4963.00***
Log Likelihood	-5504.32	-5074.00	-4968.00
AIC	11019.00	10167.00	9950.00
BIC	11054.00	10230.00	9999.00
	Diagnostic Tests		
Ljung-Box-Q^2	0.159	0.346	0.304
	[0.689]	[0.556]	[0.581]
ARCH-LM	0.028	0.054	0.012
	[0.867]	[0.815]	[0.911]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 13: Results of AR (8)-GARCH (1,1) Model with Additional Explanatory Variables for the zone North

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
		Mean Equation	
Constant	2.339***	-0.104	3.072***
	(0.0241)	(0.444)	(0.0138)
ϕ_1	0.510***	0.477***	0.460***
	(0.010)	(0.011)	(0.012)
ϕ_2	0.156***	0.133***	0.121***
	(0.014)	(0.013)	(0.014)
ϕ_3	0.0700***	0.0636***	0.0561***
	(0.010)	(0.010)	(0.010)
ϕ_4	0.0626***	0.0429***	0.0483***
	(0.010)	(0.009)	(0.008)
ϕ_5	0.0207**	0.0102	0.00493
	(0.009)	(0.009)	(0.008)
ϕ_6	0.0326***	0.0246***	0.0174**
	(0.008)	(0.006)	(0.007)
ϕ_7	0.0464***	0.0324***	0.0306***
	(0.007)	(0.008)	(0.008)
ϕ_8	0.0498***	0.0182**	0.00975
	(0.006)	(0.007)	(0.008)
Log(Wind)		-0.0569***	
		(0.004)	
Log(Load)		0.506***	
		(0.070)	
Wind/Load			-0.914***
			(0.0481)
		Variance Equation	
ω	0.0348***	12.07***	-3.340***
	(0.0008)	(0.416)	(0.0149)
α	0.382***	0.469***	0.495***
	(0.012)	(0.011)	(0.014)
β	0.594***	0.479***	0.329***
	(0.006)	(0.004)	(0.006)
Log(Wind)		0.586***	
		(0.010)	
Log(Load)		-2.832***	
		(0.070)	
Wind/Load			2.465***
			(0.0406)
		Information Criteria	
Wald χ^2	32653***	5977.00***	5647.00***
Log Likelihood	-5300.00	-4931.00	-4837.00
AIC	10624.00	9893.00	9702.00
BIC	10708.00	10006.00	9800.00
		Diagnostic Tests	
Ljung-Box-$Q^2(8)$	0.221	0.838	0.679
	[0.637]	[0.359]	[0.409]
ARCH-LM	0.022	0.063	0.012
	[0.882]	[0.801]	[0.912]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 14: Results of AR (1)-GARCH (1,1) Models with Additional Explanatory Variables for the Zone Mohawk Valley

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
		Mean Equation	
Constant	2.984***	0.841**	3.177***
	(0.006)	(0.276)	(0.009)
ϕ_1	0.620***	0.635***	0.617***
	(0.007)	(0.009)	(0.007)
Log(Wind)		-0.0673***	
		(0.00450)	
Log(Load)		0.358***	
		(0.0409)	
Wind/Load			-1.521***
			(0.0771)
		Variance Equation	
ω	0.0169***	0.213***	-3.476***
	(0.0003)	(0.302)	(0.0143)
α	0.190***	0.363***	0.434***
	(0.011)	(0.010)	(0.011)
β	0.763***	0.468***	0.362***
	(0.003)	(0.007)	(0.006)
Log(Wind)		0.430***	
		(0.00619)	
Log(Load)		-0.762***	
		(0.0469)	
Wind/Load			3.947***
			(0.0633)
		Information Criteria	
Wald χ^2	6581.733***	5058.7929***	6705.4919***
Log Likelihood	-4567.978	-4285.1123	-4121.552
AIC	9145.9561	8588.2247	8257.1039
BIC	9181.2873	8651.7708	8306.5652
		Diagnostic Tests	
Ljung-Box-Q^2	0.148	0.029	0.131
	[0.700]	[0.863]	[0.716]
ARCH-LM	0.005	0.004	0.005
	[0.941]	[0.948]	[0.943]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Table 15: Results of AR (10)-GARCH (1,1) Model with Additional Explanatory Variables for the Zone Mohawk Valley

Type	AR-GARCH	AR-X-GARCH-X	AR-X-GARCH-X
	Mean Equation		
Constant	2.889***	1.499***	3.159***
	(0.0177)	(0.269)	(0.0105)
ϕ_1	0.420***	0.433***	0.429***
	(0.009)	(0.010)	(0.009)
ϕ_2	0.178***	0.153***	0.122***
	(0.011)	(0.012)	(0.011)
ϕ_3	0.044***	0.059***	0.069***
	(0.009)	(0.011)	(0.009)
ϕ_4	0.0752***	0.0552***	0.0602***
	(0.008)	(0.012)	(0.011)
ϕ_5	0.0151	-0.0118	0.0227**
	(0.011)	(0.010)	(0.009)
ϕ_6	-0.0145	-0.0199*	-0.0243***
	(0.012)	(0.010)	(0.009)
ϕ_7	0.0177	0.0414***	0.0445***
	(0.012)	(0.008)	(0.009)
ϕ_8	0.0198*	0.0257***	0.0227**
	(0.010)	(0.009)	(0.009)
ϕ_9	0.0297***	0.0184**	0.00884
	(0.009)	(0.007)	(0.006)
$\phi_1 0$	0.0814**	0.0656***	0.0654***
	(0.008)	(0.006)	(0.006)
Log(Wind)		-0.0470***	
		(0.005)	
Log(Load)		0.247***	
		(0.0391)	
Wind/Load			-1.408***
			(0.0663)
	Variance Equation		
ω	0.0173***	1.852***	-3.571***
	(0.00004)	(0.320)	(0.0179)
α	0.204***	0.318***	0.432***
	(0.005)	(0.009)	(0.012)
β	0.745***	0.541***	0.388***
	(0.004)	(0.008)	(0.007)
Log(Wind)		0.412***	
		(0.007)	
Log(Load)		-1.027***	
		(0.0493)	
Wind/Load			3.829***
			(0.0653)
	Information Criteria		
Wald χ^2	7134.16***	6650.54***	10256.69***
Log Likelihood	-4274.888	-4063.32	-3914.26
AIC	8577.777	8162.65	7860.53
BIC	8676.704	8289.75	7973.58
	Diagnostic Tests		
Ljung-Box-Q^2	0.003	0.144	0.366
	[0.953]	[0.703]	[0.544]
ARCH-LM	0.004	0.004	0.005
	[0.947]	[0.950]	[0.943]

***, ** and *: indicate 1%, 5% and 10% significance levels, respectively. Robust standard errors of estimates are reported in parentheses. The p-values associated with the statistical tests are presented in brackets.

Appendix C List of Abbreviations and Acronyms

AIC	Akaike information criterion
ARCG	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
BIC	Bayesian Information Criterion
BMA	Bayesian Model Averaging
CLCPA	Climate Leadership and Community Protection Act
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
IESO	Independent Electricity System Operator
ISO NE	Independent System Operator of New England
MISO	Midcontinent System Operator
NY ISO	New York Independent System Operator
OLS	Ordinary Least Squares
REV	Reforming the Energy Vision
RGGI	Regional Greenhouse Gas Initiative
RPS	Renewable Portfolio Standard
U.K	United Kingdom
U.S	United States
VAR-TARCH	Vector Autoregressive-Threshold Autoregressive Conditional heteroscedasticity
VaR	Value at Risk