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Three Essays on “Energy , Environment, and Developmental Economics”

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Three Essays on "Energy , Environment, and Developmental Economics"

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ABSTRACT

THREE ESSAYS ON "ENERGY , ENVIRONMENT, AND DEVELOPMENTAL ECONOMICS"

Bolarinwa Ajanaku

This dissertation examines topics related to renewable energy development and investment planning, energy markets, environment degradation and economic development. The substantial ecological costs of deforestation are well known and considered globally important due to biodiversity loss, land degradation, soil erosion, and contributions to climate change. The first essay focuses upon understanding the tradeoff between development and deforestation in Africa. In the second essay, spatial analysis and Geographic Information System (GIS) are applied to determine potential locations for wind farms development in the state of West Virginia. Lastly, the third essay examines the role of wind power penetration on wholesale electricity market.

The first essay explores the relationship between economic growth and deforestation in African countries. During the past half-century, the continent of Africa has suffered massive losses of forested areas due to the changing structure of economies, increasing population, and expanding globalization. This research examines statistical evidence for the Environmental Kuznets Curve (EKC) hypothesis as applied to deforestation occurring within Africa from 1990 to 2016. Changes in forest cover data are explained with Generalized Method of Moments (GMM) estimators to overcome the endogeneity problems arising from reverse causality between deforestation and explanatory variables. The empirical results of a panel GMM confirm the EKC hypothesis is valid for deforestation in Africa with a turning point estimated to be US $3,000. Heterogenous panel non-causality findings suggest that Africa could deter and reverse deforestation through appropriate land-use and forest products trade policies, and the consequences of these policies would not impact their economic growth.

In the second essay, a multi-criteria decision analysis employing Analytic Hierarchy Process (AHP) and GIS are used for assessment of potential sites for future utility-scale wind farms in West Virginia. Worldwide, demand is increasing for renewable energy. While wind power is a proven, sustainable energy source, siting can be challenging. Identifying potential sites for wind turbines is a significant step in renewable energy resource planning. Wind turbine site suitability is primarily dependent upon wind speed at a location along with other environmental, social, and economic factors. It is critical to arrive at a robust wind farm decision to improve public acceptance, preserve the environment, and maintain pristine habitats. This research builds upon previous studies and contributes to the literature by incorporating two important components into siting: (1) inclusion of critical wildlife habitat for birds and bats as an elimination criterion within the AHP, and (2) the participation by wind power experts in the AHP decision-making process. By incorporating expert opinions with the weighing of ten siting factors, about 70,000 hectares of land are identified as 'highly suitable' for wind power development throughout the state of West Virginia. This area represents the potential to yield an estimated 29,000 MW of future utility-scale wind power capacity, which is larger than the current coal dominated electricity generation capacity in West Virginia.

The third essay examines the wind power penetration impacts on wholesale electricity markets. Using data from two wholesale electricity markets (Pennsylvania – New Jersey – Maryland (PJM) and Electric Reliability Council of Texas (ERCOT)), four energy policy questions are addressed: (1) How much does wind power integration impact wholesale electricity prices under different markets? (2) Does the merit-order effect (MOE) exist at different quantiles of wholesale electricity prices? (3) What drives the day-ahead market (DAM) and real-time market (RTM) prices at different market conditions in both markets? (4) Does the increasing penetration of wind power undermine its market value along with the market values of other generating technologies? To answer these questions, quantile regression is used to obtain coefficient estimates that indicate wind penetration has unequal impacts on wholesale electricity prices and market values across quantiles, reinforcing the need for this type of analysis. The empirical analyses confirmed the existence of the merit-order effect across different quantiles of the conditional distribution of wholesale prices for both DAM and RTM, implying that the increasing deployment of wind power for electricity generation significantly suppresses the wholesale electricity prices in the PJM market. Contrary to the PJM estimations, merit-order effects are confirmed across quantiles of wholesale prices for only the DAM in the ERCOT market. Furthermore, the findings show that as wind generation expands within the market, the revenue earned by wind power producers reduces across all quantiles of the conditional distribution of its unit revenue. Specifically, each additional GWh increase in electricity from wind is associated with a fall in its unit revenues across quantiles by an amount that ranges from approximately $0.01/MWh to $0.06/MWh. Results also confirm cross-cannibalization impacts such that each additional GWh increase from wind is associated with decreased gas and baseload unit revenues across all quantiles ranging from $0.02/MWh to $0.06/MWh. Contrary to unit revenue results, there is weak evidence of increasing wind supply's cannibalization effect for value factor as positive impacts occur below the 90% quantile and negative impacts occur at quantiles 90% and greater. The negative impacts of wind power on gas and baseload generators demonstrate the need for corrective policies.

DEDICATION

I would like to dedicate my dissertation to my family: my wife, my handsome children, prince Alexander Adekunle Ajanaku, prince Samuel Adedamola Ajanaku, and prince Emmanuel Adetokunbo Ajanaku.

I would also like to dedicate my research to my parents: my grandmother Mrs. Alice Jolayemi Kayewumi, my mother Mrs. Esther Apeke Ajanaku, and my father, late Alhaji Fatai Alawiye Ajanaku.

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CHAPTER 1

Background and Significance

The quest for worldwide economic growth has negative impacts on the environment. It has become progressively clear that global human activity, particularly deforestation, has considerable impacts on the natural environment which, if unregulated, could have severe impacts on human well-being and sustainable development (IPCC, 2014; Lucas and Wilting, 2018; Robert and Zakri, 2005). Deforestation is a significant environmental problem contributing to biodiversity loss, land degradation, desertification, flooding, soil erosion, and climate change (Bhattarai and Hammig, 2001; Chiu, 2012; Durán et al., 2011; Murtazashvili et al., 2019). Meanwhile, as more impacts are observed from climate changes globally, demand increases for renewable energy (Baseer et al., 2017; Latinopoulos and Kechagia, 2015; San Cristóbal, 2011). Expanding renewable power generation is vital for mitigating greenhouse gas emissions and promoting environmental sustainability (Mekonnen and Gorsevski, 2015). However, the rapidly increasing integration of renewable power into the electricity grid poses fundamental concerns about the potential impacts of this transition on the current electricity system. In this dissertation, topics related to renewable energy development and investment planning, energy markets, environmental degradation, and economic development are examined in light of these concerns and growing literature.

1.1. Purpose of this study

This research aims to empirically clarify the impact of economic growth on environmental quality, to create a spatial analysis framework for utility-scale wind farms development, and to gain a better understanding of the role of wind energy penetration on the wholesale electricity market. This research is composed of three essays.

1.1.1. Aim of Essay 1: Examines statistical evidence for the Environmental Kuznets Curve (EKC) hypothesis as applied to deforestation occurring within Africa

The first essay seeks to establish statistical evidence for the EKC hypothesis applied to deforestation occurring within the Africa continent from 1990 to 2016. This study attempts to address the following question: is it feasible to reduce deforestation among Africa countries while simultaneously developing an economy? To this end, the study examines effects on deforestation emerging from changes in GDP per capita along with control variables that reflect rural efficiency, agricultural productivity, population density, the real gross domestic products, political liberty, trade of forest products, and bioenergy.

1.1.2. Aim of Essay 2: Create a spatial model using multiple-criteria decision-making for utility-scale wind farms in West Virginia, employing an analytic hierarchy process

Globally, demand is increasing for renewable energy. While wind power is a proven, sustainable energy source, siting can be challenging. The identification of potential wind turbine sites is a significant step in renewable energy resource planning. Wind turbine site suitability depends upon numerous factors, including location wind speed, environmental, social, and economic factors. Appropriate siting is critical to improve public acceptance of wind farms, preserve the environment, and maintain pristine habitats. This study demonstrates a modeling approach that incorporates expert opinions of siting criteria in determining potential locations for wind farms in the state of West Virginia. The research involved a two-stage holistic approach of: (1) a multi-criteria decision analysis – Analytic Hierarchy Process (AHP), and (2) Geographic Information System (GIS) assessment of sites. As a note to the reader, there is a difference in the format of this essay (figures and tables are located at the end of the essay rather than embedded in the text) compared to the other two essays due to GeoJournal publishing format requirements.

1.1.3. Aim of essay 3: Examine the wind power penetration impacts on the wholesale electricity market

The motivation of this third essay is to gain a better understanding of and empirically clarify the role of wind generation on wholesale electricity market outcomes at different quantiles of the conditional distribution of revenues and prices in this market.

The specific objectives for this essay are listed as follows:

1. To examine the impacts of increasing wind power deployment on wholesale electricity prices across different price distribution quantiles.
2. To investigate the potential existence of the merit-order effect in the Pennsylvania – New Jersey – Maryland (PJM) market (with relatively low wind energy penetration) versus the Electric Reliability Council of Texas (ERCOT) market (with a relatively high percentage of wind power penetration, for contrast) concurrently.
3. To quantify the effects of wind generation on the market values of baseload and non-baseload sources across the entire distribution of wholesale electricity market outcomes.

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CHAPTER 2

Essay 1: Economic Growth and Deforestation in African Countries: Is the Environmental Kuznets Curve Hypothesis Applicable?

2.1. Introduction

According to the Millennium Ecosystem Assessment (Robert and Zakri, 2005), environmental quality and natural resource stocks are critical segments of wellbeing for the developing nations. However, these resources are being degraded at a disturbing rate (FAO, 2016). It has become progressively clear that global human activity, particularly, deforestation, has considerable impact on the natural environment which, if unregulated, could have a serious impact on human well-being and sustainable development (IPCC, 2014; Lucas and Wilting, 2018; Robert and Zakri, 2005). Deforestation is a significant environmental problem contributing to biodiversity loss, land degradation, desertification, flooding, soil erosion, and climate change (Bhattarai and Hammig, 2001; Chiu, 2012; Durán et al., 2011; Murtazashvili et al., 2019). Another critical problem of deforestation includes degradation of water quality from increase sedimentation. More specifically, destruction of essential ecosystem services within the forest may affect human safety and health (Lucas and Wilting, 2018; Robert and Zakri, 2005). Culas (2007) notes that deforestation affects the economic activities of a country, both its cultural integrity and livelihood. Deforestation determinants at the international level have been extensively investigated in the economic literature (e.g., Barbier, E. B., Burgess, 2001; Barbier, 2004; Culas, 2009, 2007; Damette and Delacote, 2012; Ferretti-Gallon and Busch, 2014; Geist and Lambin, 2002; Li et al., 2017b; López and Galinato, 2005; Murtazashvili et al., 2019; Wang and Qiu, 2017).

Deforestation is highly prominent among low-income tropical countries owing to the level of poverty, population explosion, and a high level of indebtedness (Culas, 2007). Poverty calls for overdependence on forest and agricultural products, while overpopulation, which is equally associated with many developing nations, puts extra pressure on the forests. These increase in the demand for farming activities and forest products is orchestrated by the need for economic growth and expansion of income (Tsurumi and Managi, 2014). As an example, the continent of Africa has suffered massive losses of forested areas during the past half-century due to exceptional economic changes and uncontrolled globalization (Chiu, 2012; Li et al., 2017a; Scrieciu, 2007). The Food and Agricultural Organization (FAO, 2015, 2010) reports that more than 150 million hectares of land were deforested worldwide between 1990 and 2010. The continent of Africa suffered the highest forest loss during this period (FAO, 2015). Globally, forests serve as carbon dioxide sink – the sequestered carbon is accumulated in live woody plant tissues and gradually decaying organic matter in litter and soil (Bhattarai and Hammig, 2001; Lubowski et al., 2006; Luyssaert et al., 2008; Zhou et al., 2006). Deforestation discharges carbon dioxide into the air, which adds to environmental change all over the world (Nepstad, 2007). Locally, forests provide ecosystem services such as protection from flooding and managing temperature and rainfall (Culas, 2007; Ehrhardt-Martinez, 1998; Shandra, 2007).

The degree to which the economic activities of a country affect its environment constitutes to its ecological footprint (EF). A study conducted by Uddin, Alam, and Gow (Uddin et al., 2016) showed that a country's Gross Domestic Product (GDP) is directly dependent on its EF because resources must be extracted from the environment for a country to develop. However, as countries develop, citizen's desire for and ability to sacrifice for an improved environment expands. As a result, different features of the environment have been evaluated to examine the validity of the Environmental Kuznets Curve (EKC) hypothesis. The EKC is a hypothesized relationship between the quality of the environment and national economic growth (Grossman and Krueger, 1995). The EKC hypothesis states that at the initial phase of economic development, environmental deterioration expands as per capita income rises. After a specific level of income (called a defining moment), however, environmental degradation starts to diminish as development advances (Grossman and Krueger, 1991, 1995).

In this research, I seek to establish statistical evidence for the EKC hypothesis as applied to deforestation occurring within the Africa continent from 1990 to 2016. This study attempts to address the following question: is it feasible to reduce deforestation among Africa countries while simultaneously developing an economy? To this end, I examine effects on deforestation emerging from changes GDP per capita along with control variables that reflect rural efficiency, agricultural productivity, population density, the real gross domestic products, political liberty, trade of forest products, and bioenergy. Variables are included to reflect the powerful influence and interactions among economic structure, institutional changes, and demographic components across countries in this region. Also, I include biomass use as a variable that potentially contributes to increases in deforestation rates in developing countries.

The reasons for and contributions of this investigation are as follows. To begin with, although several studies have tested the EKC hypothesis in Africa (see Bhattarai, M., Hammig, 2004; Bhattarai and Hammig, 2001; Chiu, 2012; Culas, 2007; Scrieciu, 2007), all of the previous studies are either conducted on few nations in Africa or particular period considering specific variables, but the current study is conducted on panel data of most extensive and the most extended data span available (1990 – 2016 and 45 countries). Secondly, the vast majority of the previous studies on an EKC for deforestation have utilized regression approaches such as regular panel OLS or Within estimator (random or fixed effects models) that often have heteroskedasticity and autocorrelation, potentially leading to wrong inference, ambiguous conclusions and unsuitable theoretical interpretations. To resolve this unaccounted phenomenon, I used a dynamic panel GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). The GMM estimator permits us to manipulate the time-series dynamics and the country-specific characteristics of the data while controlling for a different kind of endogeneity and omitted variable bias.

Thirdly, most of the existing EKC studies in Africa do not include testing for cross-sectional dependence in their variables. The problem of cross-sectional dependence may arise in panel data analysis because of the presence of common shocks and surreptitiously factors that influence the error term leading to spurious regression results (De Hoyos and Sarafidis, 2006; Edward and Štefan, 2009; Pesaran, 2006). To resolve this weakness, I assessed for the presence cross-sectional dependency the panel data using the Pesaran's CD (Cross-section Dependence) test (Pesaran, 2004, 2020). Besides, traditional unit root testings are not effective when utilized on the data series that has a cross-sectional dependence because of their lower power (Paramati et al., 2016). Thus, this study has also considered the cross-sectional dependency by using the second-generation panel unit root test, CIPS (Cross-sectional augmented IPS)(Pesaran, 2007). Finally, we performed heterogeneous panel causality tests to determine short-run dynamic panel causality among data series.

This research findings confirm the EKC hypothesis in Africa. The empirical results using GMM show an inverted U-shaped EKC relationship between GDP per capita and deforestation rate. This result validates that deforestation rate increases with economic development, reaches a defining moment, and begins to decline with advanced levels of economic progress. The turning point is estimated to be US $3, 000. This value, however, is significantly higher than the present estimation of GDP per capita for several of the African nations used in the model. Specifically, 51% of the countries used in the study fall below this turning point. This result indicates that significant forest loss may happen in these countries before the turning point is achieved. This is, however, similar in magnitude to research work by Bhattarai and Hammig (2001), who examines the effects of institutional quality and environmental policies on the EKC relationship for deforestation in Africa, Latin America, and Asian nations (which is based on different methodology). A significant feature of the approach I develop is that it takes into account and solve the problem of the issues of unobserved heterogeneity, simultaneity, and dynamic endogeneity.

In succeeding sections, this paper provides a brief discussion on related literature and empirical studies on deforestation and the EKC hypothesis. This literature review is followed by a section on model specification and data. The final two sections cover empirical results and the conclusion.

2.2. Literature review

The patterns of deforestation in Africa is among the most important environmental problems within the developing world. Just like tropical deforestation around the globe, forest areas loss in countries across Africa is driven by several factors, including population growth, timber harvesting, and agricultural production. To uncover the principal influences behind deforestation, different economic models have examined the extent and site of deforestation as an object of various factors that specify the logics of agent choices regarding the sharing of land among competitive purposes (Angelsen and Kaimowitz, 1999).

The EKC idea unfolded in the early 1990s with a Grossman and Krueger (1991) study on the environmental impacts of the North American Free Trade Agreement. Later, Shafik and Bandyopadhyay (1992) and Panayotou (1993) presented the term "Environmental Kuznets Curve" in the economic literature. Since then, the validity of the EKC hypothesis has been extensively investigated by different researchers over the years (examples include, Bhattarai and Hammig, 2001; Dinda, 2004; Stern, 2004). EKC was viewed to be among the explanations for portraying the connection between per capita income and the measured levels of ecological indicators (Mehmet and Gülden, 2016).

Applying the EKC theory to analyze net deforestation suggests that toward the beginning periods of economic progress, the increasing rate of net deforestation can rise as economies develop. However, eventually, forested areas can increase as the level of economic development grows. The EKC theory for net deforestation offers warnings regarding the environmental effects of past and present economic improvement directions undertaken by developing countries. Studies of the EKC on deforestation include Cropper and Griffiths (1994), Koop and Tole (1999), Nguyen Van and Azomahou (2007), Bhattarai and Hammig (2001), Bhattarai, M., Hammig (2004), and Culas (2007), Wang et al. (2007), Mbatu (2015), Joshi and Beck (2017), Caravaggio (2020). Most of the empirical results reveal the existence of the EKC; however, analytical backing is not the same across all indices of ecological quality. The results are mixed based on the type of ecological indicator chosen, country or group of countries selected, other explanatory variables used in the study, and the selected period of the investigation (see Barbier, 2004; Bhattarai and Hammig, 2001; Chiu, 2012; Culas, 2007).

Table 2.1 presents a summary of previous empirical studies that have used econometric methods to evaluate EKC and analyze the microeconomic determinants of deforestation (For detailed litearture review on EKC for deforestation, see (Caravaggio, 2020)) . The majority of the studies introduced in Table 2.1 used time-periods before the 2000s. Exceptions include Jorgenson (2008), Motel et al. (2009), Chiu (2012), Li et al. (2017), Leblois et al. (2017), and Cary and Bekun (2021). This literature review shows that over half of the Table 2.1 studies have provided statistical evidence for the EKC trajectories for deforestation. Various studies have established a turning point in EKC from which deforestation starts to decrease; hence, confirming the EKC hypothesis. For example, Bhattarai and Hammig (2001) utilized a combination of RE and Fixed Effects (FE) models to analyze the data from thirty-one African countries and established that the per capita income at the turning points from where deforestation started to decrease, and increase were US$1,300 and US$5,000 respectively. Chiu (2012) found that deforestation declines at an income level of US$3,021 for fifty-two developing countries between 1972 and 2003.

Some of the studies that argue that the EKC hypothesis exists have suggested that deforestation rates can be reduced by enhanced educational attainment in collaboration with agricultural technology improvement (e.g.,Bhattarai, M., Hammig, 2004). Bhattarai and Hammig (2004) conclude that the governance quality and improved educational system are crucial determinants of the conservation of forest resources. On the other hand, other studies have established that the EKC hypothesis does not exist (e.g.,Barbier, 2004; Koop and Tole, 1999) Nevertheless, it should be noted that the developing countries in which the per capita income is at the initial stages of EKC, whereby deforestation increases alongside the increase in per capita income, has not been receiving adequate attention. Thus, there are still research needs involving the examination of significant factors contributing to the rate of net deforestation in emerging and developing countries.

Table 2.1. Summary of the empirical literature regarding EKC relationship on deforestation

Author (s)	Data (dependent variable)	Model	Period(s)	Findings
Shafik and Bandyopadhyay (1992)	Annual & total deforestation (WB)	FE	1961-1988	No EKC
Panayotou (1993)	Forest cover change (WRI)	OLS	Late 1980s	EKC
Cropper and Griffiths (1994)	Deforestation rate-FAO	FE	1961-1991	EKC for Africa and Latin America. No EKC for Asia
Rudel and Roper (1997)	Deforestation rate-FAO	OLS	1975-1990	EKC
Barbier and Burgess (2001)	Deforestation rate-FAO	OLS, FE and RE	1961-1994	EKC for all countries, Latin America, and Asia. No EKC for Africa
Bhattarai and Hamming (2001)	Deforestation rate-FAO	FGLS	1972-1991	EKC for Africa and Latin America. No EKC for Asia
Ehrhard-Martinez et al. (2002)	Deforestation rate-FAO	OLS	1980-1995	EKC
Bhattarai and Hamming (2004)	Deforestation rate-FAO	FE	1980-1995	EKC
Ferrira (2004)	Deforestation rate-FAO	Partial regression	1990-2000	No EKC
Barbier (2004)	Arable land-FAO	RE	1960-1999	No EKC
Culas (2007)	Deforestation rate-FAO	OLS, FE and RE	1972-1994	EKC for Latin America. No EKC for Asia and Africa
Shandra (2007)	Deforestation rate-FAO	OLS	1990-2000	No EKC
Nguyen-Van and Azomahou (2007)	Deforestation rate-FAO	FE and Non-parametric	1972-1994	No EKC
Scriecu (2007)	Arable land-FAO	OLS, FE	1980-1997	No EKC
Jorgenson (2008)	Deforestation rate-FAO	OLS	1990-2005	No EKC
Arcand et al. (2008)	Deforestation rate-FAO	OLS, FE and GMM	1961-1988	EKC
Motel et al. (2009)	Deforestation rate-FAO	FE	1970-2005	EKC
Koop and Tole (1999)	Deforestation rate-FAO	OLS, FE and RE	1961-1992	EKC for Latin America. No EKC for Asia, Africa, and all countries
Damette and Delacote (2011)	Deforestation rate-FAO	FE	1972-1994	EKC

Culas (2012)	Deforestation rate-FAO	FE and RE	1970-1994	EKC for Latin America and Africa. No EKC for Asia
Damette and Delacote (2012)	Deforestation rate-FAO	FE and Quantiles	1972-1994	EKC
Chiu (2012)	Arable land-FAO	PSTR	1972-2003	EKC
Joshi and Beck (2016)	Forest Area (FAO)	GMM	1990-2007	EKC for Africa. No EKC for OECD, Latin America, and Asia
Li et al (2017)	Deforestation rate-FAO	FGLS	1990-2010	EKC
Leblois et al. (2017)	Deforestation change (Hansen et.al., 2013)	FE	2001-2010	No EKC
Andrée et al. (2019)	Tree cover loss (Hansen et.al., 2013)	KRLS	1999-2014	EKC
Cary and Bekun (2021)	Deforestation rate-FAO	OLS	1990-2010	No EKC

Note: OLS: ordinary least square; FGLS: feasible weighted least-square; FE: fixed-effects model; RE: random-effects model; GMM: generalized method of moments, KRLS: Kernel Regularized Least Squares, PSTR: Panel Smooth Threshold Regression.

2.3. Model specification and data

2.3.1. Econometric Models and Estimation

Following EKC theory models by Bhattarai and Hammig (2001) and Culas (2007), a model can be specified as:

$$DEF_{it} = \psi + \mu_i + \pi_1 Y_{it} + \pi_2 Y_{it}^2 + \sum_{j=3}^{k} \pi_j X_{j\,it} + \varepsilon_{it} \qquad (2.1)$$

where *DEF* is the environmental degradation indicator in country *i* ($i = 1, \ldots, n$) at period *t*. Y_{it} is the gross domestic product per capita; X_{it} is a vector representing all other explanatory variables (including macroeconomic and institutional variables), π and λ are parameters to be estimated; ψ is the intercept, and μ represents the country-specific (fixed) effects, and ε denotes the error term of the regression.

The vast majority of the previous work on deforestation and economic growth estimate deforestation indicators as the annual change in forest cover (e.g., Arcand et al., 2008; Bhattarai and Hammig, 2004; Culas, 2007; Damette and Delacote, 2012; Li et al., 2017). However, changes in forest cover are, in reality, a net measure of the deforestation rate minus the rate of reforestation. While deforestation typically occurs on "natural" forests, reforestation is often a process that occurs from the establishment of a "plantation" forest (Lemenih and Bongers, 2010; Rudel, 2009). Planting trees does not necessarily provide the range of environmental services (and thus economic benefits) provided by natural forests. With that in mind, the most appropriate way to model net deforestation is by using two separate models as: (i) Deforestation rate model and (ii) Reforestation rate model. Reforestation is the process of natural or intentional restocking of trees in forest areas that have already been deforested.

While separate models for deforestation and reforestation are the ideal, comprehensive land cover data are not available across most African countries. Thus, rather than investigating separate models of deforestation and reforestation, changes in forest cover will be modeled as net deforestation based on forest land changes. Based upon the above discussion, we transform equation (2.1) to:

$$Net\_def_{it} = \psi + \mu_i + \pi_1 ln(GDP_{it}) + \pi_2[ln(GDP_{it})]^2 + \sum_{j=3}^{k} \pi_j X_{j\,it} + \varepsilon_{it} \quad (2.2)$$

As mentioned above, the net deforestation (Net_def_{it}) measures annual changes in the forest cover area as an indicator of deforestation (that is, Net_def_{it} = ForestCover_{t-1} – ForestCover_t). In this case, a positive value implies that there has been a net loss in forest cover, and a negative value will indicate a net gain in forest cover. Thus, the linear term of GDP per capita is expected to be positive, while the coefficient of the quadratic term of GDP per capita is expected to be negative. A quadratic functional form in *GDP* has been used to account for the potential nonlinearity relationship between net deforestation and GDP per capita. I employ this functional form to examine the validity of the EKC theory for the 45 selected African countries and analyze all the explanatory variables on environmental quality. However, as Caravaggio (2020) suggests, there is a more complicated relationship between net deforestation and economic growth over time. The author proposed that the EKC for deforestation could show another turning point, less pronounced than the first one, reflecting the maximum stage for reforestation rates. Furthermore, Caravaggio (2020) suggests that changing the classic quadratic functional form could be to introduce a third order of the GDP, accordingly, including the second turning point. However, with only 27 years of forest cover data available for this analysis, this time series is judged to be inadequate to incorporate several changes for long-lived resources like forest cover (Caravaggio, 2020).

The EKC hypothesis is determined based upon the statistical significance of and signs of the estimated coefficients for π_1 and π_2. The EKC hypothesis will be supported if π_1 is positive, and π_2 is negative, and both estimates are significantly different from zero. In the case of deforestation, however, the turning point is the income level where the deforestation rate is at the peak value. Once a nation attains this greater level of economic growth, a rise in each unit of income will be proportional to an expansion in the forested area. This inverted U-shaped curve implies the presence of the EKC. The above conditions are assumed to expect that albeit each considered nation could have distinctive EKC structures and defining moments, at a specified level of economic progress, all the nations have a similar income elasticity.

2.3.2. The dynamic panel data model

The vast majority of the previous studies on an EKC for deforestation have utilized regression approaches such as regular panel OLS or within estimator (random or fixed-effects) models that often have heteroskedasticity and autocorrelation problems, potentially leading to wrong inference (Joshi and Beck, 2017; Scrieciu, 2007). In this study, dynamic panel data methodology is utilized to estimate the impact of economic growth (GDP) and other explanatory variables on net deforestation across the 45 African countries. Specifically, this study adopts the dynamic panel system GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) to overcome potential endogeneity problems arising from reverse causality.

Both difference *GMM* and system *GMM* estimators are explicitly designed to capture some independent variables' endogeneity by applying an internal transformation process and incorporating lagged dependent variables in the regression model. While the difference GMM applies lagged level values as an instrument for differenced variables, the Blundell-Bond system GMM utilizes lagged level values as instruments for differenced variables as well as lagged differenced values as instruments for level variables. The system GMM, as pointed out by Roodman (2009), yields consistent and efficient parameter estimates in a regression model, in a situation such that the explanatory variables are not strictly exogenous. Furthermore, the system GMM estimator permits us to manipulate the time-series dynamics and the country-specific characteristics of the data while controlling for a different endogeneity, including unobserved heterogeneity, simultaneity, and dynamic endogeneity, and omitted variable bias. Thus, GMM estimation provides superior results compared to the traditional OLS (Flannery and Hankins, 2013; Ullah et al., 2018).

Based upon the above discussion, the empirical model utilized is the modified Arellano-Bover and Blunder-Bond (Arellano and Bover, 1995; Blundell and Bond, 1998) two-step system GMM dynamic panel estimation. The net deforestation model in equation (2.2) is transformed into:

$$Net\_def_{it} = \psi_i + \pi_1 Net\_def_{it-1} + \pi_2 ln(GDP_{it}) + \pi_3 [ln(GDP_{it})]^2 + \lambda X_{it} + \mu_{it} + \phi_{it} + \varepsilon_{it} \quad (2.3)$$

The Net_def_{it-1} signifies one lag of the net deforestation (previous year deforestation rate), with the expectation that high deforestation rate in the past suggested current and future high deforestation rates. μ represents the group effect, and ε denotes the error term of the regression. Finally, time dummies ϕ_{it} are included in the regression model.

There are several estimation steps involved in the system GMM estimation process. The first step is to remove group effects such as initial forest cover and climate (Joshi and Beck, 2017; Sharma, 2011) through a first differencing transformation.

$$\Delta Net\_def_{it} = \psi_i + \pi_1 \Delta Net\_def_{it-1} + \pi_2 \Delta ln(GDP_{it}) + \pi_3 [\Delta ln(GDP_{it})]^2 + \lambda \Delta X_{it} + \Delta\mu_{it} + \Delta \phi_{it} + \Delta\varepsilon_{it} \quad (2.4)$$

For i = 1, …, N and t = 3, …, T.

In this case, two assumptions are made. First, it assumed that the errors are not serially correlated.

$$E(\varepsilon_{it}\ \varepsilon_{is}) = 0 \text{ for } t \neq s \quad (2.5)$$

Second, the initial conditions Net_def_{i1} are predetermined:

$$E(Net\_def_{i1}\ \varepsilon_{it}) = 0 \text{ for } t \geq 2 \quad (2.6)$$

The two assumptions above in equations (2.5) and (2.6) indicate the following moment restrictions as proposed by Arellano and Bond (1991):

$$E(Net\_def_{i,\ t-s}\ \Delta\varepsilon_{it}) = 0 \text{ for } t = 3, \ldots, T \text{ and } s \geq 2 \quad (2.7)$$

$$E((ln(GDP_{it-s}) + [ln(GDP_{it-s})]^2 + \lambda X_{it-s}))\Delta\varepsilon_{it} = 0 \text{ for } t = 3, \ldots, T \text{ and } s \geq 2 \quad (2.8)$$

Nevertheless, the lagged levels of the independent variables are weak instruments for the first-differentiated equation under certain circumstances as Blundell and Bond (1998) demonstrated. They are weak instruments if the independent variables are persistent over time, and when the sample's time dimension is small (Blundell and Bond, 1998). Thus, Blundell and Bond (1998) recommend that as an alternative to differencing the regressors, instruments should be differenced to make them exogenous to the fixed effects. This recommendation advances the dynamic panel estimator from Arellano-Bond difference GMM to the Blundell-Bond system GMM estimator, a combined estimate of the levels equation and first differences. Blundell and Bond (1998) therefore establish moment restrictions as shown in equations (2.9) and (2.10) in order to remove the finite sample bias resulting from weak instruments.

$$E[\Delta Net\_def_{i,\,t-1}\,(\mu_{it} + \varepsilon_{it})] = 0 \text{ for } t = 3, \ldots, T \tag{2.9}$$

$$E[(ln(GDP_{it-1}) + [ln(GDP_{it-1})]^2 + \lambda X_{it-1}).(\mu_{it} + \varepsilon_{it})] = 0 \text{ for } t = 3, \ldots, T \tag{2.10}$$

Furthermore, the system GMM estimator's consistency heavily depends on whether the independent variables' lagged values are valid instruments. In order to test the model's validity and ensure that the instruments are correctly specified, the Sargan test of over-identifying restrictions is conducted. Also, this study performed the Arellano and Bond (1991) test that detects first and second-order serial correlation, AR(1) and AR(2), to examine if the error term displays evidence of serial correlation. Finally, to avoid the problem of finite sample bias resulting from overfitting the model, this study follows the recommended rule of thumb by Roodman that the number of instruments should be less than the number of individuals or groups (Roodman, 2009b).

Moving forward, there various factors that may impact economic development or deforestation. Thus, this necessitates incorporating other control variables in the primary EKC model as these could have some effect on the level of deforestation by increasing or reducing it. These variables include agricultural production index, trade of forest products, biomass consumption, institutional variables (political liberty and civil liberty indices), and population variables (population density and rural population percentage)[1]. Incorporating these variables into equation (2.3) to:

$$Net\_def_{it} = \psi_i + \pi_1 Net\_def_{it-1} + \pi_2 ln(GDP_{it}) + \pi_3 [lnGDP_{it})]^2 + \pi_4 lnAPIINDEX_{it} + \pi_5 POPDEN_{it} + \pi_6 PRCL_{it} + \pi_7 lnBIOMASS_{it} + \pi_8 RURALPOPTAGE_{it} + \pi_9 lnFRST\_TRADE_{it} + \mu_{it} + \phi_{it}\,\varepsilon_{it} \quad (2.11)$$

where $\pi_1\, \pi_2\, \pi_3, \pi_4, \pi_5, \pi_6, \pi_7, \pi_8$ and π_9 are the parameters to be estimated for the explanatory variables. Section 2.3.5. explains the justification of the inclusion of each of these variables.

2.3.3. Cross-sectional dependence and unit root tests

For this panel framework analysis, it is essential to determine if there is a cross-sectional dependence of error terms across countries due to increased economic integration. Many researchers have investigated EKC for deforestation by using the deforestation rate as an indicator of deforestation. This dependent variable is then regressed against a combination of explanatory variables without considering the presence of cross-sectional dependency as well as the stationarity of the variables (e.g., (Culas, 2007; Joshi and Beck, 2017)). Non-stationary is a problem of concern when time-series variables are used to formulate cross-country panel data. When using non-stationary time series, the regression outcome may provide spurious regression results in that it may stipulate a relationship between two variables where there is none (De Hoyos and Sarafidis, 2006; Edward and Štefan, 2009).

Consequently, this empirical analysis employs Pesaran's (2004) CD test to identify the presence of cross-sectional dependence in the data series. Traditional unit root testings are not effective when utilized on a data series that has a cross-sectional dependence because of their lower power (Paramati et al., 2016). Thus, cross-sectional dependency is considered by using a second-

[1] While there are a variety of factors that could impact economic development and deforestation, however, I cannot incorporate all these variables, therefore I have selected the variable used based on its importance to the countries investigated and data availability.

generation panel unit root test, CIPS (Cross-sectional augmented IPS)(Pesaran, 2007). This test assumes cross-sectional dependence in the series with the null hypothesis that data series are non-stationary. The alternative hypothesis is that at least one cross-section of the data series is stationary.

2.3.4. Panel causality analysis

The two-step system GMM discussed in section 2.3.2. only tells us there is some relationship between net deforestation, GDP per capita, and the other explanatory variables but does not indicate the direction of causality. In order to investigate potential causal relationships between the variables utilized in this analysis, short-run dynamic panel causality relations among the variables in 45 Africa countries are examined with the panel causality test proposed by Dumitrescu and Hurlin (2012). This test is an explicit structure of Granger (1969) non-causality test edition for heterogeneous panel series with fixed coefficients. Moreover, it also considers two heterogeneous classifications – the heterogeneity of the causality relations and the heterogeneity of the regression model utilized to examine Granger causality. Following Dumitrescu and Hurlin (2012), the following model is utilized:

$$y_{i,t} = \lambda_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{2.12}$$

In this context, x and y signify two stationary variables surveyed for N individuals in T periods. $\beta_i = \beta_i^{(1)}, \ldots, \beta_i^{(k)}$ together with individual effects λ_i are known to be fixed in terms of time dimension specification. Also, the lag orders of K are held to be the same for all cross-section components of the panel data under the investigation. Besides, the autoregressive parameters $\gamma_i^{(k)}$ along with $\beta_i^{(k)}$ which are the regression coefficients, are allowed to change across groups.

This test approach's null hypothesis is no causality relationship is assumed for any components available (i.e., x and y) in the panelized data. Consequently, if the null hypothesis is rejected, we will report that causality exists from x and y. Moreover, there is a possibility for x and y

to be switched to explore causality in the opposite direction in what is known as feedback effects (bidirectional causality). In this context, this assumption is frequently classified as the Homogenous Non-Causality (HNC) hypothesis, and the null hypothesis is expressed as follows:

$$H_o: \beta_i = 0, \forall_i = 1, \ldots N \tag{2.13}$$

The alternative hypothesis is often identified as the Heterogenous Non Causality hypothesis, in which the regression coefficient slope may be different across groups. Under the alternative hypothesis, two subdivisions of cross-section components are allowed. First, there is no causality connection from *x* to *y*. Second, there is a causality connection from *x* to *y* for the original model, though it is not adequately created upon the same regression structure. In this case, I consider the heterogeneity of the panel data regression model with a fixed coefficient. Thus, the alternative hypothesis is defined as:

$$H_1: \beta_i = 0, \forall_i = 1, \ldots N_1$$

$$\beta_1 \neq 0, \forall_i = 1, \ldots, N_1 + 1, N_1 + 2, \ldots N \tag{2.14}$$

Here, β_i is allowed to be different across groups, and there $N_1 < N$ individual activities with no causality from x to y. N_1 in this scenario is unknown; however, it meets the condition $0 < N_1 / N < 1$.

For each cross-section, the Wald statistics for the test of Granger non-causality are calculated independently. The panel test value is then calculated by averaging the cross-sectional average of individual Wald statistics.

2.3.5. Variable selection and description

Angelsen and Kaimowitz (1999) take note that previous empirical investigations combine entirely different explanatory variables without identifying distinctive layers of the main impetuses behind deforestation. Since it is noted that deforestation is a consequence of a complicated process created at different stages, I specify that the underlying political institutions, demographic changes, and other economic variables that are appropriate for our models. Important explanatory variables included in equation (2.3) are described below.

GDP per capita

According to Culas (2007), it is anticipated that a rise in GDP per capita will activate increased demand for farming and forest products, thereby increasing net deforestation. However, Culas further demonstrates that that high per capita income may decrease deforestation if there is the implementation of policies that mandate forests to be secured rather than depleted. Thus, this study uses GDP per capita, purchasing power parity (PPP) measured in constant 2017 international dollars as a proxy for income. A quadratic form of the regression model is adopted in this investigation to provide a flexible specification of the EKC correlation.

Agricultural production index

The role of the farming sector in developing nations cannot be overemphasized. The agricultural sector contributes significantly to employment, national income, and exports (Culas, 2007). Moreover, agriculture remains a vital part of African economies, although its shares of production and employment have largely been declining. All over the African continent, the contribution of agriculture production in the gross domestic product (GDP) plunged from almost 40% in the mid-1970s to less than 25% in 2015 (World Bank, 2015). The contribution averages 25% in Sub-Saharan Africa, however, only 18% in North Africa. Conceivably, agriculture's importance in production is far beyond its direct contribution in GDP, since farming yield is the reason for agro-processing, and the agricultural sector is as well a source of demand for other agribusiness enterprises and administration (ACET, 2017)

Despite a decreasing contribution in GDP, agriculture remains significant to GDP growth, through both its direct and secondary contributions. Accordingly, an agricultural production index (APIINDEX) used in this study to demonstrate the impacts of these agricultural activities on deforestation. According to the Food and Agricultural Organization (FAO), the APIINDEX is the total amount of agrarian production where productivity at the national level have been analyzed using international commodity prices. The assumption is that agricultural land expansion would come at the expense of forest area. Thus, a positive coefficient for APIINDEX would be expected in the regression model.

Trade of forest products

Forest-based products are traded extensively and signify a significant source of income and foreign exchange earnings to many emerging nations. Despite its physical potential, Africa has been reported as a minor contributor to forest products' international markets primarily due to low competitiveness and limited purchasing power (Simula, 1999). However, increased forest products' export may put more pressure on the forest resources, leading to more significant deforestation, and worsening land degradations. The lumber industry promotes forest exploitation, frequently through unsustainable logging and, in most cases, with the governments' agreement (Cropper and Griffiths, 1994). Besides, trade policies impact the environment directly and indirectly (Simula, 1999). As Angelsen and Kaimowitz (1999) pointed out, policies encouraging trade in forest goods appear to increase prices and pressure on forests. For example, reduction in tariff and non-tariff barriers and market liberalization and structural adjustment have led to trade expansion with some adverse effects on forests (Simula, 1999). Consequently, this study has included forest products' trade as a potential factor driving up forest exploitation and expect to have a positive coefficient in the regression model. In this study, the trade of forest products (FRST_TRADE) is the value of export/imports of aggregate forest products.

Population

Population increases tend to raise demand for agricultural activities, forest resources, and another form of land uses and therefore causes more deforestation. Rural population density (Bhattarai and Hammig, 2001; Chiu, 2012; Culas, 2007) and (Bhattarai and Hammig, 2001; Cropper and Griffiths, 1994; Li et al., 2017b) are the most widely used variables in the literature related to deforestation. Given the role of population pressures on forest resources, population density, and rural population are used as variables independently in this study. In this study, increased population density and rural population are project to increase forest cover loss, and the effects are expected to be positive in the model.

Political liberty

According to Bhattarai and Hammig (2001), institutional instruments can influence the EKC connection as among the essential thrusts behind the market and political exercises, which could have a more significant effect than increasing the population alone. Winslow (2005) suggests that nations with more advanced levels of democracy have improved environmental quality, considering that democratically elected leaders will probably be more inclined to provide public goods like environmental quality. In this investigation, I have used an aggregate of political rights and civil liberty indices as an institutional variable. As measured by Freedom House (2015), political rights and civil liberties are represented on a one-to-seven scale, with one being the highest degree of freedom and seven the lowest. Following Bhattarai and Hammig (2001) and Chiu (2012), I reversed political and civil liberties indices to interpret the regression results easily and have a comparable conclusion with other variables. Thus, an increase in values implies increased political rights and civil liberties. In this context, an improvement in institutional quality is projected to reduce deforestation levels and shift an EKC relationship downward. Therefore, the coefficient associated with political liberty (PRCL) should assume a negative value.

Biomass consumption

Bioenergy generation and consumption as a significant source of renewable energy are believed to be among the essential remedies to reduce the exploitation stress on natural assets and air pollution reduction. Lopez-Menéndez et al. (2014) demonstrate that nations with high sustainable energy assets are found to encounter the EKC model at minimal levels of air pollution and ecological degeneration. While the literature has given careful consideration of how sustainable power sources can decrease air contamination levels, very little debate is available on whether renewable power sources may impact the extraction rate of natural resources such as the rate of loss of forest resources. Hence, this study have incorporated biomass consumption as a variable in the model.

2.3.6. Data

This study investigates the relationship between deforestation levels and economic development in countries from Africa for the period of 1990 to 2016. The selection of countries for this analysis is mainly based on the availability of annual data.[2] Other EKC studies on deforestation in Africa had used fewer countries and covered less duration than this present study (e.g., Chiu, 2012; Culas, 2007).

obtain data on forest cover, trade of forest products, and the net value of agricultural production from the database of the Food and Agriculture Organization (FAOSTAT, 2018). Data on per capita gross domestic product (GDP) and population density come from the World development (WDI) indicators (World Bank, 2018). Data on political liberty were taken from the Freedom House database (Freedom House, 2015), and data on biomass consumption from the database of the United Nations Environment International Resource Panel Global Material Flows (United Nations, 2017) (http://www.resourcepanel.org/global-material-flows-database). Descriptive statistics for all variables are presented in Table 2.2.

[2] The list of the countries includes: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verdi, Cameroun, Central Africa Republic, Chad, Comoros, Congo Republic, Coted'Ivoire, DR Congo, Egypt, Equatorial, Ethiopia, Gambia, Guinea, Gabon, Ghana, Guinea Bissau, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Sierra Leone, South Africa, Tanzania, Togo, Tunisia, Uganda, Zambia, and Zimbabwe.

Table 2.2. Descriptive statistics of variables selected in the study

Variables	Description	Mean	Std.dev.	Min.	Max.
Net Def	Annual change in forest cover	0.4	13.36	-168.09	395.68
GDP	GDP per capita, PPP (constant 2017 international $)	4,633.24	5486.17	436.72	41,249.44
APINDEX	Index of agricultural production (Base period 2004-2006)	98.95	24.62	37.78	231.96
POPDEN	Population density (People/ha)	82.82	111.58	1.74	622.4
PRCL	Aggregate of political liberty and civil liberty indices (Index)	8.73	3.08	2	14
BIOMASS	Biomass resource (DMI, million tons)	46.38	68.6	0.07	561.04
RURALPOPTAGE	Rural population (% of total population)	61.8	16.28	11.44	94.58
FRST_TRADE	Trade of forest products (exports/import, 1000 US$)	79,841	210,199	0	1,785,600

Note: Data cover the period from 1990 to 2016 with 1,215 observations.

2.4. Empirical results

2.4.1. Cross-sectional dependence and panel unit root testing results

The vast majority of previous studies of the EKC hypothesis on deforestation and economic growth have largely ignored the issue of cross-sectional dependence and heterogeneity in the analysis. In this paper, I begin the analysis by examining cross-sectional dependence using a general diagnostic test developed by Pesaran (2004). The results are presented in Table 2.3, and I reject at a 1% significance level the null hypothesis of cross-sectional dependence. This result implies that cross-sections are significantly dependent on each other, thus satisfying the requirement for second-generation unit root tests' applicability. Thus, I employed the cross-sectional augmented panel unit root test (CIPS) developed by Pesaran (2007). This test assumes the cross-sectional dependence in the data series. The CIPS's null hypothesis is that series are non-stationary, and the alternative hypothesis is that at least one cross-section of the series is stationary. The results illustrated in Table 2.3 show this study failed to reject the CIPS null hypothesis. Variables are found to be integrated of order one, I(1), therefore I can conclude that the variables described in the panel are stationary after first difference.

Table 2.3. Cross-sectional dependence and unit root tests results

		The unit root test with cross-sectional dependence	
Variables	Pesaran CD test	CIPS (level)	CIPS (first difference)
Net Def	19.191***	-2.083	-5.545***
GDP	65.161***	-2.514	-5.542***
GDP2	67.109***	-2.507	-5.521***
APIINDEX	8.705***	-3.372	-6.247***
POPDEN	159.651***	-2.657	-4.752***
PRCL	13.821***	-2.747	-6.037***
BIOMASS	114.100***	-3.272	-6.206***
FRST_TRADE	59.458***	-2.973	-5.562***
RURALPOPTAGE	122.243***	-2.186	-4.809***

Note: *** denotes the rejection of null hypothesis of CD test and unit root test at 1% significance level, respectively.

2.4.2. Two-step system of GMM of EKC for deforestation

Arellano-Bover and Blunder-Bond (Arellano and Bover, 1995; Blundell and Bond, 1998) suggest the GMM estimators to overcome the endogeneity problems arising from reverse causality, including unobserved heterogeneity, simultaneity, dynamic endogeneity, and omitted variable bias. Table 2.4 presents the empirical results of GMM estimation for estimating the factors influencing net deforestation in 45 African countries.

When using the generalized method of moments model for analysis, it is necessary to conduct post estimation analysis to establish the appropriateness of the econometric model applied and validity of the instruments (Ullah et al., 2018). An essential assumption of the validity of GMM estimates is that the instruments used are exogenous. To test the model's validity and ensure that the instruments are correctly specified, the Sargan test of over-identifying restrictions and Arellano-

Bond serial correlation test is conducted. The J-statistic probability value for the Sargan test in Table 2.4 is 0.413 and insignificant, implying that the instruments are valid and the GMM estimates are reliable. The Arellano-Bond test results with AR(1) having a p-value of 0.006 and statistically significant and AR(2) with a p-value of 0.149, statistically insignificant confirmed the validity of strong exogeneity assumption and efficiency of the GMM estimator. The Arellano-Bond test result implies that the lagged variables are not correlated with the net deforestation equation's error term. In other words, there is no serial correlation in residual.

Table 2.4. GMM estimation results for deforestation (Dependent variable: Deforestation rate)

Variables	System GMM
Net_def(L1)	0.0187***
	(0.0007)
LnGDP	39.4510***
	(0.1554)
LnGDP2	-2.4574***
	(0.0099)
LnAPIINDEX	2.4308***
	(0.0060)
POPDEN	-0.0219***
	(0.0007)
PRCL	-0.1447***
	(0.0012)
LnBIOMASS	-1.9386***
	(0.0046)
LnFRST_TRADE	0.2673***
	(0.0007)
RURALPOPTAGE	0.0347***
	(0.0017)
Constant	-0.774***
	(0.06)
Observations	1125
Number of Countries	45
AR(1)	0.006***
AR(2)	0.149
Sargan test statistics	0.413

Note: Year dummies are included in the system GMM specification but not reported in this table. Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$, p-values are reported for AR(1), AR(2), and Sargan statistics, Real gross domestic product, Biomass, Trade of forest products, and Agricultural production index are in their natural logarithms.

According to the results of the system GMM model, all coefficients are statistically significant at 1% significance level. There is a statistically significant positive relationship between net deforestation and real GDP per capita in Africa. These results, however, show evidence for an inverted U-shaped EKC for net deforestation in Africa with statistically significant positive and negative coefficients for the GDP and quadratic GDP variables, respectively[3]. This implies that the rate of deforestation is increasing at low levels of GDP per capita, but net deforestation will ultimately peak and start declining with increasing real GDP per capita. Hence, with these two estimated coefficients, the EKC hypothesis is confirmed and is consistent with previous research (Bhattarai and Hammig, 2001; Culas, 2007; Damette and Delacote, 2012; Motel et al., 2009). Consistent with our net deforestation of equation (2.3), the per capita income associated with the turning point is approximately US $3,000. This monetary value is close to the estimated income associated with the turning point for developing countries (US $3,021) found by Chiu (2012).

A per capita real GDP of US $3,000 is significantly higher than the present estimation of GDP per capita for many African nations. Less than half of the countries in the data set (22) have a 2016 GDP per capita higher than this turning point[4], while the other 51% of countries in the study have GDP per capita that fell below the EKC turning point. This result indicates that there is a potential for a significant amount of net deforestation damage that may happen in these African countries before the turning point is achieved. The result of the present study, however, is similar in magnitude to the research work findings by Culas (2007), who examines the effects of institutional

[3] This study performed a robustness check analysis to further confirm the result from the system GMM estimation. In the robustness, the study employed a Pooled Mean Group (PMG) estimator from an autoregressive distributed lag model to establish long-run and short-run equilibrium relationships among our variables. The result from the PMG estimation also confirm the EKC hypothesis is valid for net deforestation in 45 African countries utilized in this study. These results are available from the authors upon request.

[4] These include Seychelles ($26,421), Equatorial Guinea ($24,827), Mauritius ($20,646), Botswana ($17,117), Gabon ($15,358), South Africa ($12,703), Algeria ($11,637), Egypt ($10,795), Tunisia ($10,524), and Namibia ($10,266). Others include Angola ($7,568), Morocco ($7,109), Cabo Verde ($6,482), Nigeria ($5,284), Mauritania ($5,045), Ghana ($4,724), Cote d'Ivoire ($4,615), Kenya ($3,952), Congo Republic ($3,603), Cameroun ($3,524), Zambia ($3,467), and Senegal ($3,067).

quality and environmental policies on the EKC relationship for deforestation in Africa, Latin America, and Asian countries.

As an example of an estimate for the net deforestation damage that may occur in countries before the turning point, Tanzania is choosen. Tanzania's 2016 GDP per capita is US $2,441 and forest lands of 47.6 million hectares. Using the model coefficients and forecasted changes in the independent variables along with a projected turning point of US $3,000 to be reached in 2023 and amount of forest land estimated to be 45 million ha, the additional deforestation that would take place in Tanzania is about 2.5 million ha (approximately 5.33% of the current forest land). However, this loss in forest land is also driven by the other independent variables in the model beyond only economic growth as measured by per capita GDP. For Tanzania, reaching the GDP turning point results in an accelerated decline rate in the forest loss after 2023.

Now, I turn attention to the coefficient estimates for other deforestation drivers. Much emphasis has been placed on population pressure as a factor contributing to increasing the rate of deforestation in developing nations (Cropper and Griffiths, 1994; Palo, 1994). The results show less convincing evidence as population density has a negative and statistically significant. The estimated coefficient of population density is not in line with a priori expectation. Nevertheless, some previous studies have demonstrated a similar pattern in their results for population density (Chiu, 2012; Culas, 2007). This result, however, is in opposition to the research findings of Motel et al. (2009), Ehrhardt-Martinez et al. (2002), Koop and Tole (1999). In the research by Koop and Tole (1999), both the population growth and population density did not have any statistically significant impact on deforestation.

However, I do find a statistically significant, positive relationship between deforestation rate and the rural population (RURALPOPTAGE) so that increasing rural communities expand rate of deforestation in the analyzed African countries. The result indicates that rural population pressure is a more important factor adding to deforestation in Africa than population density. This impact of the rural population on deforestation conforms to research findings by Bhattarai and Hammig (2001).

Despite the initial reasoning that increased consumption of biomass (LnBIOMASS) as a renewable energy source could be attributed to the high rate of deforestation in Africa, the results here are less convincing. Surprisingly, the estimated coefficient for biomass is negative and statistically significant. The analysis indicates that increased consumption of biomass as a renewable energy source is not statistically linked to increased net deforestation occuring with the African countries in this study.

Political liberty (PRCL) is another factor that has a statistically significant, negative relationship with deforestation rate in the model. Specifically, the result implies that given a one-unit increase in overall governance quality, deforestation is expected to reduce by 1.4 million ha, holding all other variables constant. This result is consistent with other research findings in the literature (Barbier and Burgess, 2001; Culas, 2007). The political institution variable estimates suggest that as institutional quality improves, there is a decrease in deforestation. Thus, improvement in overall governance quality in Africa through better forest polices and improved environmental policies will lessen the pressure on forest resources. Therefore, it is more compelling to control deforestation through improvement in quality governance and environmental policies than to focus on rationing economic development (Culas, 2007).

Finally, both trade of forest products (LnFRST_TRADE) and agricultural production variable (LnAPIINDEX), have positive and statistically significant coefficients at a 1% significance level. This implies that both increased trade of forest products and expansion of agricultural land contribute to increases in net deforestation occurring within the African countries. Both results confirm prior expectations.

2.4.3. Panel causality test results

This section illustrates the results from investigating the direction of causality between the variables, employing the approach proposed by Dumitrescu and Hurlin (2012). This technique is a simplified version of Granger's (1969) non-causality test, which accounts for data series for heterogeneity when calculating pairwise causal relationships between the variables of net deforestation, GDP per capita, agricultural production index, trade of forest products, population density, rural population percentage, political liberty, and biomass consumption. This approach allows for a more detailed analysis of the data and necessitates that all variables be stationary.

The empirical results of short-run panel non-causality tests are summarized and presented in Figure 2.1. There are five statistically significant unidirectional causal relations to the variable net deforestation, and these are from GDP, POPDEN, PRCL, FRST_TRADE, and APIINDEX. All other variables impact net deforestation through either of these variables. However, there are nine other statistically significant unilateral short-run relations between APIINDEX-PRCL, GDP-POPDEN, APIINDEX-BIOMASS, APIINDEX-GDP, PRCL-GDP, POPDEN-BIOMASS, PRCL-POPDEN, RURALPOPTAGE-FRST_TRADE, and APIINDEX-RURALPOPTAGE. There are statistically significant bidirectional causalities between GDP-RURALPOPTAGE, GDP-BIOMASS, APIINDEX-FRST_TRADE, and BIOMASS-FRST_TRADE. The unidirectional linkage between GDP and net deforestation from the short-run heterogenous causality findings suggest that African nations can seek to deter and reverse deforestation through proper land-use and trade of forest products policies such that the consequences of these policies would not impact their economic growth.

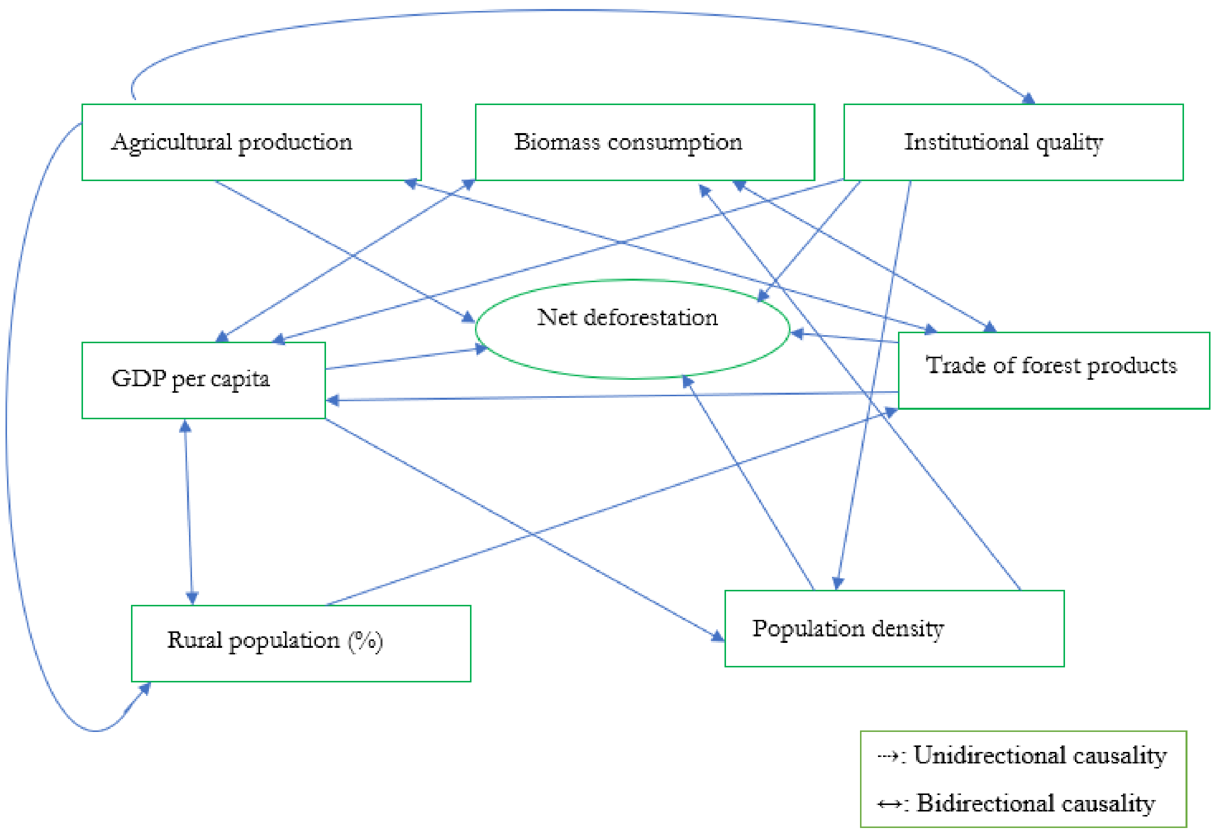

Figure 2.1: Short-run, statistically significant causalities among the variables explaining net deforestation.

2.5. Conclusions

This paper investigates the effect of economic growth on net deforestation in Africa. Using a balanced panel data of 45 African nations from 1990 to 2016, I examine whether the EKC is confirmed for net deforestation. I also explore the impacts of institutional, trade of forest products, bio-energy consumption, and demographic factors on deforestation as measured by annual change in forest cover. The results from the generalized method of moments (GMM) estimation confirm the validity of the EKC hypothesis. These results support an inverted U-shaped EKC relationship between GDP per capita and net deforestation in Africa. This result is consistent with prior EKC research results using various indicators of ecological protection (Bhattarai, M., Hammig, 2004; Chiu, 2012; Culas, 2007; Motel et al., 2009).

The result implies that economic development can provide environmental protection if such growth is close to or beyond the turning point. In this research, a turning point of US $3,000 per capita GDP is estimated, which is higher than the GDP per capita in 51% of the 45 countries utilized in this research. This indicates that significant damage may happen to forests in these countries before an EKC turning point is reached, as is demonstrated with the country Tanzania. However, Granger causality test identified a unidirectional Granger causality from GDP to net deforestation. This suggests that if these nations decide to deter and reverse deforestation, this action would not have negative impact on their long-run economic development.

This study contributed a new perspective on the analysis of deforestation and economic development in Africa by exploring the possibility of biomass use contributing to deforestation in the region using an econometric methodology that account for endogeneity and omitted variable bias. Contrary to the a priori expectation, the model results show a negative and statistically significant relationship between biomass consumption and deforestation. In addtion, a panel Granger causality test demonstrates that biomass consumption is not statistically linked to net deforestation in Africa. In the short run, there are five statistically significant unidirectional causal variables related to our measure of deforestation. These variables are GDP, population density, political liberty, trade of forest products, and agricultural production index. All other variables impact net deforestation through either GDP and/or population density.

This study is not without a few limitations. Previous studies on this topic based on deforestation have utilized several socioeconomic factors that may affect forests, such as income, population, technological development, political institutions, export price index, debt, and trade openness. There are other possibly important explanatory variables, including agriculture production price, agriculture and forestry taxes, afforestation policies, export price index, technological development, debt, and trade openness that could be viable for inclusion in this analysis, however, data were not available for all the countries.

The relationship between net deforestation and economic growth is complex as noted by Caravaggio (2020). According to Caravaggio, the EKC for deforestation could have a second, less articulated turning point, signaling the optimum for reforestation. Caravaggio (2020) recommends that one possibility is adding a third order to the GDP, thereby including a second turning point, to the transition of the conventional quadratic functional form. Nevertheless, the 27 years of tree cover data available for this study was considered an insufficient amount of time to account for many shifts in seemingly perpetual resources such as forest.

The FAO-sourced forest cover data used in this analysis also is not without shortcomings. According to the FAO (2011), statistics for emerging countries are difficult to collect, and expectations and assumptions differ greatly, resulting in a degree of potential unreliability. Thus, future research could utilize satellite data to provide a more accurate forest cover measure to determine deforestation.

Regardless of the above limitation, the present research findings have important policy implications. Firstly, as the EKC hypothesis is shown to exist for deforestation for a group of 45 countries in Africa. Eventually, these countries should concentrate on effective economic development policy formulation and implementation in tandem with forest conservation policies. Particularly for those countries still in the development phase where economic growth may have a positive impact of deforestation, adequate enforcement of forest policy and environmental laws must be taken as a priority in these nations to reduce forest conversion and improve environmental qualities.

Secondly, the Granger causality test identified a unidirectional Granger causality from GDP per capita to net deforestation. This one direction of causality means that changes in GDP impacts net deforestation but not the other way around. Thus, changes in forest loss do not impact economic growth as measured by GDP per capita within the African countries examined in this study. This suggests that these nations could deter and reverse deforestation through proper land-use and trade of forest products policies such as quantitative restrictions, and the consequences of these policies would not impact their economic growth. Thus, there is a need to propagate and improve land-use efficiency in these countries, and authorities in these nations should continue to focus more on intensification in sustainable agricultural system. One way that can be achieved is through proper monitoring. The vital role that forests play in environmental quality improvement suggests that these countries at various levels of government should actively encourage the protection of forest resources and afforestation.

Finally, the findings of statistical evidence that better institutional quality leads to a reduction in deforestation and helps to cut down the period of the significant phase of deforestation. This suggests that African countries need to improve their governance quality. In fact, Culas (2007) indicates that it is more compelling to increase the efforts for controlling deforestation through improvement in quality of governance and enforcement of environmental policies than focus on limiting economic development. Bhattari and Hammig (2001) note that low-income nations cut forest trees without adequate replanting. Based on these observations, there should be formulation and implementation of special intervention programs that encourage sufficient reforestation in those countries with per capita GDP well below the EKC turning point.

In a nutshell, it is suggested for all African countries included in this analysis that environmental policies for sustainable development be formulated and implemented in the early stages of development. Strictly speaking, developing countries, in general, should not anticipate until the turning point is attained before deriving the gains of effective forest conservation and other environmental policies to lessen pressure of forest resources. Finally, this study's results should give further attention to the opinion of Arrow et al. (1996) that economic development is not adequate for achieving better environmental conditions or suppressing ecological degradation. Therefore, additional efforts are needed to prevent deforestation.

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CHAPTER 3

Essay 2: GIS-based Multi-Criteria Decision Analysis of Utility-Scale Wind Farm Site Suitability in West Virginia

3.1. Introduction

As more impacts are observed from climate changes across the world, demand is continuuing to increase for renewable energy (Baseer et al., 2017; Latinopoulos and Kechagia, 2015; San Cristóbal, 2011). Expanding renewable power generation is vital for the mitigation of greenhouse gas emissions and promoting environmental sustainability (Mekonnen and Gorsevski, 2015). Among renewable energy resources, wind power is a proven sustainable energy source, which has been effectively employed for electricity production around the world. A compelling advantage of wind energy is that it does not emit carbon emissions during operations and uses practically no water resources (AWEA, 2018). In addition to environmental benefits, wind power is one of the lowest-cost generating sources for electricity (Wiser Ryan et al., 2018). In the past few years, wind power has been purchased at or below a price of $20 per megawatt-hour in the U.S. (W. Ryan et al., 2018). Thus, wind power is advocated as being among the most environmentally desirable and financially feasible types of renewable energy resources (AWEA, 2018).

Regardless of its economic and environmental benefits, a substantial transition to wind energy has not occurred within West Virginia. In this state, fossil fuel energy production has historically been an economic strength with coal-fired power plants producing electricity exports to surrounding states. About 95% of the electricity generated in West Virginia still comes from coal, with only six operational wind farms at 686 MW of generating capacity (Figure 3.1). In recent years, however, wholesale prices of electricity have been declining due to higher penetrations of renewables and falling natural gas prices (Jenkins, 2018; Wiser et al., 2017). These declines have resulted in coal no longer being as cost-competitive as wind and natural gas for producing electricity. This economic shift is evidenced by a surge in retirements of coal power plants in the Pennsylvania – New Jersey – Maryland (PJM) market where West Virginia is located (EIA, 2019). This lack of cost competitiveness, along with environmental challenges presented by coal, have created a need to diversify electricity generation sources in West Virginia beyond coal.

According to the American Wind Energy Association (AWEA, 2018), West Virginia has a land-based technical wind potential of about 69,098 MW at 80m hub height[5], considerably more than the current generating capacity. This substantial difference between potential and current wind power capacity suggests an abundant opportunity for comparing installed wind capacity by state (see Figure 3.2).

To adequately advance wind power resources in West Virginia, it is essential to find suitable geographic locations for future utility-scale wind farm projects. Decision-making processes regarding the development of wind farms involves substantial ecological and spatial planning. Wind power is not without undesirable effects, including adverse impacts on bird and bat mortality and migration, viewsheds, aesthetics, wildlife habitats, deforestation, and noise (Van Haaren and Fthenakis, 2011). While ecological effects could increase construction and infrastructure costs for investors, the construction of wind farms is not predominantly forbidden (Bailey et al., 2012).

The fact that the state of West Virginia has viable land resources for generating wind electricity is not enough for siting, building, and operating utility-scale wind-powered electric generation facilities. The state is almost entirely forested (85% of land cover) (NAIP, 2016) and mountainous, with an average elevation of 1,500 feet (460m) (NAIP, 2016; USGS, 2003) above sea level (the highest of any state east of the Mississippi River). Thus, unlike other U.S. states such as Texas or Iowa, West Virginia has diverse landscapes and geographical formations characterized by mountainous terrain that encompasses most of the state. Land surface configurations in West Virginia may restrict and impede the development of wind projects, create design and operational challenges, and increase the cost and risks of wind projects. These challenges to wind power development create the need to use a GIS-based analytic framework for identification of locations

[5] The height of the hub is characterized as the interval between the ground level and the midpoint of the turbine blades. extending the development of wind energy generation in West Virginia. Moreover, West Virginia is ranked 26th among U.S. states and below neighboring states of Pennsylvania and Ohio when However, wind resources tend to increase as the hub height increases.

appropriate for future utility-scale wind power plants. To the best of our knowledge, there has not been any spatially explicit assessment of potential wind power facilities in West Virginia. It is worth nothing that unlike many other regions for siting wind farms, West Virginia is in a terrain and land challenged area.

As demonstrated in previous studies (Carrete et al., 2012, 2009), wind farms situated in inappropriate geographic locations may have adverse impacts on birds, including increased mortality rates and habitat destruction. While there has been a great deal of research on wind power site development and multiple factors have been identified plus utilized for suitability modeling of wind farms, few studies have incorporated site evaluation based upon potential impacts on wildlife habitat fragmentation (Aydin et al., 2010; Ayodele et al., 2018; Peri and Tal, 2020; Xu et al., 2020). In addition, few studies have utilized the participation of energy development experts in the screening and weighting of the criteria used in their studies (e.g.,(Ayodele et al., 2018; Xu et al., 2020; Yousefi et al., 2018)). The participation of experts would ensure not only that the specified requirements are based on economic, environmental, and technical principles, but also that they comply with the legal and regulatory framework.

The goal of this study was to create a spatial model using multiple-criteria decision-making (MCDM) for utility-scale wind farms in West Virginia, employing an analytic hierarchy process (AHP). This model utilized a two-stage approach to identify suitable wind farms sites using Geographical Information System (GIS) and multi-criteria decision making. The first stage was the development of spatial modeling operations for multiple-criteria decision analysis using AHP, which incorporated the perceptions of wind power experts into the weighting criteria. The second stage involved implementation of spatial modeling processes within a GIS environment. Finally, sensitivity analysis was performed as a check for model robustness.

Using this model, locations throughout the state were identified to be suitable for potential development of future wind farms. In addition, current wind turbine locations in West Virginia were assessed to determine the consistency of the model. This research builds upon previous studies and contributes to the literature by incorporating two important components into this present research methods: (1) inclusion of critical wildlife habitat for birds and bats as an elimination criterion within the AHP, and (2) the participation by wind power experts in the AHP decision-making process for the utility-scale wind farm suitability modeling.

In the next section, the relevant literature is reviewed. Section 3.3 provides a detailed methodology, while Section 3.4 details the research findings and discusses some fundamental ideas underlying the results of the study. Finally, Section 3.5 provides conclusions and recommendations.

3.2. Literature review

As a decision analysis tool, multi-criteria decision analysis (MCDA) is a broad term for a range of methodologies and tools. As defined by(Saarikoski et al., 2015), MCDA is an overarching structure for supporting complex circumstances where there exist numerous interested parties who frequently have clashing goals and different perceptions of what is important. Its application in different sectors has proliferated considerably in the past decades (For detailed literature review on MCDA applications for renewable energy site selection, see (Shao et al., 2020)). The level of complexity, interaction with stakeholders and decision-makers, and the level at which potential details are used in the decision-making process can be varied substantially. Nonetheless, decision-makers follow the same process. Over the last decade, much attention has been focused on the use of GIS-based MCDA as a decision rationale system in the spatial procedure for land-based wind farms. Numerous researchers have sought to appraise the land suitability siting for renewable power plants (Gorsevski et al., 2013; Ibrahim et al., 2020; Kumar and Sinha, 2016; Mekonnen and Gorsevski, 2015; Messaoudi et al., 2019; Villacreses et al., 2017; Xu et al., 2020). Generally, decision-making is acknowledged as a mechanism for identifying and choosing possible choices from multiple alternatives via a cumulative scoring process that considers the consequences of each alternative relative to objectives covering environmental, technical, economic, and social (Al-Yahyai et al., 2012).

Created by Saaty (1980), AHP is rated high among the most exhaustive approaches proposed for decision-making processes that involves multiple factors. AHP has been extensively employed in various realms associated with renewable energy development (e.g.,(Al Garni and Awasthi, 2017; Ayodele et al., 2018; Höfer et al., 2016; Kumar and Sinha, 2016; Messaoudi et al., 2019; Xu et al., 2020). This technique makes it practical to express problems hierarchically (Noorollahi et al., 2016). In his discussion of the decision-making process, San Cristobal (2011) openly acknowledges that this decision-making tool usually performs efficiently when the information accessible for the decision-makers is complex and not easily quantifiable or when it is obligatory to depend on professional judgments or inclinations in various viewpoints.

In a similar vein, Ali et al. (2017) note that with AHP multiple criteria for complex challenges can be decomposed into one-to-one comparisons. As a result, several studies have employed this method to explore renewable energy development. Specifically, Hofer et al. (Höfer et al., 2016) utilized a GIS-based AHP method to enhance social acceptance of wind farm sitting in Germany by integrating environmental, technical, social, political, and economic factors in decision-making criteria. The authors identified 1.74% of the study area was as highly suitable for wind energy development.

Aydin et al. (2010) completed an analysis for a wind farm project in Western Turkey by applying a multi-criteria decision-making (MCDM) model built on Fuzzy sets combined with GIS. The authors analyzed various factors that impact the performance of a wind farm operation in the region. While Aydin et al. (2010) incorporated wildlife conservation areas as siting criteria; however, they did not utilize experts' participation in assigning weights to the siting criteria. In a related study, Ayodele et al. (2018) employed a model based on GIS combined with the type-2 fuzzy AHP method to select appropriate sites for establishing wind power facilities in Nigeria. The authors employed five wind energy development experts' participation to choose siting criteria and determine the weights of the criteria. Their models comprised two sets of criteria (social or economic and environmental), including important bird areas in assessing that the most suitable sites are the northern part of the country. However, the authors only incorporated bird areas as a constraint, but not as a weighted criterion.

Kaya and Kahraman (2010) proposed a modified AHP technique that integrates a compromise ranking method (VIKOR) to select the most appropriate sustainable energy alternatives and production sites for Istanbul in Turkey. The authors employed a pairwise comparison format for the weighting of their selection factors. Their result established wind energy as the most suitable renewable energy alternative and identified the preferred area for constructing wind turbines. More recently, Xu et al.(2020) proposed a GIS-based interval AHP model combined with stochastic VIKOR to determine high-suitability areas for wind farm development in Wafangdian, China. The authors showed that MCDM was practical and useful in guiding renewable energy site selection, particularly wind farms that involve complex spatial analysis. The authors also incorporate bird migration channels as one of the restriction factors and determine the criteria weights by experts in their analysis for wind farm site suitability.

Several studies have examined wind farm siting in the U.S. For example, Kumar and Sinha (2016) employed GIS-based spatial analysis for sitting utility-scale wind farms in Indiana, accounting for ten different suitability factors, including bird and bat habitats. Then, they utilized a fuzzy-based scoring and AHP for weighting by involving the participation of a group of experts. Depending upon the wind speed at different hub heights 100, 70, and 50, their results identified 2 – 6.7 percent of Indiana's land area as suitable for utility-scale wind farm development.

Another example is Gorsevski et al. (2013) who demonstrate the benefit of applying a spatial decision support system framework for evaluating the suitability for wind farm siting in Northern Ohio. These authors used GIS functionality and weighted linear combination method to integrates economic and environmental factors for wind farm siting. Similarly, Janke (2010) developed a technique using GIS-based multi-criteria decision-making to specify possible optimal areas for Colorado's wind farms development. The author employed various elements consisting of wind possibility and population density, distance to municipalities from geospatial databases, transformed to a raster data format to create a wind farm suitability map for the northeastern part of Colorado state. In a survey of onshore wind farm arrangements for Northern California, Rodman and Meentemeyer (2006) completed a spatial evaluation to locate ideal wind farms' ideal locations. They applied a rule-based spatial method to weigh possible choices that combined three components-environmental, physical, and human. Finally, Miller and Li (2014) used a multi-criteria technique to pinpoint the appropriate wind farm sites in the Northeast part of Nebraska, United States.

While there has been a great deal of research on wind power site development and the factors identified for suitability modeling of wind farms, very few studies have included evaluation of potential impacts on wildlife habitat (specifically bats and birds) (e.g., (Aydin et al., 2010; Kumar and Sinha, 2016; Peri and Tal, 2020; Van Haaren and Fthenakis, 2011; Xu et al., 2020) and/or utilized the participation of energy development experts in the screening and weighting of the criteria used in their studies (e.g., Ayodele et al. 2018; Yousefi et al. 2018). In the present study, I fill this gap in the literature by incorporating critical wildlife habitat as an elimination criterion as well as employing participation by experts in the decision-making process for the utility-scale wind farm suitability modeling.

3.3. Methods

3.3.1. Multi-criteria decision-making

The goal of this study was to identify the most suitable places for developing wind farms by employing a combined process of two evaluation instruments, Multi-Criteria Decision Making and Geographic Information Systems. The research design for this analysis is presented in Figure 3.3.

This study adopted the AHP method because of its several advantages over other techniques. The AHP depends on utilizing pairwise examinations, which are utilized both to contrast the choices with respect to the different factors and to evaluate weights associated with the factors (Løken, 2007). Among the advantages of the AHP is that it can easily be used in decision analysis. As noted by Velasquez and Hester (Velasquez and Hester, 2013), it is scalable as well as able to modify the extent of decision making efforts as a result of its hierarchical formation.

Furthermore, AHP, through a series of pairwise comparisons, as opposed to using numerical values directly, generates all criteria weighting and compares alternatives within each measure by these values from the decision-makers. Also, AHP has a solid theoretical background and tends to integrate the standardized criteria weights into a GIS model in a straightforward manner (San Cristóbal, 2011). The AHP method also allows individual and group comparisons to identify changes and potential compensation within the decision making arrangement (Strager and Rosenberger, 2006). This study takes into consideration different criteria by blending expert's information to establish the most suitable areas for wind farm construction. Several factors that could impact the construction of wind farms include those that impact construction cost, revenue potential, social acceptability, ecological impacts, and performances of wind turbines. Ten criteria were chosen based upon a detailed review of previous studies on this topic, expert's opinion and those factors considered as appropriate to determine the siting of wind power projects in West Virginia, as presented in Table 3.1.

Based on previous studies, the process applied for establishing a wind farm can be summarized in the following steps:

1. Determine spatial features and other factors of wind farm siting via AHP or related methods[6]

[6] Other related methods include TOPSIS – The Technique for Order of Preference by Similarity to Ideal Solution, CP – Compromise Programming, PROMETHEE – Preference Ranking Organization Method for Enrichment Evaluation, ELECTRE – Elimination Et Choix Traduisant la REalite (Elimination and Choice Expressing Reality), MACBAC – Multiple Attributive Border Approximation Area Comparison, ANP – Analytic Network Process, DEMATEL –

2. Standardize/normalize various features using fuzzy logic or other methods
3. Define weights for standards using pairwise comparison survey
4. Combine features and constraints using GIS instruments and the weighted linear combination technique.

3.3.2. Analytical Hierarchy Process (AHP)

To apply AHP, four steps were accomplished sequentially (San Cristóbal, 2011). First and foremost, the goal of the decision problem must be defined and structured into a hierarchy model. In this case, the goal was to determine the best suitable geographic locations for wind farms incorporating environmental, technical, economic, and social factors. Second, obtaining the weights for individual criteria influencing the objective of the defined problem (Pairwise comparison matrix). The purpose of this was to show the significance of each criterion comparative to one another. To achieve this, a judgmental matrix, the pairwise comparison was formed through the use of linguistic terms, which are the verbal judgment of the experts (San Cristóbal, 2011). Once the pairwise comparisons were made, it's required to test for its consistency because the pairwise comparison of criteria may sometimes be inconsistent. Figure 3.4 displays the flowchart for generating criteria weight from expert judgements. The AHP technique seeks to address the problem of consistency through the implementation of a consistency index that is a function of opposing comparisons.

I checked for consistency by first computing a consistency vector. Next, I computed the maximum Eigenvalue (λ) and the consistency index (CI). This can be shown as follows:

$$CI = \frac{(\lambda - N)}{N-1} \tag{3.1}$$

where N represents the number of criteria in the evaluation by the experts. Then, I compared the consistency Index to the Random Index (RI) table as provided by Satty (1980) (Saaty, 1980) to

Decision Making Trial and Evaluation Laboratory, MAIRCA – Multi Attributive Ideal-Real Comparative Analysis, IVFRN – Interval-valued fuzzy-rough numbers.

calculate the consistency ratio (CR).

$$CR = \frac{CI}{RI} \tag{3.2}$$

In the event that the estimation of the consistency ratio is lower than 0.10 (or 10%), at that point, the level of consistency is acceptable, and the matrix is considered consistent (Saaty, 1980). On the other hand, if the estimation of the consistency ratio is greater than 0.10, it implies inconsistencies. In this circumstance, the AHP may produce spurious results (San Cristóbal, 2011). Next, the score of each alternative by individual criteria was determined. Finally, the overall rating for a particular alternative was obtained.

Because this study incorporated wind power experts' participation in the AHP decision-making process for the utility-scale wind farm suitability modeling, several matrices had to be aggregated. Individual judgments can be aggregated in two different ways: (1) by the aggregation of individual judgments (AIJ), or (2) by aggregation of individual priorities (AIP) (Forman and Peniwati, 1998). Since preference of method primarily depends on if the group is assumed to act as a group or separate individuals, AIJ would be chosen as the most appropriate when individuals are prepared to relinquish their own preferences for the organization's good, thus acting to form and become a new individual. On the other hand, if individuals act on their own right or interest, with different value systems, AIP should be applied with the aggregation of each individual's priority vectors computed by either arithmetic or a geometric mean (Forman and Peniwati, 1998). Since survey experts were assumed to act as independent individuals, I employ the AIP for preferences aggregation and geometric mean.

3.3.3. Criteria representation as fuzzy sets

After calculating the estimation ranges, the identified criteria were expressed as fuzzy logic, employing the fuzzy set principle. The notion of the fuzzy set provides a way to obtain inferences from indefinite, vague, or ambiguous information (Clementini et al., 1997). This approach provides a suitable technique of dealing with imprecision and the lack of clearly defined criteria of class membership rather than the existence of random variables.

In this study, membership functions of the criteria were used to evaluate individual's degree of satisfaction for a given factor. It should be noted that a fuzzy degree is not the same as a probability percentage. Probabilities measure whether something will happen or not. Fuzziness measures the extent to which something will happen, or some conditions exist. Fuzzy sets are functions that outline the score of connection of a component *m* in the set, which takes the estimates between zero and one (where value zero implies no satisfaction, and one means satisfied) (Latinopoulos and Kechagia, 2015). Fuzzy memberships are linear, S (sinusoidal), and J shaped. Following Latinopoulos and Kechagia (Latinopoulos and Kechagia, 2015), this present analysis, employed linear function accordingly for individual satisfaction levels to be expressed as presented in equations (3.3) or (3.4)

$$\text{Increasing fuzzy function: MF }(m_i)= \begin{cases} 0 & for\ m_i < n_i \\ \frac{m_i - n_i}{y_i - n_i} & for\ n_i \leq m_i \leq y_i \\ 1 & for\ m_i > y_i \end{cases} \quad (3.3)$$

$$\text{Decreasing fuzzy function: MF}(m_i) = \begin{cases} 1 & for\ m_i < y_i \\ \frac{m_i - n_i}{y_i - n_i} & for\ y_i \leq m_i \leq n_i \\ 0 & for\ m_i > n_i \end{cases} \quad (3.4)$$

where *n* is the lower threshold value signifying its minimum suitable value, and *y* is the higher threshold value signifying that the values above this spot are considered highly appropriate.

3.3.4. Data sources and spatial analysis.

The spatial and categorical data of variables used in this study were obtained from the West Virginia GIS Technical Center (WVGISTC, 2019), National Renewable Energy Laboratory (NREL, 2019), US Census Bureau ("US Census Bureau. TIGER/Line Geodatabases," n.d.), and Audubon[7] (Audubon, 2019). For this spatial analysis phase, different GIS functions were employed to produce the factor maps. All the layers of the data were projected into NAD 1983 UTM Zone 17 using Data Management Tools in ArcGIS ArcMap (ESRI, 2011) . Similarly, all layers were converted into a raster data structure. Additional variables were derived from the original data that was obtained from the above-mentioned sources. Using the Euclidean distance command found in the Spatial Analyst toolbar of ArcMap (ESRI, 2011), I created a grid of distances from transmission lines, paved major roads (Arterial roads)[8], airports, residential developments, protected areas, and ranges from lakes and rivers, and bird and bat habitats respectively.

To derive a map of suitable areas for wind power facilities, the site suitability index in the study area was calculated. The ArcMap (ESRI, 2011) spatial analyst command (Raster Calculator) was used to determine distance "away from" each of the spatial features in Table 3.1. The features created a minimum and maximum distances in meters that would be economically, socially, physically, and environmentally reasonable for wind power facility development in West Virginia. Then, the *con* function in ArcMap, which acts as an "if-then-else statement," was used to create the fuzzy membership functions. As an example, the fuzzy distance to paved major roads would be:

Con("d_major_roads" > 15000, 0, Con("d_major_roads" < 5000, 1, ((15000 - "d_major_roads") / 10000.0))) (3.5)

where d_major_roads is the distance away from the paved major roads, and 10,000 is the maximum distance in meters that would be economically reasonable for wind farm development in the study area. For residential development, the fuzzy distance to residential development would be:

Con("d_towns" < 250, 0, Con("d_towns" > 750, 1, ("d_major_roads" - 250) / 500.0)) (3.6)

[7]The only available dataset that gives a few details on birds and bats habitats was acquired from Audubon. (www.audubon.org). The Audubon is a nonprofit conservation organization. The Important Bird Areas (IBA) is one of the organization's international bird conservation program, which is focused on identifying IBAs.
[8] These types of roads are designated for trucks bearing turbine components.

where d_towns is the distance away from residential development, and 500 is the minimum distance in meters that be socially acceptable for wind turbine installation in the study area.

The Fuzzy membership command in ArcMap was used to produce a standardized layer for every criterion. It is necessary to standardize criteria scores since criteria are measured on different scales. All of the criteria maps were scored positively with suitability (Eastman et al., 1995). The raw data needed to be transformed into comparable units. "Fuzzy membership converts the input into a 0 to 1 scale, implying that the intensity of membership in a set, centered on a specified fuzzification algorithm"(Environmental Systems Research Institute (ESRI), 2018). Figure 3.5 presents the maps for each of the data sets, categorized from excellent to poor (1 – potential area and 0 – exclusion area).

Next, the Weighted Sum command in ArcMap (ESRI, 2019) was applied to integrate the criteria and weights for each standardized grid. Finally, the suitability index was reclassified into four categories using classification tools in the ArcMap. Following Miller and Li (Miller and Li, 2014), the Natural Breaks (Jenks) classification approach was applied due to its ability to statistically standardize any difference within classes (JENKS and F., 1967; Miller and Li, 2014). The outcome of the four categories are: non-suitable (0.247283459 - 0.58674386), low suitability (0.58674386 - 0.672346917), medium suitability (0.672346917 - 0.749094486), and high suitability (0.632658777 - 0.999899983).

3.3.5. Criteria weights solicitation and estimation

Evaluation criteria may have different relative importance in the decision process (Tegou et al., 2010). Thus, the AHP technique was utilized to apportion weights to the criteria used in this study. The evaluation criteria identified, as presented in Table 1, were used to establish a 10 x 10 pairwise comparison matrix. Then, the precedence vector, which symbolizes the significance of a factor, was estimated. As in a few of the previous studies on renewable energy planning processes such as Hofer et al. (Höfer et al., 2016), this analysis expanded the application of AHP from the traditional single expert to a class of *N* experts[9]. The survey participants were regarded as decision-makers. The combined weights provided by each of them would be used as the criteria weights for the assessment. Thus, the geometric mean method is employed to determine each of the expert's ratings following Duke and Aull-Hyde (2002) and Strager and Rosenberger (2006):

$$P_g(Q_j) \ = \ \prod_{i=1}^{n} P_i\,(A_j)^{w_i} \tag{3.7}$$

where $P_g(Q_j)$ represent the group priority of alternative, j, $P_g(Q_j)$ refers to individual i's priority vector for alternative j, w_i represent the weight of individual i; $\sum_{i=1}^{n} w_i \ = 1$; and n denotes the number of wind energy experts interviewed.

To create aggregated weights, local wind power development experts were contacted in July 2019 for their opinions on the research and potential criteria for wind power site selection[10]. The selected participants constituted a small sample and not a random set of local energy development experts from renewable energy industry or government. Participants were solicited to complete the survey of pairwise comparison in which they rated the importance of each of the ten criteria based on a simplified four-point likert scale[11] (Table 3.3). These scales were used to note the relative significance of the selected criteria. Based upon complied survey data, priority vectors were estimated using the eigenvalue approach. After determining criteria weights, the weighted Sum command in ArcMap was used to calculate the total Suitability Index for individual cells of the entire study area.

[9] AHP is usually utilized on a single decision maker or in most cases in a very few group of decision-makers (Strager and Rosenberger 2006).

[10] Table 2 present the description of the individual participants and their areas of expertise and experience

[11] Traditionally, nine-point scale were used in AHP. Following Strager and Rosenberger (2006), we have adopted a simplified form (4-point scaling framework) to diminish the intellectual weight of the survey participants because of challenges respondents experienced in recognizing forces with the 9-point conventional scale.

3.3.6. Test of statistical differences

A sensitivity analysis estimation of the stability of the weights from the AHP procedure was performed to verify whether or not the weights from all the different individuals should be averaged for one overall weight set. As in Strager and Rosenberger (Strager and Rosenberger, 2006), a nonparametric Friedman's *Q* statistic (Siegel, 1954) was employed to test for statistical differences of the individual expert's weights. Friedman's *Q* statistic tests whether participants comprise a homologous group and whether participants vary from one another (Strager and Rosenberger, 2006). The null hypothesis states that there is no difference between the samples from the population, and the alternative hypothesis says that there is a difference between samples from the population. Equation (3.8) presents the Friedman's Q statistic:

$$Q = \frac{12}{Nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3N(K+1) \tag{3.8}$$

The Q statistic is dispersed in the form of a Chi-squared associated with a degree of freedom of $k - 1$, *k* denotes the number of criteria, *N* represents the number of individuals while R_j^2 represent the square of the rank-aggregate connected with the *k*th (Siegel, 1954). All statistical tests were conducted in an EXCEL Spreadsheet (Microsoft, 2016).

3.3.7. Sensitivity analysis

Following the multicriteria GIS assessment of potential utility-scale wind power locations, to gain confidence in the result, several sensitivity tests were done to evaluate the robustness of the model. This is because the priorities of the multi-criteria decision-making model can depend on the weights of the decision criteria. Moreover, the weighs provided by the experts may be subject to bias or error (Watson and Hudson, 2015). In this study, the sensitivity analysis involves factors and variable manipulations by varying the criterion weights, generating new outputs, and compared with original suitability assessment. After an extensive review of relevant literature, there are different methods for conducting sensitivity analysis in MCDM and AHP study. The sensitivity analysis of the model result was done in two ways. First, the model was estimated by modifying each criterion to have equal weights (10% each). Second, suitability analysis was done without the inclusion of critical wildlife habitat.

3.4. Results and discussion

AHP is a valuable and proficient approach for evaluating local expert preferences for renewable energy development criteria. A total number of 8 responses were received from a sample of 14 experts (a 57.14% response rate). The efficiency of the AHP comparison matrix and performance depends largely on the pairwise comparison consistency. Thus, a CR from each expert's judgments was determined, and responses of seven of the eight experts were considered valid based upon CR being less than the allowable threshold of 0.10 (or 10%) (Table 3.4). Experts were consistent in their results and implies awareness of the criteria. Across criteria, the results show that the criteria wind potential (C3 = 24.9%) received the highest priority rating. The next highest priority came from distance near transmission lines (C4 = 13.5%), then elevation (12.8%), and the fourth-highest was proximity to the nearest paved road.

From the perspectives of experts, distance from bird and bat habitat (C7 = 3%) had the least priority on the siting of wind farms in the study area. The weighted result of the experts prioritizing bird and bat habitat in this study is inconsistent with experts' scores in Xu et al. (Xu et al., 2020). In Xu et al. (Xu et al., 2020), experts ranked protected bird areas as the second-highest priority with approximately 26% score behind wind speed, 40% weight. There may be several reasons for the low priority of this variable compared to other criteria. One possible explanation may be due to the professional background of the experts utilized in the weighting survey. The experts involved in this study are neither wildlife resources managers, ornithologist, nor wildlife biologists, and they may have opined that the construction of wind farms in West Virginia may not necessarily result in potential wildlife conflicts.

I also examined whether participants comprised a consistent group in responses with Friedman's Q statistic. Table 3.5 presents the result for Friedman's Q statistic. For 9 degrees of freedom at alpha = 0.05, the Chi-square critical value is 16.92, thus with a Q statistic of 14.84, which means this study fail to reject the null hypothesis. This result implies that experts are from the same population as a result of their preference weights and that weights from all the different individuals could be averaged for in one overall weight set.

The results of the study identified four classes of suitability using Natural Break (Jenks) classification: high suitable, medium, low, and not suitable, and sites. Based on the analysis, about 70,000 hectares of land were identified as highly suitable for utility-scale wind farm development, which represents about 1.1% of the landmass of West Virginia (Figure 3.6). The top ten counties contain 97% of high suitability rating locations and were predominantly situated in the south-central and eastern portions of the state. The quantity of land and percentage of high suitable area in the top ten counties within the study region is shown in Table 3.6.

Interestingly, Pocahontas County was found to be the county with the largest amount of high-suitable locations for utility-scale wind farms, but there are currently no existing or proposed wind turbines in this county. The economy of this county relies heavily on tourism and recreation. Comments from a wind developer in the state indicate that the presence of nearby National parks and the fact that the Green Bank Observatory and quiet area exist in this county has kept wind developers from serious development considerations in this area. Another possible factor for lack of wind farms in Pocahontas County may be the costliness of wind power permit applications on National Forest land. Anderson et al. (Anderson et al., 2018) note that the development of wind farms on federal lands can require compliance with an overwhelming collection of federal regulations that further propagate the already complex and often cumbersome prerequisites enforced by local and state authorities.

According to the multicriteria GIS wind model, the potential locations for future utility-scale wind farms fell within the 'high suitability' areas as identified by the Natural Break classification. To obtain and visualize a more detailed portion of the high suitable areas, I zoomed in to a more specific area on the map. Following the zooming, I received the most appropriate 'realizable' locations in the study area, which are shown circled, as presented in Figure 3.7. Finally, examining the suitability of turbine siting on existing wind farms, 83.3% of turbines fell within 'high suitable' areas for the 376 wind turbines located in West Virginia.

Following an estimate from the Black Rock Wind Farm that was recently approved for construction in West Virginia, if the entire land areas identified as highly suitable throughout the region was exploited for wind power projects, it could yield more than 29, 000 megawatts (MW) of wind generating capacity. This generating capacity is greater than the existing electricity generating capacity of all energy sources (17,120 MW) in West Virginia. At this capacity, wind power can provide power output within the range of 64.20-terawatt hour (TWh) to 105.29 TWh per year assuming a capacity factor range between 25% - 41% (Enevoldsen et al., 2019; McKenna et al., 2020) This power output range compares favorably with the current annual electric power generation in West Virginia of 73.4 TWh.

Compared with the American Wind Energy Association (AWEA) estimate, this value from this study (29,000 MW) is less than half of its estimation of about 69,098 MW. However, this study's estimate is judged to be superior because the AWEA estimate only considers wind potential, whereas this present study considers wind speed and other economic, environmental, and social factors. However, it is worth noting that the evaluation of possible potential site size must not be misinterpreted as the same as feasible attainable potential. As argued by Enevoldsen et al. (2019), not all the identified potential locations would be available for wind farm projects because of land ownership issues, social opposition, political influences, and other land-use conflicts.

Several external factors or individual views influence energy decision making (Ozdemir and Saaty, 2006). Sensitivity analysis helps consider various circumstances and their effect on the final judgment (Alizadeh et al., 2020). A sensitivity analysis of the results was conducted to find possible locations that are influenced by preference weights. The sensitivity analysis involved factors and variable manipulations by varying the criterion weights, generating new outputs, and comparing results with the original suitability assessment. The influence of preference weights indicated that the integrated process was sensitive to variations in the weights of the evaluation parameters.

The sensitivity model generated a result with less non-suitable areas (see Figures 3.8 and 3.9). Specifically, the suitable areas increased to over 206,000 hectares with equal weights for each criterion, which represents an approximately 200% increase in highly suitable areas. Similarly, the suitable areas increased to about 310,000 hectares at the initial weightings of criterion but without the inclusion of wildlife habitat into the analysis, representing roughly a 340 % increase in highly suitable areas. Figure 3.9 demonstrates the scenario's result without critical wildlife habitat for birds and bats as a criterion, which tremendously increases the suitable areas for wind farms.

Although critical wildlife habitat is ranked as the lowest priority by the experts; however, based on the sensitivity analysis, it can be seen that this evaluation variable has a significant impact on the site selection. The sensitivity analysis showed evidence of this impact without critical wildlife habitat produced targeted site areas of 310,000 hectares. However, when considering all the criteria presented in this study, the number of feasible wind farm sites in hectares was significantly less than when critical wildlife habitat was not considered. The sensitivity analysis results show the importance of incorporating critical wildlife habitat as criteria for this study. Overall, this analysis demonstrated substantial opportunities for future utility-scale wind power development in the region while minimizing environmental, social, and economic impacts.

3.5. Conclusions and recommendations

Renewable energy has been a rapidly developing aspect of electric generation, stimulated by various domestic and global policy drivers. However, the decision-making processes regarding the development of wind farms involves substantial ecological and spatial planning. Most of the existing literature lacks quantifiable models that involve environmental consideration and participation by diverse experts. This analysis identified and evaluated environmental, economic, social, and technical factors for site suitability modeling for utility-scale wind farms in West Virginia. In particular, this study incorporated critical wildlife habitats as an elimination criterion as well employing participation by experts in the decision-making process. A fuzzy-based AHP multi-criteria analysis within a GIS setting was utilized to evaluate the suitability of the potential location of utility-scale wind farms. The GIS-based model used in this analysis can serve as a benchmark for wind power developers, public service commission regulators, and policymakers in the energy sector for deciding future permit applications and policies on wind power and optimum locations for wind power projects. Wind power project developers can easily find cost-effective locations in which investment could be channeled in the wind power project.

The results of the study identified high suitable sites for utility-scale wind farms across the state. Based upon this analysis, about 70,000 hectares of land were identified as highly suitable for wind power development, which represents about 1.1% of the landmass of West Virginia. Most of the highly suitable locations were located in ten counties, of which only three (Tucker, Grant, and Mineral Counties) currently have wind farms. The county with by far the most highly suitable locations in the state (Pocahontas County), currently has no wind power projects due to siting considerations from federal land-use constraints.

While this research has identified high suitable areas as the best locations for wind farm construction within the state of West Virginia, the actual development of a wind farm project requires additional evaluation and analyses before making such an investment. There are many other variables that could be considered for modeling wind power to enhance the robustness of the results. For example, the final assessment may be impacted by land ownership issues, social opposition, public opinion, political influences, and other land-use conflicts.

While this study was carried out with appropriate tools, the proposed technique and results are not without limitations. The application of energy output maps requires further validation in the field with measurement of wind speed at a particular location (Janke, 2010). The wind potential data utilized in this analysis are estimated, not measured. In addition, West Virginia serves as a migratory bird route (Brodeur et al., 1996; Buler and Dawson, 2014; Katzner et al., 2012; Merker and Chandler, 2020); this research only incorporates defined bird and bat habitats in critical habitat but lacks data on their migratory routes. The study also lacks bird and bats experts, including wildlife resource managers, ornithologist, or wildlife biologists in the analysis. While this analysis suggests that there is sufficient land area for utility-scale wind projects, a wind farm will not be sited unless the landowner agrees if it is on private land. One impediment not accounted for in this research is the ownership category (private or public) of the land located on highly suitable sites.

Therefore, several extensions to this present study could be considered, including incorporating other criteria such as bird and bat migratory paths if data becomes available, land ownership status, and land use in the suitability modeling process. Further research could apply the MCDA technique and available GIS software used in this study with the focus on the county-level analysis to gain insight into the amount of land in each county that are best for utility-scale wind farm development.

The economics of any given business is greatly influenced by the policies in place where the business is located (Bailey et al., 2012). This is true for wind power development in West Virginia. Based on the result of this analysis, there is adequate potential for future utility-scale wind power generation. However, there are several requirements and policy instruments that can strengthen the development of wind power in the state. These include but are not limited to policies of: a) the guaranteed purchase of electricity, b) establishment of regulations or tariffs that will ensure fixed cost recovery for power produced from wind power plants, and c) the development of a stable electricity market for renewable energy to encourage wind power developers to assume the liability of the capital cost required in the establishment of wind farms.

As one possible example, the state's repealed Renewable Portfolio Standard (RPS) [12] could be reconsidered such that new legislation would not be a burdensome mandate on utilities to increase renewable energy production from wind. As recommended by Bailey et al. (Bailey et al., 2012), state government could create policies in support of community wind projects as has been done the states of Maine and Minnesota with a Community Based- Renewable Energy Act. Bailey et al. note that state policy can be used to compel state utilities to organize the acquisition of power produced by community wind project similar to giving utility customers the choice to buy electric power from renewable source. State, stakeholders, and community leaders, environmental organizations can also play important roles in promoting sustainable alternatives to existing forms of power in the state. In summary, the success of developing renewable power such as wind in West Virginia will depend on regulatory policies, financial incentives, and public participation.

[12] In 2015, West Virginia revoked the Alternative and Renewable Energy Portfolio Act, which required utilities in the state to get 25% of their power from sustainable or alternative (natural gas) energy sources by 2025.

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Figures:

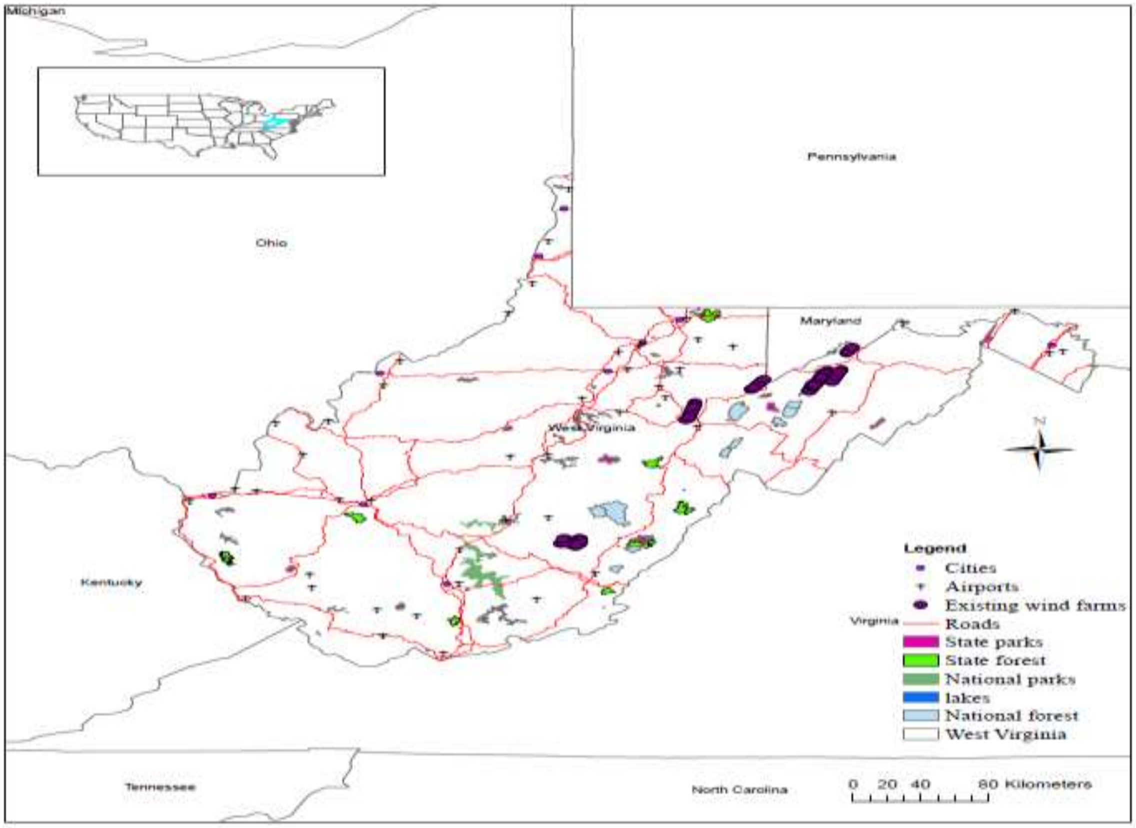


Figure 3.1. Wind farms and other features in West Virginia.

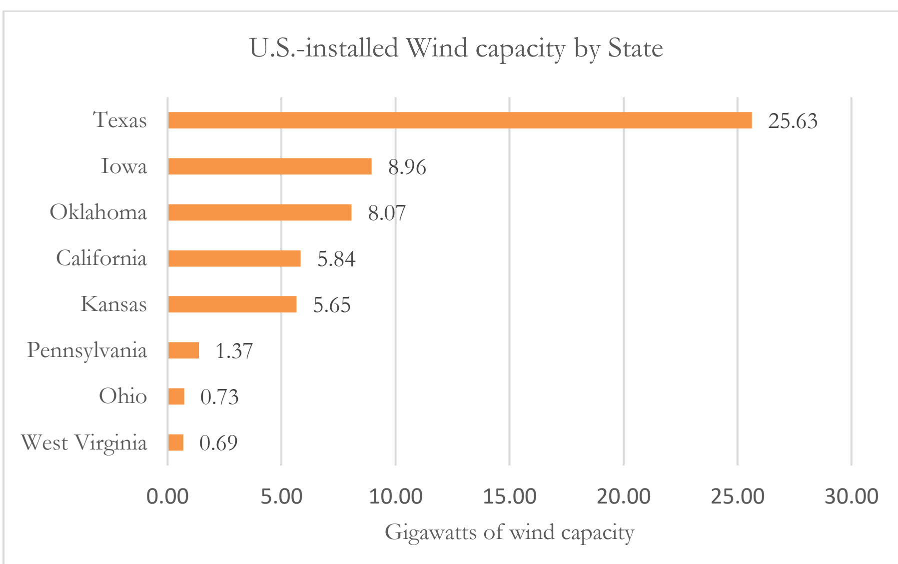


Figure 3.2. A comparison of installed wind capacity in West Virginia with top-five and neighboring states in the U.S., as of August 2019.

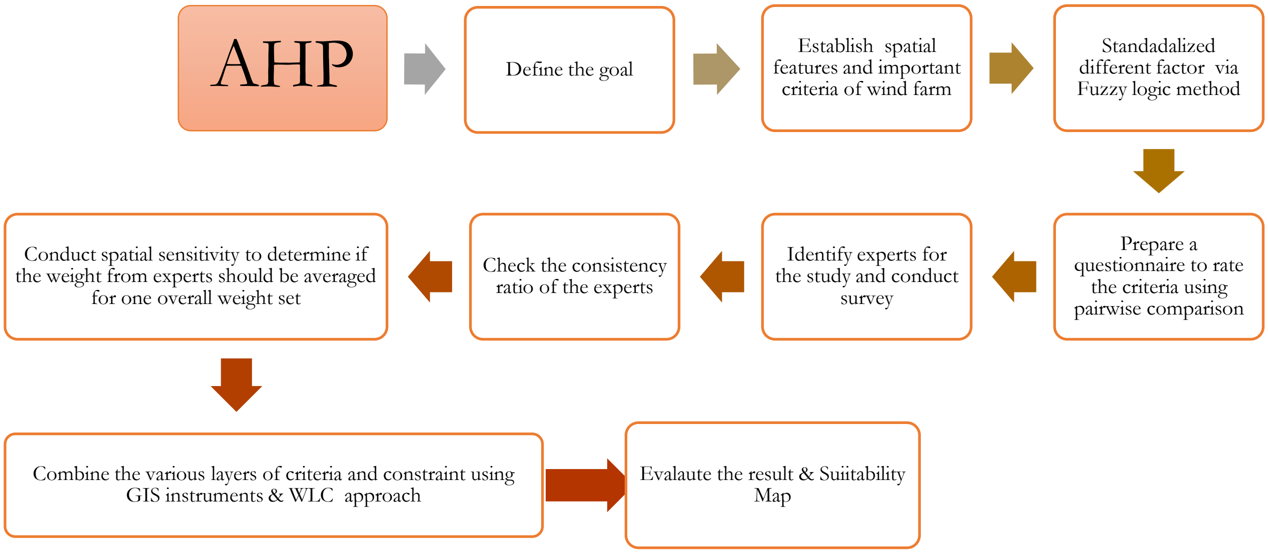


Figure 3.3. Schematic diagram of the research methodology.

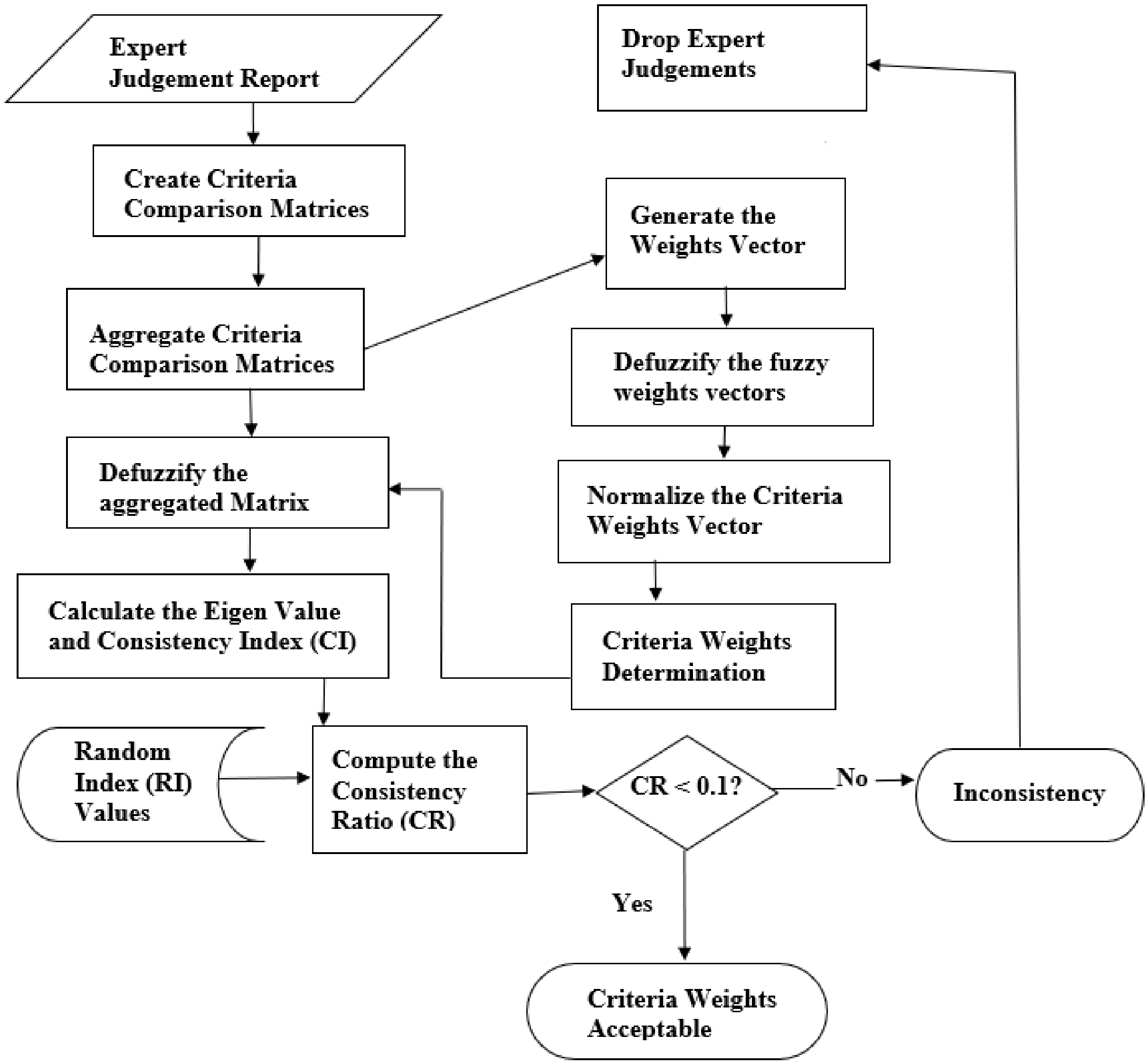
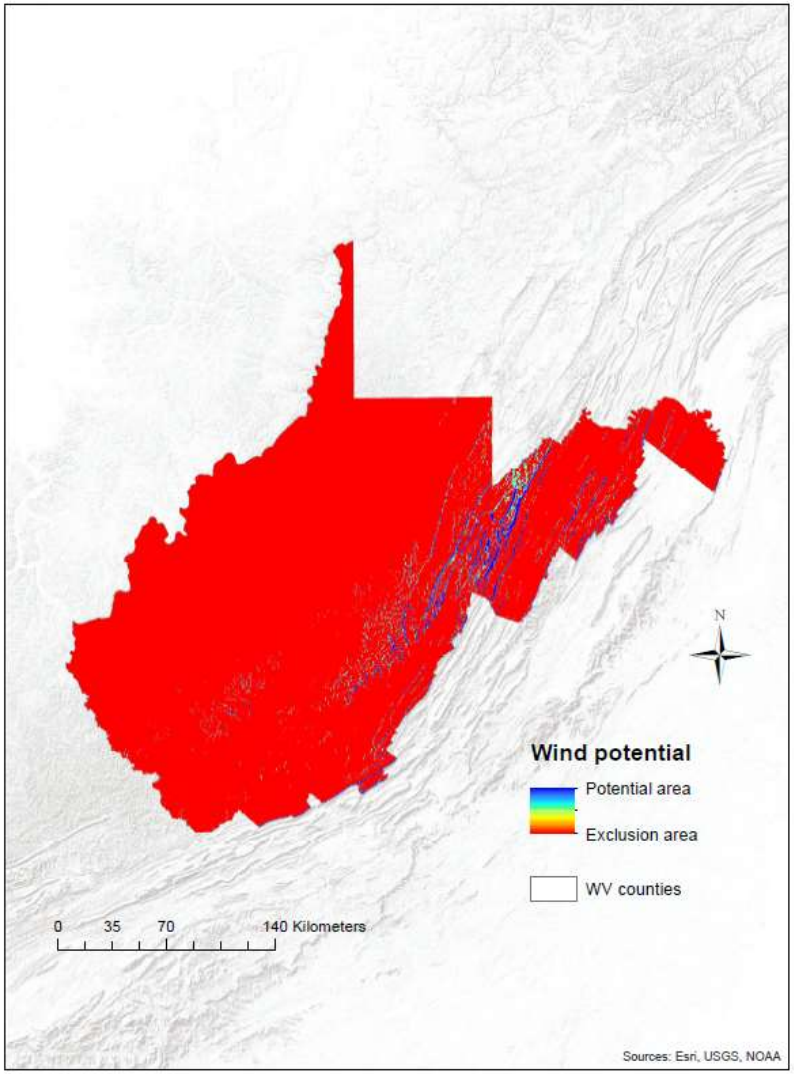
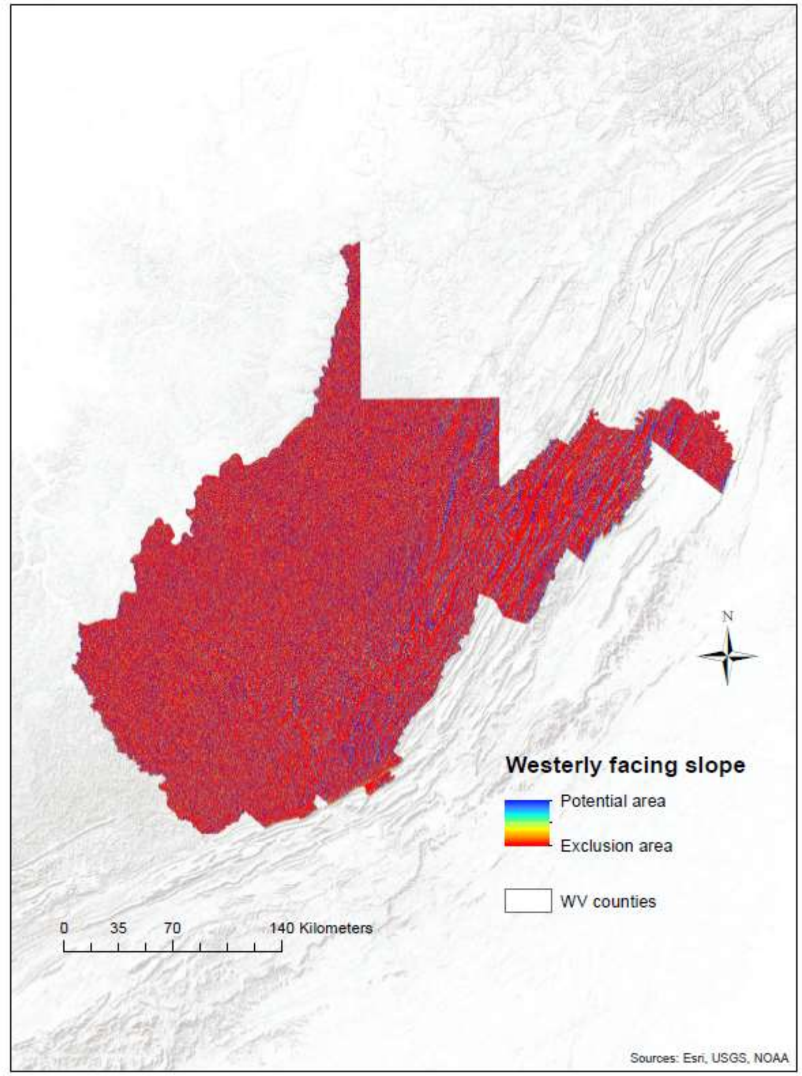


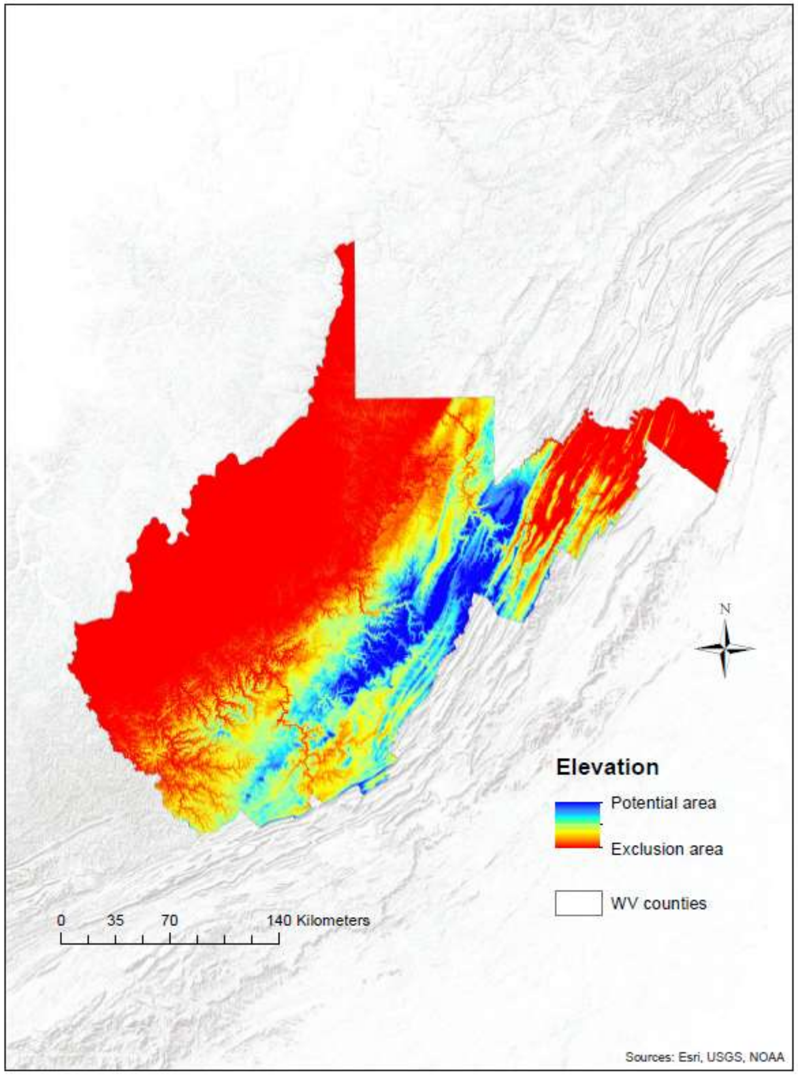
Figure 3.4. Flowchart for generating criteria weight adapted and modified from (Ayodele et al., 2018).



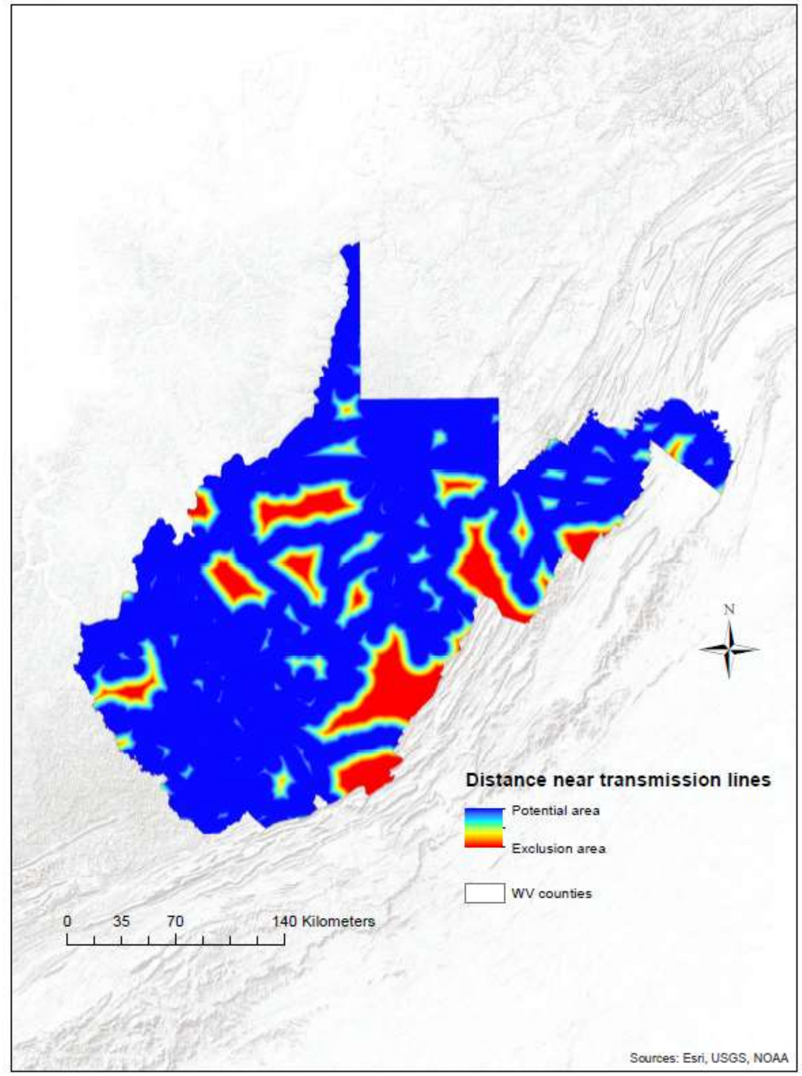
a. Wind potential



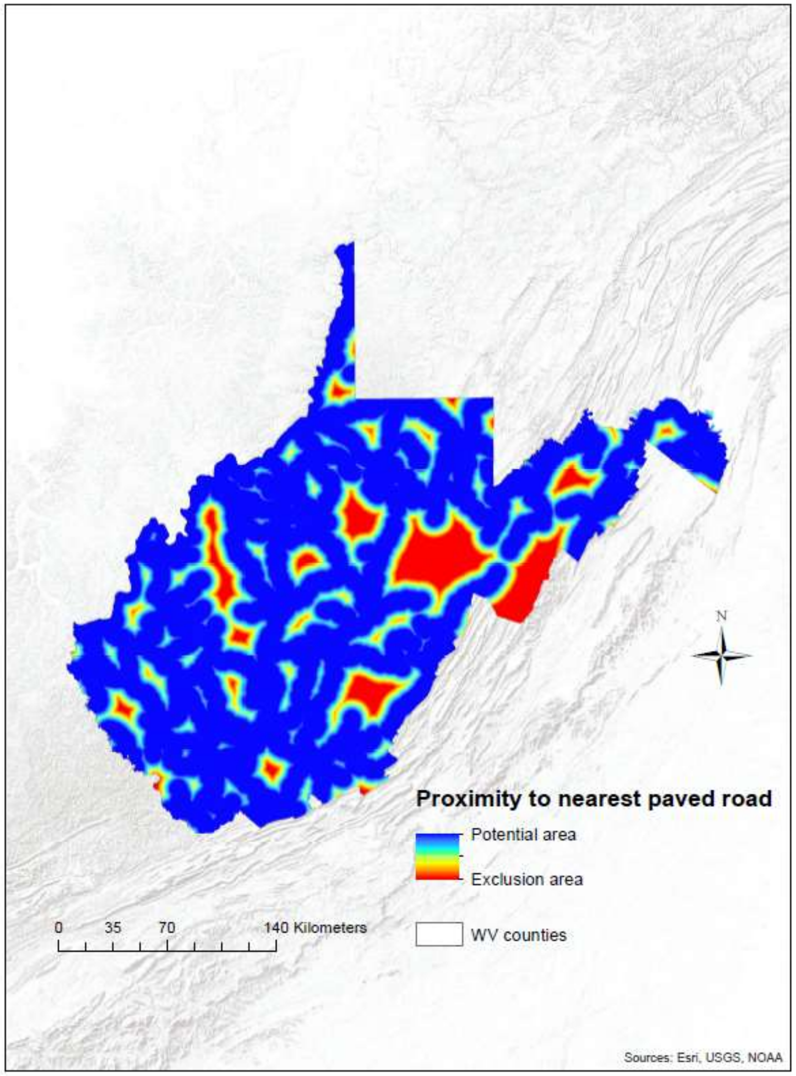
b. Slope



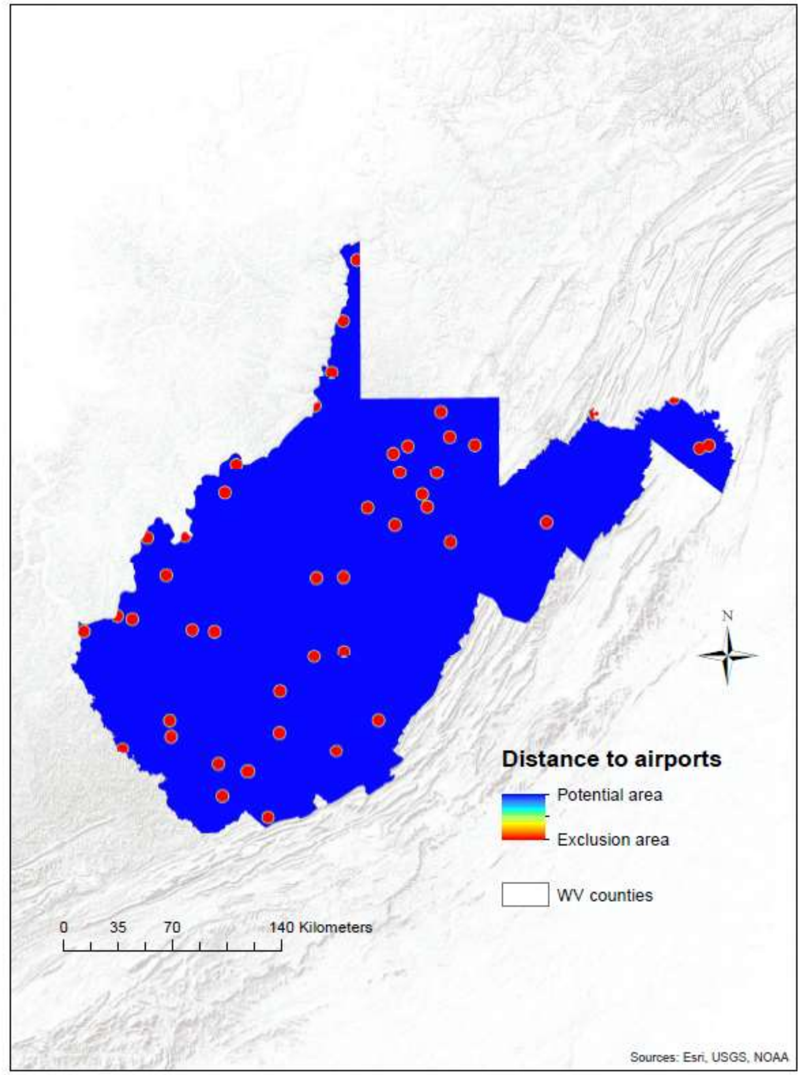
c. Elevation



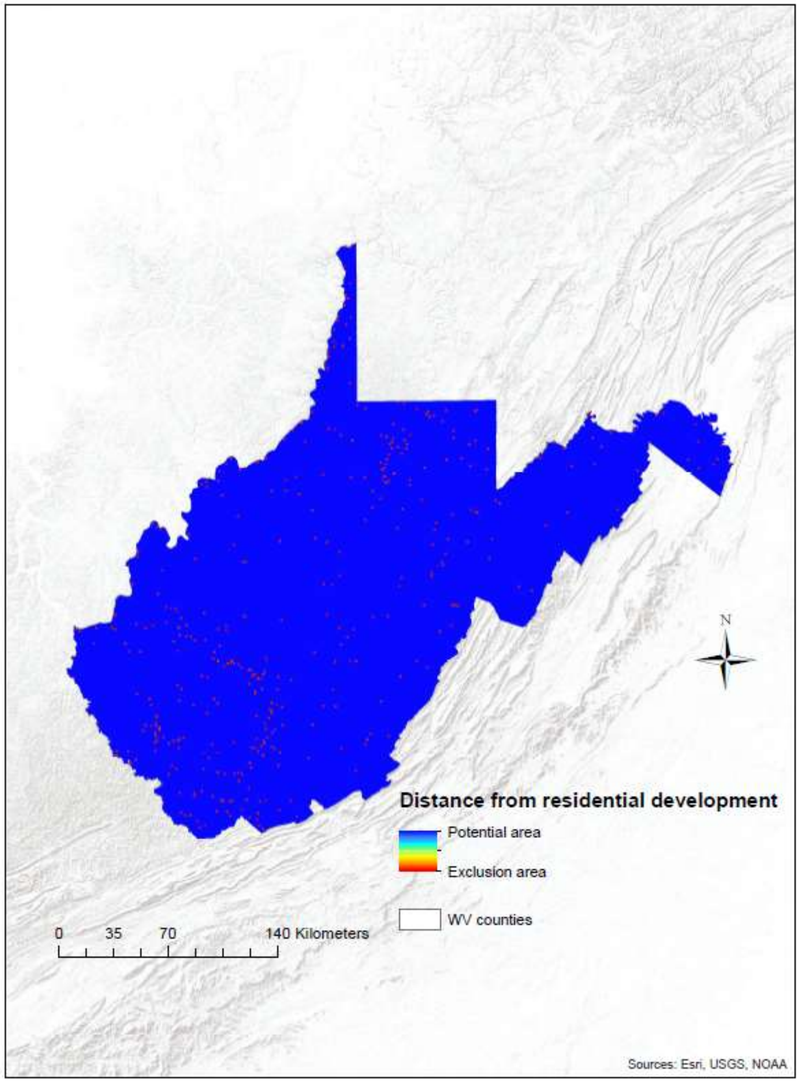
d. Distance near transmission lines



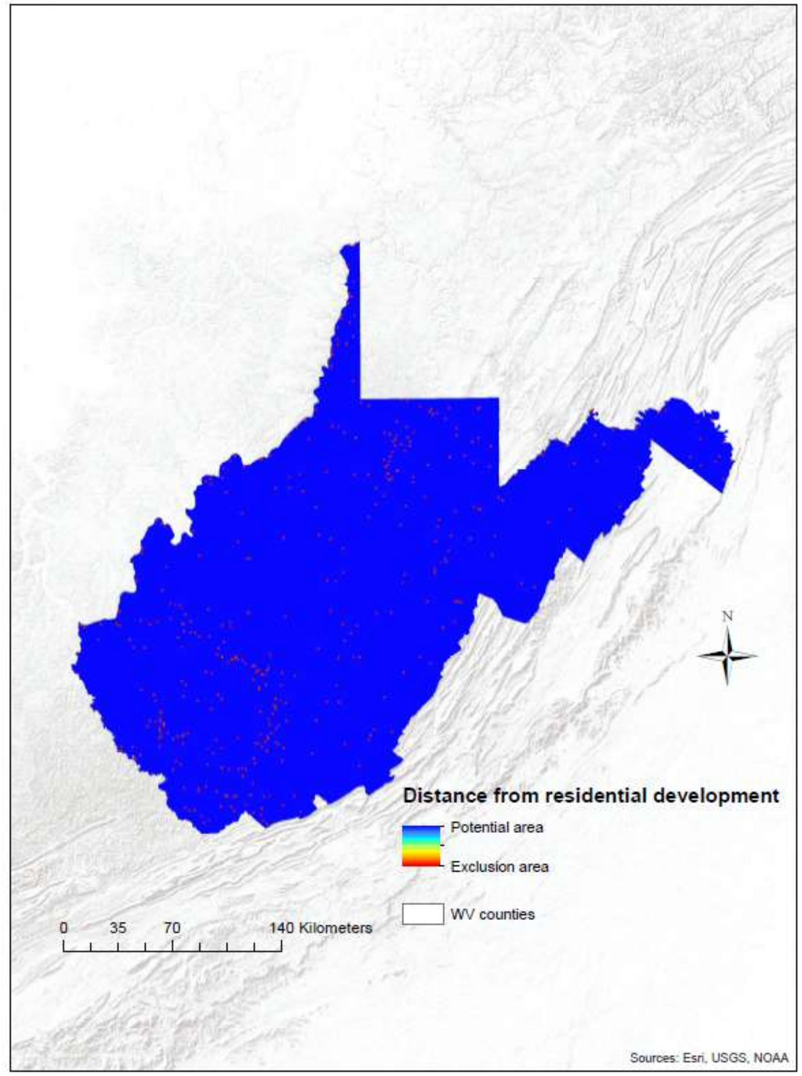
e. Proximity to nearest paved road



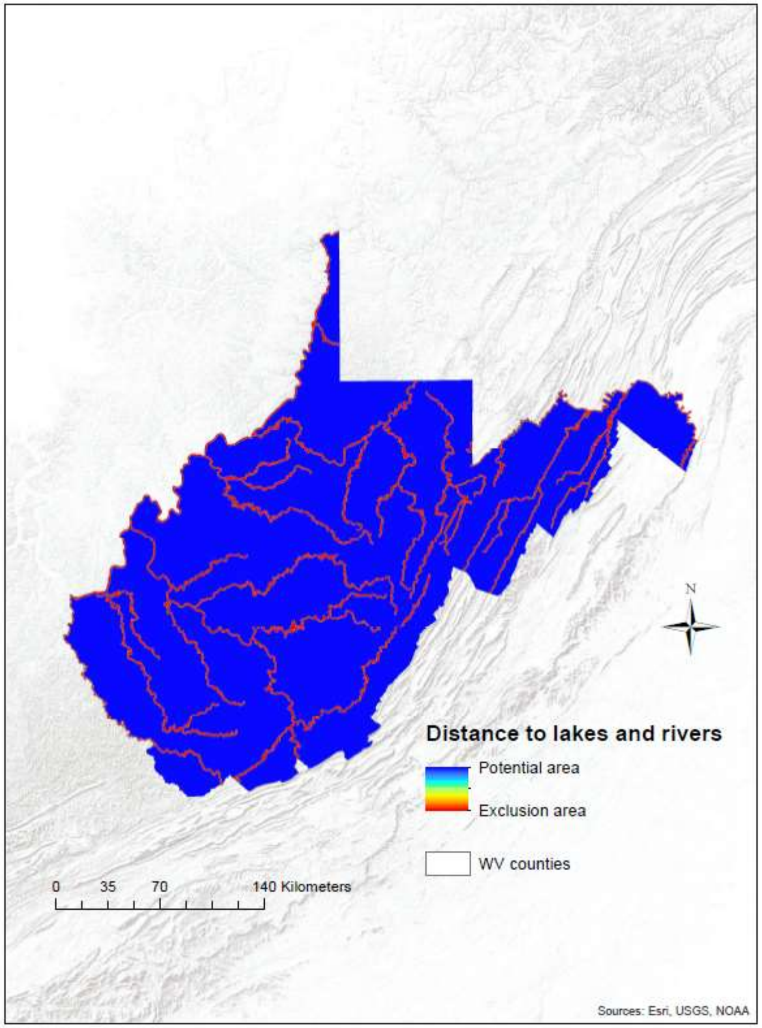
f. Distance to airports



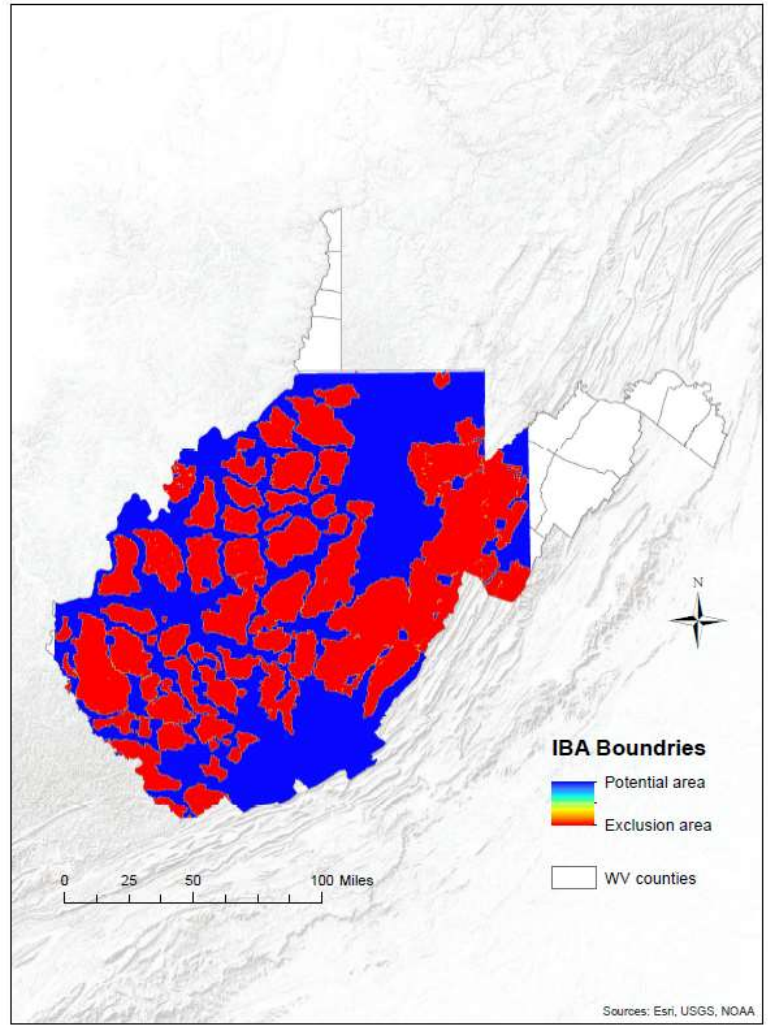
g. Distance from residential development



h. Protected areas



i. Distance to lakes and rivers



j. Wildlife habitats (IBA- important bird area)

Figure 3.5: Suitability maps according to the criteria: (a) wind potential (b) Slope (c) Elevation (d) Distance near transmission lines (e) Proximity to paved major road (f) Distance to airports (g) Distance from residential development (h) Protected areas (i) Wildlife habitats.

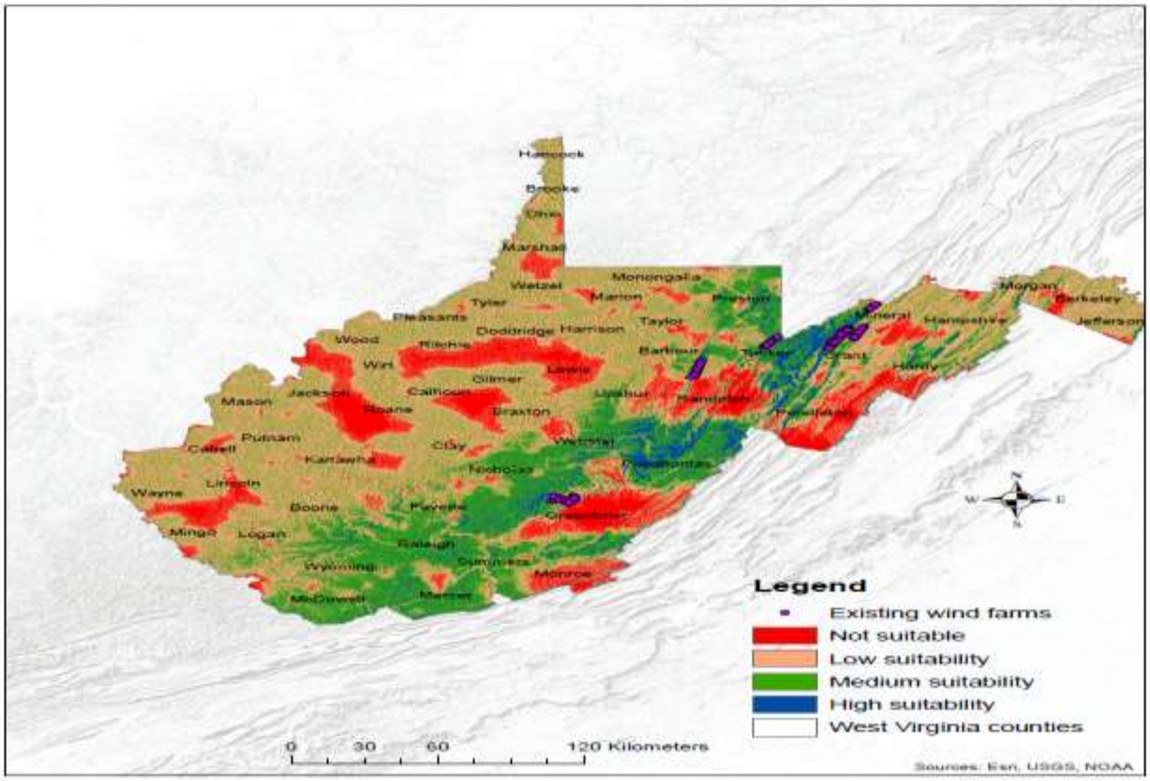


Figure 3.6. Suitability analysis for potential wind farms in West Virginia, U.S.

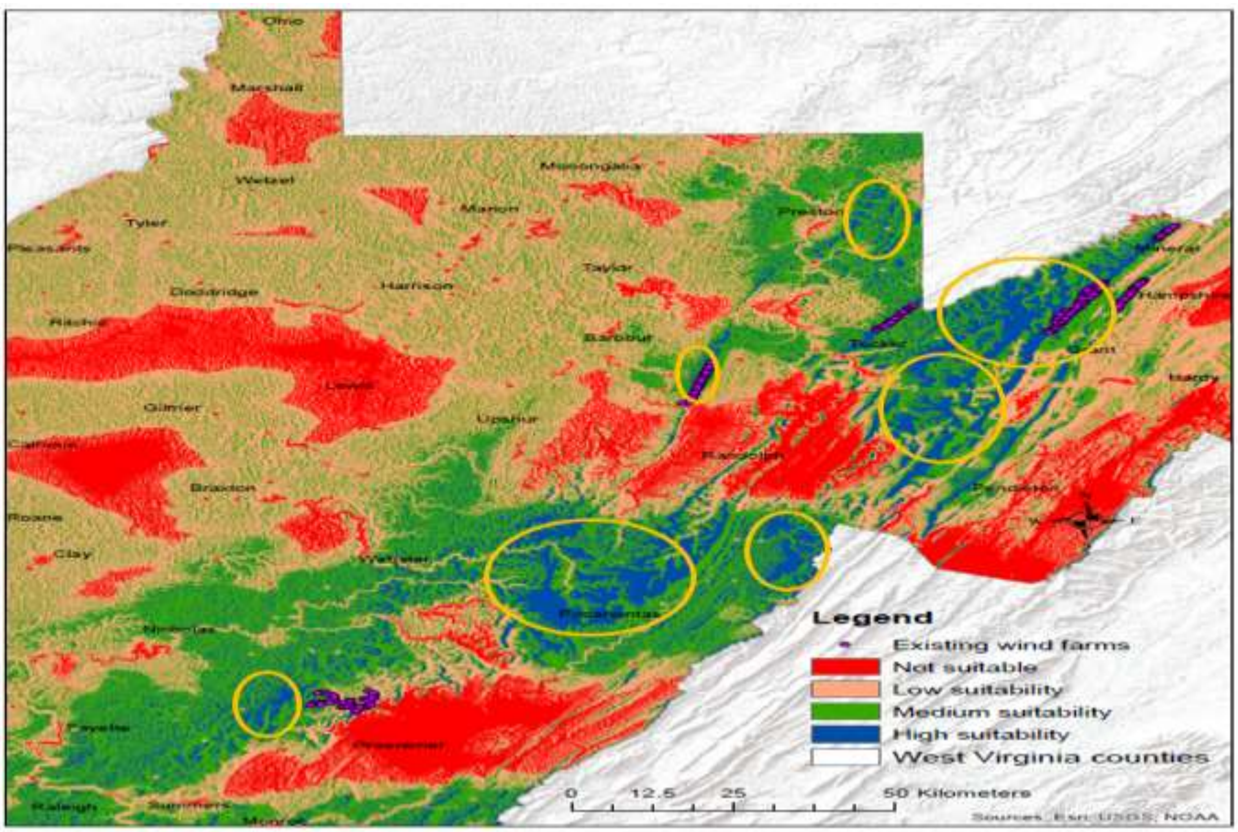


Figure 3.7. High suitability areas.

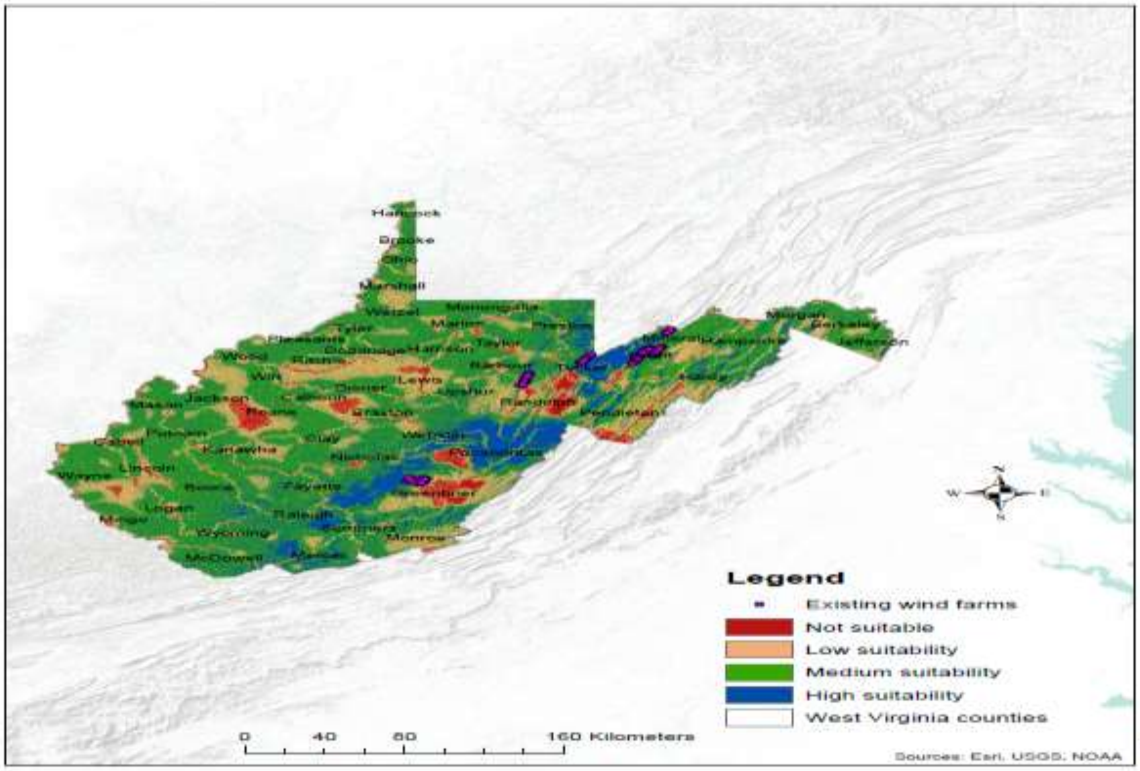


Figure 3.8. Sensitivity analysis based on equal weight for each criterion.

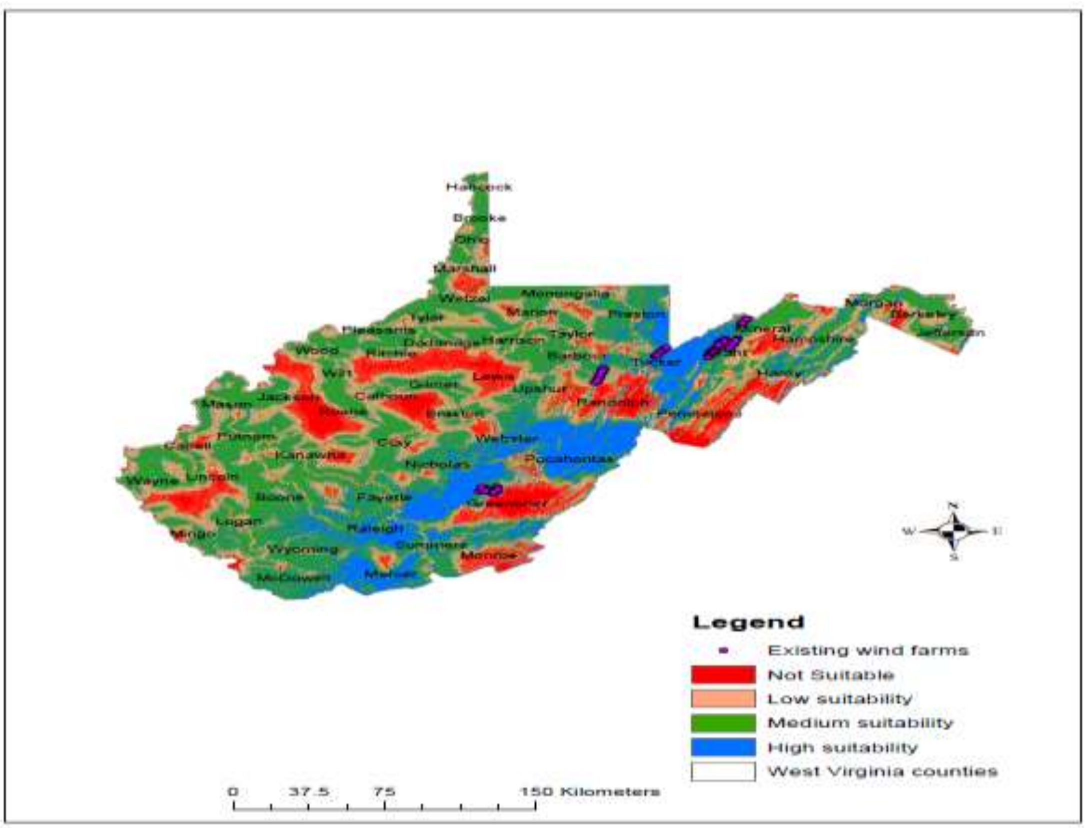


Figure 3.9. Sensitivity analysis based suitability model without critical wildlife habitat.

Tables:

Table 3.1. Evaluation criteria and constraint

Category	Criteria	Description/Justification	Constraint
Technical	Wind Potential	This is the critical starting point for any wind farm project. Regions that have yearly average wind speed about 6.5 meters per second and above at 80-m height are commonly considered to have an appropriate source for wind power development. (e.g.,(Latinopoulos and Kechagia, 2015; Løken, 2007)).	>5 (m/s) (Baban and Parry, 2001)
	Slopes	Slopes affect the ease of construction and maintenance (Tegou et al., 2010).	<10 (%) (Atici et al., 2015)
	Elevation	Although West Virginia's land surface rises to higher elevations in the northeastern and east-central regions of the state. However, from a potential technical perspective, all fields with an altitude higher than 1500 m have been excluded for this study.	>2000 (m) (Al-Yahyai et al., 2012; Atici et al., 2015)
Socio-economic	Distance from transmission lines	Wind turbines are more qualified at territories which are near gridlines to circumvent additional expenses of development of new gridlines (Baban and Parry, 2001), and reducing the initial cost of wind farm construction.	>10,000 (Baban and Parry, 2001; Miller and Li, 2014)
	Proximity to the nearest paved major road	The size of wind turbine components creates several transportation barriers. Therefore, locations close to roads are generally regarded as suitable for siting wind farms to take into account better access for development and support (Baban and Parry, 2001).	<10,000 (m) (Baban and Parry, 2001)
	Distance from airport	For safety reasons, areas near airports are considered not suitable for wind turbines installation (Atici et al., 2015; Carrete et al., 2009).	>3000 (m) (Atici et al., 2015)
	Distance from residential development	The development of wind farms near neighborhoods is limited to forestall noise from turbines and visual interruption (Höfer et al., 2016).	>500 (m) (Baban and Parry, 2001)
Environmental	Proximity to protected areas	West Virginia has several lands that are under federal protection, including national historical parks, national forests, national wildlife refuges, recreation areas, etc. Raising wind turbines in these preservation zones is not recommended the same as in residential areas. (see (Baban and Parry, 2001; Watson and Hudson, 2015)	>2000 (m) (Al-Yahyai et al., 2012; Atici et al., 2015)
	Distance from lakes and rivers	This is considered as an environmental and technical constraint in the construction of wind farms. Lakes and small water bodies are considered not appropriate as it may obstruct the waterway and therefore increase the cost of construction (Carrete et al., 2009; Xu et al., 2020)	>2000 (m) (Al-Yahyai et al., 2012; Atici et al., 2015)
	Critical Wildlife Habitat	West Virginia has about 63.5 percent of its land area (9.7 million acres) identified as the important bird habitat based on the Audubon Society's dataset. Thus, it is essential to evaluate sites based upon their potential impacts on bird and bat populations and other wildlife species. While some studies have argued that bird collision is not a significant problem (Cox, 2017; Erickson et al., 2014), fragmentation of bird habitat by wind farms can be a problem. (see, e.g., Van Haaren and Fthenakis 2011; Yue and Wang 2006).	>500 (m) (Aydin et al., 2010; Yue and Wang, 2006)

Table 3.2. Description of expert's expertise and experience

Experts	Description
1	This person is an energy expert with over 25 years of experience in energy development and has been developing wind farms since 2001. He had expertise in acquisition and development, environmental impact assessment, government/regulatory, management of electricity facilities, and risk management. He operates jointly with local and international energy investors during project development and operation stages.
2	This person is a renewable energy project director with significant experience in wind project acquisition and development. She works in the private industry as a project manager.
3	This person is an energy developer and an environmental impact assessment specialist. She worked with both the private sector and public agencies on the evaluation of different energy projects.
4	This person has expertise in energy development with a focus on acquisition and development. He has over ten years of experience in overall energy development with about five years of specialization in wind energy development. He works in private industry
5	This person has over ten years of experience in renewable energy development with expertise in environmental impact assessment and government regulations. He works in the government sector
6	This person is an energy development specialist. He works in the energy development and alternative fuels industry with about over five years of experience in energy development regulatory and management.
7	This person is a Professional Geologist and remediation specialist with 14 years of experience in various capacities in environmental field with particular expertise in site assessment and permitting. She works in private industry as an Environmental Division Manager.
8	This person is an energy development specialist with over ten years of experience in energy program development and administration. She works in the private industry as a regional field director.

Table 3.3. Conventional pairwise measurement and Condensed scales utilized in the analysis (Strager and Rosenberger, 2006)[13]

Conventional pairwise intensities	Simplified alternatives
Equal	Equal
Barely prefer	
Weakly prefer	Somewhat Prefer
Moderately prefer	
Definitely prefer	
Strongly prefer	Prefer
Very strongly prefer	
Critically prefer	
Absolutely prefer	Strongly prefer

Table 3.4. Criteria, normalized weights, consistency ratio by experts.

Criteria	Symbol	E1	E2	E3	E4	E5	E6	E7
Elevation	C1	0.154	0.091	0.180	0.107	0.145	0.160	0.090
Slopes	C2	0.128	0.066	0.029	0.122	0.101	0.088	0.055
Wind Potential	C3	0.192	0.224	0.257	0.278	0.163	0.341	0.343
Distance from transmission lines	C4	0.125	0.142	0.117	0.134	0.183	0.116	0.138
Proximity to the nearest paved road	C5	0.114	0.206	0.111	0.163	0.150	0.104	0.054
Distance from airports	C6	0.047	0.041	0.037	0.027	0.029	0.042	0.150
Critical Wildlife Habitat	C7	0.040	0.035	0.027	0.033	0.035	0.027	0.018
Distance from residential development	C8	0.070	0.132	0.101	0.077	0.121	0.077	0.090
Proximity to protected areas	C9	0.081	0.030	0.071	0.032	0.035	0.023	0.027
Distance from lakes and rivers	C10	0.050	0.032	0.070	0.028	0.037	0.021	0.036
Consistency ratio	**CR**	**0.096**	**0.047**	**0.050**	**0.083**	**0.025**	**0.039**	**0.077**

Note: E1- E7 represent individual experts.

[13] The condensed scale alternatives were utilized in this study because of the difficulty test respondents experienced in distinguishing between intensities with the 9-point conventional. The 4-point scaling system was adopted to reduce the cognitive burden.

Table 3.5. Summary of Friedman's Q statistics

K	10
N	7
DF	9
RS	15775
Statistic	14.84416

Note: K represents the quantity of criteria, N represent the number of experts used, RS denotes squared of the rank-aggregate.

Table 3.6. High suitable land in top ten counties

County Name	total land(ha)	High suitable land (ha)	Percent of county
Pocahontas	243,534	19,970	8.2
Grant	123,597	9,764	7.9
Tucker	108,487	8,462	7.8
Pendleton	180,748	5,242	2.9
Randolph	269,288	4,847	1.8
Greenbrier	264,505	4,761	1.8
Webster	143,995	4,176	2.9
Preston	167,915	3,862	2.3
Hardy	151,098	3,777	2.5
Mineral	84,883	3,565	4.2

CHAPTER 4

Essay 3: Wind Power Penetration Impacts on Wholesale Electricity Market: Evidence from Quantile Regression Approach

4.1. Introduction

Wholesale electricity markets in the U.S. have undergone drastic technology shifts in recent decades. There has been an influx in electricity generation from variable renewable energy sources such as wind and solar. This unprecedented technology switch, coupled with decreasing natural gas costs, has created increased competition among generators, resulting in historically decreasing wholesale electricity prices. The growth in wind power generation is driven by various factors, including tax incentives, declining costs, demand for electricity, and advanced technologies, including larger towers and lighter rotor blades (Magdi, 2017; W. Ryan et al., 2018).

However, the rapidly increasing integration of renewable power into the electricity grid poses fundamental concerns about the potential impacts of this transition on the current electricity system. These issues span from short-run, medium, to long-term impacts on wholesale and retail electricity prices (Csereklyei et al., 2019; Figueiredo and da Silva, 2019). There are uncertainties about these renewables' intermittency on electricity supply and impacts on investments in electricity generation industries. Issues of reliability, affordability, and the weather-dependent nature of their generation have been the significant points of contention (Figueiredo and da Silva, 2019).

In addition, the concerns about the financial future of the traditional generation plants have provoked a sequence of controversial proposals in the U.S. (Bushnell and Novan, 2018). Previous studies have noted that integrating large renewables in the energy market poses several challenges and compels additional research (Figueiredo and da Silva, 2019). Therefore, correctly identifying and quantifying the benefits and costs of increased renewable operating capacity is crucial for economic research on renewable power. While the literature has verified the price-reducing effect of wind power penetration (e.g., Bushnell and Novan, 2018; Dahlke, 2018; Quint and Dahlke, 2019; Tsai and

Eryilmaz, 2018; Woo et al., 2016), however, it remains unclear how wind power penetration affects the entire wholesale price distribution.

The motivation of this research is to gain a better understanding and empirically clarify the role of wind generation on wholesale electricity market outcomes at different quantiles of the conditional distribution of electricity generation and prices. This study's lesser motivation is to understand how fundamental pricing factors (demand and supply variables) induce various fragments of the electricity prices, unit revenues, and value factors distribution. Therefore, the primary research objectives are as follows:

1. To examine the impacts of increasing wind power deployment on wholesale electricity prices across different quantile of the price distribution.
2. To investigate the potential existence of the merit-order effect in the Pennsylvania – New Jersey – Maryland (PJM) market (with relatively low wind energy penetration) versus the Electric Reliability Council of Texas (ERCOT) market (with a relatively high percentage of wind power penetration, for contrast) concurrently.
3. To quantify the effects of wind generation on the market values of baseload and non-baseload sources across the entire distribution of wholesale electricity market outcomes.

Remarkably, few studies have been designed to quantify the merit-order-effect (MOE) of wind generation on both markets: the day-ahead market (DAM) and the real-time market (RTM). Examples include in the Texas ERCOT market (e.g., Zarnikau et al., 2019, 2016) and California CAISO market (e.g., (Woo et al., 2016), which attempt to simultaneously evaluate the RTM versus DAM merit-effects of wind power penetration in more than one Independent System Operator or Regional transmission organization (ISO/RTO) regions over the same period of time. Consequently, I propose to examine the impact of wind penetration on prices in both DAM and

RTM. For the sake of comparison, the effects of wind generation expansion on wholesale electricity prices will be examined concurrently in the PJM and ERCOT markets.

PJM and ERCOT are well suited markets to empirically investigate the merit-order effect of wind generation on wholesale electricity prices because wholesale electricity prices in both markets have declined over the past years along with experiencing considerable increases in wind generation. While both regions have comparable wind resource potential, wind generation of electricity in the PJM region is low relative to the ERCOT market, creating a wide range of wind penetration into markets. These generation differences allow a comparative analysis of the merit-order effects in the two markets and permitting exploration of changing impacts by market region. Besides, the market structure and price formation in these markets are easily comparable to one another. Both the PJM and ERCOT operate on a nodal market design based on the locational marginal pricing system (Stoft, 2002).

The analysis of the merit-order effects in two or more ISO/RTO regions simultaneously would permit the exploration of changing impacts by market region due to different transmission and generation capacities and various regulatory procedures (Fell and Kaffine, 2018). Undeniably, the impacts of new renewable electricity generation such as wind power in the electricity market must be thoroughly understood to evaluate renewable energy support policies' efficiency[14]. To this end, I intend to answer the following important energy policy questions:

- How much does wind power integration impact wholesale electricity prices under different market settings in PJM and ERCOT markets?[15]

[14] As argued by Würzburg et al., (2013), this effect may also generate other challenges to the system: as these lower prices may send lower investment signals and make it difficult to recover capital costs for existing producers.
[15] ERCOT has high percentage of wind power generation while the PJM market is dominated by fossil fuel-based electricity together with nuclear power plants, with relatively little wind power penetration.

- Does the merit-order effect (MOE) exist for different quantiles of wholesale electricity prices?
- What drives prices in the day-ahead and real-time markets at different market conditions?
- Does the increasing penetration of wind power undermine its market value along with the market values of other generators?

To address these questions, quantile regression is used to analyze a large hourly time-series sample of PJM and ERCOT electricity market data from 1/1/2011 to 12/31/2019. The empirical analyses confirmed the merit-order effect across different quantiles of the conditional distribution of wholesale prices for both day-ahead and real-time markets, implying that the increasing deployment of wind power for electricity generation significantly suppresses the wholesale electricity prices in the PJM market. Contrary to the PJM estimations, merit-order effects are confirmed across quantiles of wholesale prices for only the day-ahead market in the ERCOT market. However, the analyses confirmed the merit-order effect at the median quantile and greater in ERCOT market for the real-time market.

Further, this research findings show that as wind capacity grows within the market, the revenue earned by wind power producers declines across different quantiles of the conditional distribution of its unit revenue. Specifically, the results suggest that increasing wind power deployment in the PJM regional market undermines wind power market values in terms of unit revenues (the cannibalization effect). On the contrary, there is weak evidence of the cannibalization effect of increasing wind supply in terms of its value factor. Interestingly, the results also confirm the cross-cannibalization among other generators. The findings imply that wind penetration reduces the revenue earned from both gas and baseload generators. These results further suggest that an increasing expansion of wind capacity may create revenue uncertainties for other current traditional or future generators.

In summary, the main contributions of this research can be considered as follows: First, previous literature in the U.S. electricity market has relied primarily on ordinary least square (OLS) regression, which only estimates the average effect of renewable generation on electricity prices which cannot be extended into non-centric areas (distribution tails). In contrast, using quantile regression methodology analyzes the underlying merit-order effects and market values impacts of wind power supply across the spectrum of conditional quantile distributions which provides more reliable and efficient estimates of impacts on price and market value distributions. The values obtained from quantile regression indicate that wind penetration has unequal impacts on wholesale prices and market values across quantiles, reinforcing the need for this type of analysis. Second, this study provides the first empirical study of PJM's electricity market to the best of my knowledge that investigates both price and market value impacts of wind power generation.

Third, the vast majority of the existing research into the effects of wind generation on electricity prices has focused on either DAM or RTM, but has failed to simultaneously explore both market prices. To facilitate this comparison and to fill this gap, this study explores the effects of wind generation expansion on DAM and RTM prices in PJM and ERCOT markets concurrently. While the impacts between DAM and RTM in the PJM market are found to be negative and statistically significant across the different quantiles of the price distribution, in the ERCOT market, the lower quantiles show a positive impact from wind, failing to support the merit order price-dampening hypothesis. One immediate conclusion to be drawn from this result is that forecast imbalance between wind output and actual electricity demand (load) in the ERCOT market might be responsible for the RTM estimate to deviate from the DAM results. In addition, this result may be partly due to trading inefficiency in ERCOT's DAM price as noted by (Zarnikau et al., 2014).

Finally, this study provides policy implications relevant to the market regions investigated which may be equally applicable to other electricity markets in other regions with growing penetration of renewable energy sources and related behaviors in electricity prices as PJM and ERCOT (e.g., MISO and CAISO). Notably, in light of the recent debate on resource adequacy, reliability, and grid resilience, policymakers should be conscious of the negative impacts of renewable energy on investments in conventional power plants. The intuition behind this policy caution is that this study's results suggest that renewable penetration in the electricity market could create revenue uncertainty, undermine future profitability, and potentially decrease the electricity generation system's reliability.

The remainder of this manuscript is organized as follows: Section 4.2 discusses the research background and 4.3 review the existing literature on the impacts of renewable energy penetration on wholesale electricity market outcomes. Section 4.4 presents the theoretical framework. Section 4.5 is dedicated to the description of the data, exploratory data analysis, and methods. Section 4.6 presents and discusses the research findings, and finally, section 4.7 concludes.

4.2. Background

4.2.1. U.S. electric power market

The economic makeup of the U.S. electricity markets is diverse. Electricity markets in the U.S. have both wholesale and retail structures. While wholesale markets engage in electricity sales between the electric utilities and electricity traders, retail markets comprise the sales of power to the consumers. There are seven wholesale electricity markets in the U.S. The regulatory structure of the electricity market changes depending on the geographic location. Figure 4.1 displays the seven competitive wholesale electricity markets in various colors, including The California Independent System Operator (CAISO), Midcontinental Independent System Operator (MISO), New England Independent System Operator (ISO-NE), New York Independent System Operator (NYISO), Pennsylvania – New Jersey – Maryland (PJM), Southwest Power Pool (SPP), and The Electric Reliability Council of Texas (ERCOT). These competitive wholesale markets are run by an Independent Systems Operator (ISO) or Regional Transmission Organization (RTO).

The other areas on the map, including Northwest, Southwest, and Southeast portions of the U.S., remain traditionally regulated electricity markets (i.e., areas that vertically integrated utilities are responsible for the entire flow of electricity to consumers). Moreover, the U.S.'s competitive wholesale electricity market operates two formal markets for electricity: a real-time market (RTM) and a day-ahead market (DAM). The Day-Ahead Market creates financially binding plans for power generation and usage one day before the day of service. However, Real-Time Market balances variations between the energy required in the Day-Ahead calendar and the real-time load specification.

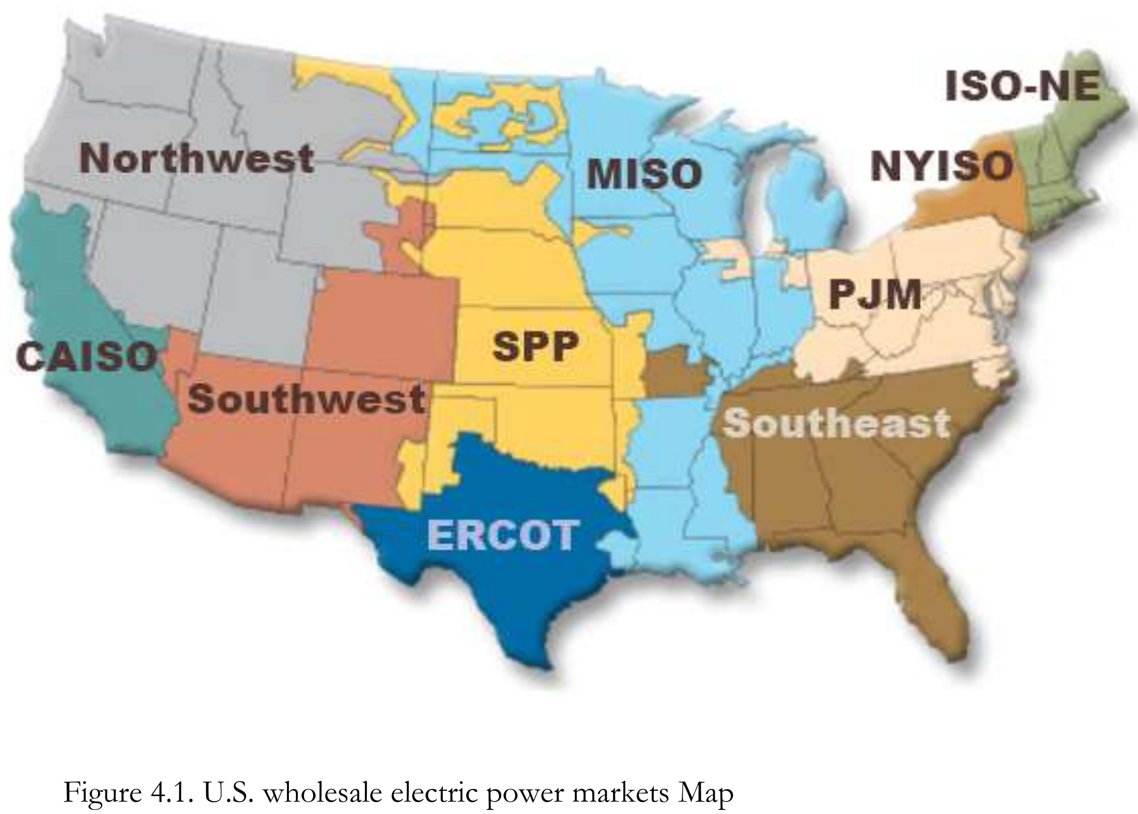


Figure 4.1. U.S. wholesale electric power markets Map

4.2.2. Why PJM and ERCOT?

While there are seven wholesale electricity markets in the U.S., this analysis investigates the merit-order effect in only two of them (PJM and ERCOT). The PJM interconnection is a regional transmission organization (RTO) and market operator constituting 20 transmission zones that run a wholesale market in all or part of 13 states and the District of Columbia. PJM performs long-term planning and coordinates wholesale electricity transmission in these states (see Figure 4.1). Moreover, PJM is a critical case study of electricity prices behavior as it coordinates over 1,379 electric generators and more than 84,236 miles of high-voltage transmission lines. It also provides electricity for over 65 million people. Moreover, it is the largest electricity market globally in terms of demand peak of over 165 GW, generating a capacity of over 180 GW, and 806, 546 GWh annual energy in 2018 (PJM, 2018). Besides, it has been the pioneer in the implementation of an electricity market based on nodal prices. As a result of its enormous success, nodal pricing has been extended to other wholesale markets such as ERCOT (Texas) and CAISO (California). PJM is a net exporter of power- on average, exporting about 2,100 MW to the neighboring system, even at the times of high loads in PJM.

Moreover, the region operated by PJM accounts for about 21 percent of U.S. gross domestic product, making affordable wholesale electricity prices particularly imperative for economic productivity in the region and the nation (PJM, 2018). The PJM market is mainly dominated by fossil fuel electricity generation and nuclear power plants, with a relatively low percentage of wind energy penetration. However, over the past few years, PJM has witnessed a drastic influx of technology shift in electricity generation. As of 2018, approximately 27 GW of the PJM older generators were retired from the system and replaced them by more than 32 GW of low emission, more efficient generators such as gas turbines, wind, and solar (PJM, 2018). Even though a minimal share (5.4%) of electricity generation in PJM comes from renewables, installed operating wind power capacity in the PJM jurisdiction is expected to continue to expand in the future as long as tax incentives continue[16], and implementation of RPS policies across states. However, the study intends to predict future price changes in the PJM jurisdiction and inform policymakers on the likely impact of increasing renewable capacity in the region.

Compared to PJM, Texas has the highest wind generation in the United States (Zarnikau et al., 2016; AWEA, 2019). Texas recently has surpassed 25 GW of installed capacity and account for more than 16% of electricity generation from wind (AWEA, 2020). On January 19, 2019, Texas witnessed a wind penetration record of 56.16%, with a wind generation of 19, 672 MW (ERCOT, 2019). As of mid-2019, the ERCOT generation mix was composed of 52.4% natural gas, 23.4% wind energy, 15.9% coal, 5.4% nuclear power, and 2.1% solar power. The wind generation capacity is expected to grow up to 40 % of the state's annual peak demand. As noted by Zarnikau et al. (2019), this has made ERCOT a particular place of research interest to various scholars and policy analysts. Besides, the state currently has 3600 miles of 354kv transmission line to accommodate approximately 18.5 GW of renewables, which further boost the substantial wind generation potential in the western region of the state (Zarnikau et al., 2019).

4.3. Literature review

The recent declines in wholesale electricity prices have been a significant driver of debate on energy policy in general and on the position of renewable energy. The trends for increasing renewable generation and declining prices have overlapped with a period of falling natural gas prices primarily due to new technologies for exploiting shale gas. It is assumed that the rising deployments

[16] In 2015, the federal government announced a 5-year extension of the present incentives, the production tax credits (PTCs) and investment tax credits (ITCs) for wind projects. Following the extension, Wind projects that commenced development in 2015 obtained either $23 per MWh in PTCs or 30 percent ITCs. However, wind projects under construction by 2016 get the full subsidies for 10 years, whereas the PTC phases down in 20 percent increments every year for projects that commenced construction from 2017 (80%), 2018(60%), and 2019 (40%).

of renewable power generation, specifically wind and solar, is significantly impacting wholesale electricity market prices in U.S. markets. In other words, the potential for a causal relationship between renewable power penetration and a decline in electricity prices has emerged.

There have been several attempts to provide evidence of causality between increasing renewable generation and a decline in wholesale electricity prices in other markets in the U.S., including Texas ERCOT (e.g., Zarnikau et al., 2019) and CAISO (e.g., López Prol et al., 2020). However, empirical evidence of such causality for the PJM regional market is limited in the economic literature. While the renewable generation capacity, particularly wind in the PJM region, is still relatively low compared to other wholesale electricity markets in the U.S., however, wholesale electricity prices in the PJM market have been declining in recent years. Therefore, the factors that drive down the electricity prices in this market region need further investigation.

Wholesale electricity prices in regions with competitive electricity markets are determined by balancing supply and demand by a supplier's mechanism to supply electricity to the consumer (Csereklyei et al., 2019). Renewable energy producers are competing within the energy market at an almost zero marginal cost, which in effect displaces high marginal cost offers that are typically associated with gas-induced peak-load generators. Borenstein (2005) argued that selling prices are generally at or above the last producer's marginal cost required to meet demand. As a result of this, it is presumed based on economic theory that an increase in the near-zero marginal cost of renewable energy sources will lead to reduced wholesale prices, in what is known as "merit-order-effect." (Sensfuß et al., 2008).

Investigating the merit-order effect (MOE) of renewable power generation on wholesale electricity market prices has been widespread in the literature. Notably, in Texas ERCOT (e.g., Tsai and Eryilmaz, 2018; Woo et al., 2016; Zarnikau et al., 2019), CAISO (Bushnell and Novan, 2018; Westgaard et al., 2021; Woo et al., 2017, 2016), MISO (Dahlke, 2018, 2017; Quint and Dahlke, 2019;

Zarnikau et al., 2020), Pacific Northwest (Woo et al., 2015, 2013a), PJM (Gil and Lin, 2013; Jenkins, 2018), and in Australia (Bell et al., 2017; Csereklyei et al., 2019), and many countries across Europe (Bublitz et al., 2017; Do et al., 2019; Gil et al., 2012; Ketterer, 2014; Klinge Jacobsen and Zvingilaite, 2010; Maciejowska, 2020; Sensfuß et al., 2008; Sirin and Yilmaz, 2020; Würzburg et al., 2013).

Specifically, using historical average hourly real-time electricity prices, wind generation, and other variables from 2008 to 2016, Quint and Dahlke (2019) provided empirical evidence of the impact of wind production on wholesale electricity prices MISO market. Their results demonstrate the significant effects of wind generation on prices, ranging from an estimated reduction between $0.14 to $0.34 per megawatt-hour for each 100-megawatt hours of additional wind generation. However, these authors documented that the estimated marginal impacts of additional wind generation have declined over time.

Tsai and Eryilmaz (2018) established a link between increasing wind power penetration on ERCOT nodal prices. The authors found that every additional 1 GW of wind generation output reduces nodal prices at non-wind resources from about $1.45/MWh to $4.45/MWh. Similarly, using hourly data on the day-ahead market and real-time market prices, wind generation, and other control variables, Zarnikau et al. (2016) confirmed the existence of the merit-order effect of wind generation on both day-head and real-time market prices in Texas. Moreover, the authors document that the increasing wind power generation has a more significant impact on real-time market prices than day-ahead market prices in that region. Zarnikau et al. (2016) further note that the estimated merit-order effects are highest in the ERCOT regions where there is a higher wind generation capacity.

Focusing on the California electricity market, Bushnell and Novan (2018) investigate how wholesale electricity prices have reacted to a remarkable increase in utility-scale solar capacity in the region. The authors document a substantial decline in daily average prices, which can be credited to solar generation, but note that it only reduces the price during daylight time and increases it during should hours. Bushnell and Novan (2018) also largely confirm that the short-term electricity markets are reacting to renewable power penetration in such a way that could sustain more flexible conventional generation, and at the same time, destabilizing the economic sustainability of traditional baseload generation technologies. In a similar study, Woo et al. (2016) established a link between wind generation in California and a decline in wholesale electricity market price. Their findings show that a one-gigawatt hour (GWh) increase in wind generation reduces the wholesale market price by $1.5 to $11.4 per megawatt-hour.

A study conducted by Gil and Lin (2013) revealed that the expected benefits of wind generation expansion to wholesale market participants in the PJM market might be considerable, notwithstanding the relatively low wind-power penetration observed in the market region. While the study results found a negative impact of wind generation on electricity prices, the research does not focus on marginal effects or use exogenous variables such as fuel costs. Furthermore, the study only focused on the day-ahead market prices in the PJM electricity market without investigating the real-time market. Conversely, Jenkins (2018), in his extensive investigation on the drivers of wholesale price reduction at nuclear generators in the PJM interconnection, concludes that natural gas price declines are the leading driver of declined electricity prices at the nuclear power stations investigated. The author claimed that wind energy growth has a relatively smaller cumulative but statistically significant impact on wholesale electricity prices in the PJM region.

Renewable energy sources, particularly wind and solar, have a higher degree of uncertainty as they produce electricity intermittently, and depending on the location where the resource is available, making their output and value differ substantially from the traditional electricity generation technologies (Joskow, 2011; Lamont, 2008; López Prol et al., 2020). While the articles cited on the MOE focus primarily on the price aspect, a few other studies have also demonstrated how increasing renewable generation is prone to impact on their revenue and market values (Clò and D'Adamo, 2015; Hirth, 2013; Lamont, 2008; López Prol et al., 2020).

Specifically, in analyzing the impact of solar generation on gas and solar revenues using the Italian day-ahead electricity market data, Clò and D'Adamo (2015) find evidence that increasing solar energy deployment negatively alters the solar source market value. Similarly, López Prol et al. (2020) show that increasing solar and wind energy penetration in the California wholesale electricity market undermines their source value. Conversely, the authors further revealed that while the increasing wind generation negatively affects the value factor of solar sources; however, increasing solar penetration positively affects the wind resources value factor.

Empirical research consistently finds negative impacts on electricity prices and market values from wind generation. MOEs vary across wholesale market regions and countries based on national or regional policies on renewable energy sources, industry size, region or country-specific trade opportunities, grid operators regulations, transmission constraints, and relevant models (Wen et al., 2020). Moreover, the results are location specific, frequently influenced by other factors such as fuel prices and fuel mix.

However, most of these previous studies only focus on estimating the average impact of renewable generation on wholesale prices, revenue, or market values. Nevertheless, this is not sufficient for risk management and other associated applications (Do et al., 2019), given the intermittent nature of the renewable generated electricity and significant regional price variation within electricity markets. Furthermore, the vast majority of the existing research into the effects of wind generation on electricity prices has focused on either DAM or RTM but has failed to explore the two market prices simultaneously. Besides, the vast majority of policy analyses developed from the impacts of averages and OLS approaches, which are not appropriate for energy conservation implications on the energy-intensive industry (Boqiang and Nelson, 2017; Nelson and Boqiang, 2019).

Moreover, these existing studies do not contemplate the probability that the wind generation's impacts on the wholesale electricity prices might vary across electricity market conditions (i.e., high demand/peak periods versus low demand/off-peak periods). As correctly stated by Jónsson et al. (2010), "the spot prices are not Gaussian distributed, and therefore it must be deemed highly unlikely that models constructed with least square techniques will have Gaussian residuals." Johnson, Pinson, and Madsen (2010) further document that "prediction intervals for such models should, therefore, be estimated using other techniques. In fact, the distributions are so far from parametrized distributions that seem reasonable to conclude that non-parametric approaches, like for instance, quantile regression, will return the most reliable prediction intervals".

Following this reasoning, I select the quantile regression method proposed by Koenker and Bassett (1978) as the central empirical instrument for this analysis. There are two principal motivations for this quantile methodological selection. First, previous studies on this topic ignore the likelihood that the merit order impacts of wind generation on the electricity price volatility may vary during high demand and low demand periods. By evaluating the reaction of the entire conditional distribution of the dependent variables to the explanatory variables, the quantile regression method can exclusively uncover the complete information about the structure and extent of dependence between the dependent variable and explanatory variables under normal and extreme market conditions (Baur, 2013; Xiao et al., 2019). In other words, the establishment of specific indications on the impacts of explanatory variables on the dependent variable under different market settings, including low times (lower quantile), regular times (median quantile), and peak times (upper quantile) are accessible.

Second, the quantile regression method captures a more accurate and precise result of the dependent variables' conditional distribution, which permits differentiating the intensity of all explanatory variables in different market situations. Moreover, this technique is less sensitive to heteroskedasticity, skewness, and outliers on the dependent variable (Koenker and Hallock, 2001). In the present study, I will examine the dependence through the quantile regression approach due to flexibility in its assumptions while analyzing the conditional relationship of individual quantiles of the wholesale electricity market outcomes to conditional explanatory variables.

4.4. Theoretical framework

This section presents a brief theoretical overview describing how wind penetration impacts wholesale electricity prices – the theory behind the MOE. In the dynamic wholesale electricity market, the hourly price of electricity is controlled through the coordination of the supply and demand curves. The mechanism through which the energy generation technologies are consistent with their value is known as the "merit order" dispatch system (Maekawa et al., 2018). Merit order is the process by which a supply curve is generated for the wholesale electricity market.

Figure 4.2 illustrates the merit order without renewable energy sources and demonstrates how a stair-step supply curve is derived for wholesale electricity by a merit order of generation technologies, illustrating their marginal costs. Typically, but contingent on the real cost of fuel, these generation systems are labeled as baseload (typically either nuclear and coal-fired power plants), medium-load (such as combined-cycle gas turbines), and peak load (open-cycle gas turbines) (De Vos, 2015). With equilibrium wholesale electricity price being the point of intersection of the supply and demand curves, the MOE results in generating sources with the lowest marginal costs being utilized first.

For illustrative purposes, Figure 4.2 also shows how a demand shift for electricity impacts the wholesale price of electricity. D_1 and D_2 reflect low and high demand conditions, respectively, and result in wholesale electricity market clearing prices of P_1 and P_2. At D_1, high-cost generators are not be required, thereby leading to lower market-clearing prices. Conversely, a shift in electricity demand from D_1 to D_2 (such as during warmer weather) moves the equilibrium condition to the right, thereby increasing the price of electricity from P_1 to P_2.

As shown in Figure 4.3, the addition of generating sources with close to zero marginal costs (such as wind energy) often results in price declines occurring at both low and high demand (D_1 and D_2) relative to Figure 4.2 prices. These price declines differ substantially between low and high demand. These Figures show the impact of MOE (Clò et al., 2015; Ketterer, 2014; López Prol et al., 2020; Sensfuß et al., 2008; Woo et al., 2016). Finally, declines in market-clearing prices impact the profits earned by every inframarginal generator, including the baseload sources (Jenkins, 2018).

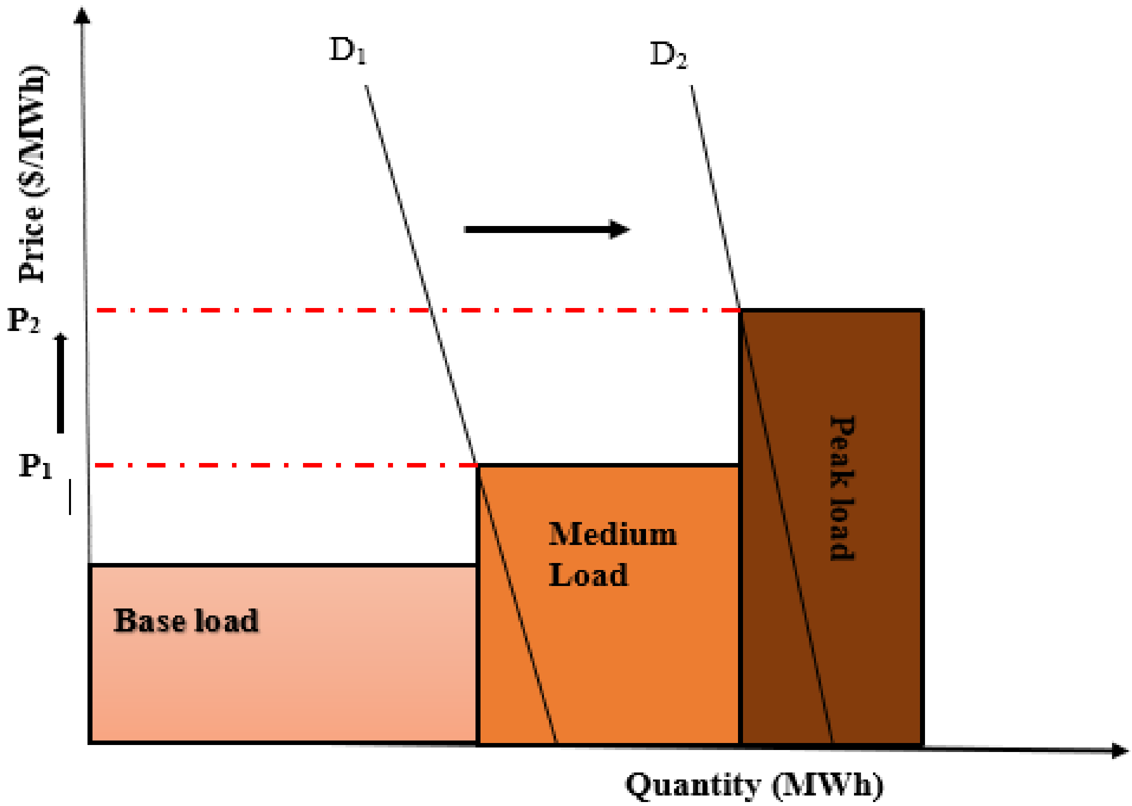


Figure 4.2. Theoretical merit order without renewable and the price effect of increasing demand

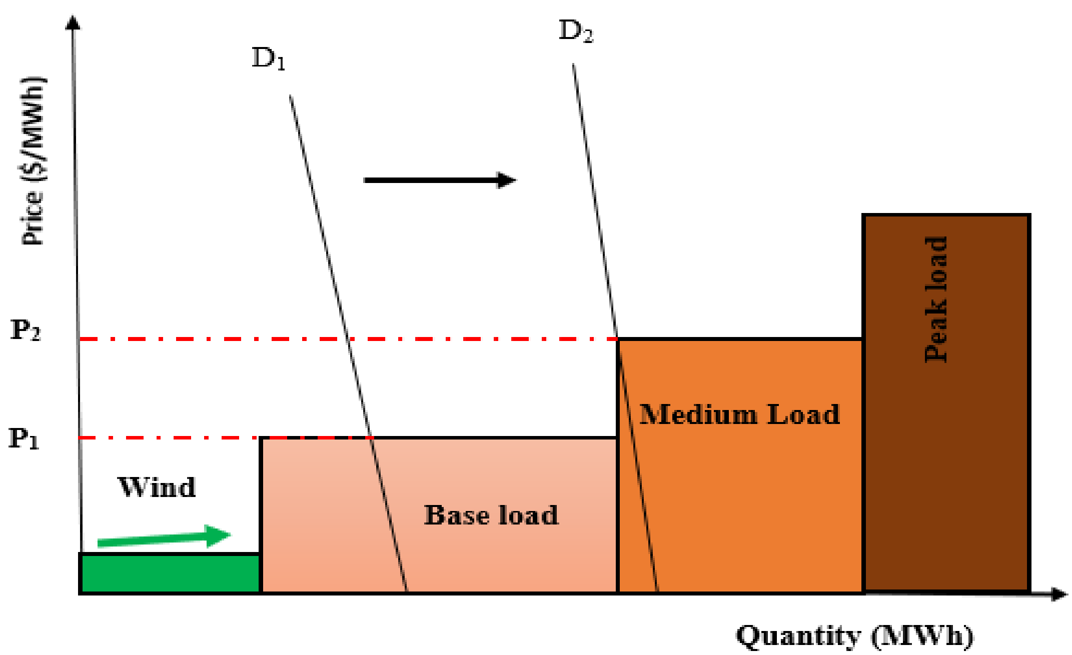


Figure 4.3. Theoretical merit order and price effect of increasing renewable power generation

4.5. Data and empirical strategy

4.5.1. Data

In this study, the DAM and RTM prices are examined for both regions and only PJM is examined for market values. The datasets of the regression analyses consist of 78,879 hourly time-series observations from 01/01/2011 through 12/31/2019 for electricity prices (RTM and DAM prices), total electricity generation from wind in MWh, actual and forecasted energy demand, demand forecast error, natural gas prices, and average regional temperature. The hourly data on real-time and day-ahead electricity prices, wind generation, demand forecast, and actual demand are sourced directly from the PJM and ERCOT websites. Electricity is generated and consumed all day, every day. Thus, data on electricity prices, wind generation, and demand include weekends and holidays and covers all hours (hourly) of the day. For natural gas prices, since the data are reported on daily frequency, daily values are repeated for each hour of a day, and for days in which no trading took place (i.e., weekends and holidays), prices are based on the previous trading day to align with the frequency of wholesale electricity prices, demand, and wind generation.

The data utilized for the market value econometric analyses consist of 35,064 hourly time-series observations from January 1, 2016, through December 31, 2019 in the PJM region. These data include real-time electricity prices, actual energy demand, and electricity generation from wind, coal, nuclear, and gas in GWh. Then, hourly measurements of these variables are combined into 1,461 weighted average daily observations in line with the frequency of natural gas prices. The hourly data on real-time electricity prices, actual demand, wind, coal, nuclear, and gas generation are sourced directly from the PJM website. Daily Henry Hub natural gas prices are gathered from the U.S. Energy Information Administration (EIA). Since natural gas price data are reported only on business days, the daily values from the most recent trading data are used to represent days when no trading took place (i.e., weekends and holidays).

Wholesale electricity prices

This analysis's primary purpose is to discover how wind power penetration affects wholesale electricity prices, undermining their unit revenues, and value factors in the PJM and ERCOT markets. This present study utilized the average hourly wholesale electricity locational marginal price (LMP) for RTM and DAM. Most of the U.S. wholesale electricity market operates on LMP. This pricing mechanism is a way for wholesale electricity rates to represent the value of electrical energy at a particular location at the moment it is distributed, thus taking into account various factors such as patterns of generation, load, and the physical limit of the transmission system. Locational marginal prices are calculated by combining the system energy price, transmission congestion cost, and marginal losses. The average hourly wholesale electricity locational marginal price for the RTM and DAM ($/MWh) will be the MOE models' dependent variables for electricity prices.

Wind generation

Over the study period, wind power has the largest share of renewable power generation in PJM and ERCOT market regions. While wind generation in PJM is still relatively low, in contrast, ERCOT has a high percentage of wind generation capacity. Figure 4.4 shows the cumulative hourly wind output from January 1, 2011, through December 31, 2019. Wind penetration in both market regions shows apparent hourly, daily, and seasonal differences in electricity production. I analyze the wholesale price' impact of wind sourced electricity in the PJM and ERCOT electricity markets concurrently.

While ERCOT has data on both actual and forecast wind output, wind output forecast information is not publicly available for the PJM interconnection. Therefore, for this analysis, I use actual hourly wind generation data in MWh to proxy the day-ahead forecast of wind output for the entire PJM region[17]. At the same time, actual MWh wind output is used for the real-time price impact modeling. Moving forward, hourly wind share (%) is calculated as the ratio of hourly wind generation to the sum of the hourly electricity demand in each market region, respectively. For this analysis, I use actual daily wind generation data in GWh for the market revenues-value factors impact modeling. In addition, I calculate the daily wind share (%) as the ratio of daily wind generation to the sum of the daily electricity demand in the PJM market.

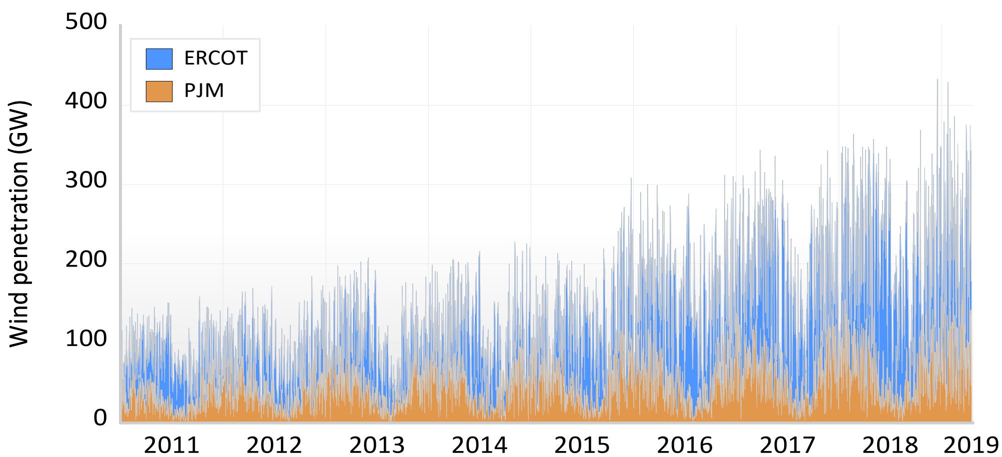


Figure 4.4: Daily aggregate of wind energy generation by electricity market territory

<u>Electricity demand</u>

Supply and demand are fundamental components of the electricity market price model. Wholesale electricity prices in regions with competitive electricity markets are determined by the balance between supply and demand by a mechanism of the supplier offers to supply electricity to the consumer (Csereklyei et al., 2019). While the supply side, as noted by Paraschiv et al. (2014), is determined by many dynamics including renewable power generation, fuel for the power generating

[17] A similar approach was once adopted by Woo et al. (2013). The authors argued that "that the actual wind generation is an adequate proxy for the unobservable consensus wind-generation forecast made by bilateral traders". Woo et al. (2013) further report that "it is not unreasonable to assume that *on average* their forecasts will approximate "tomorrow's" wind-generated output and that their forecasts are highly correlated with the actual values".

plants, and emission allowance, the demand side is determined by the electricity usage by the consumers. On the one hand, provided that electricity demand at least in the short run is almost inelastic, unplanned plant outages significantly affect the future electricity prices (Bunn and Chen, 2013). On the other hand, both vendors and generators face real-time capacity uncertainty, as generating plants can be faulty, and renewables, such as wind and solar, are stochastic generators (Bunn and Chen, 2013).

Therefore, when developing intuitions into the wholesale electricity charges, a clear understanding of the underlying features is critical. In this analysis, expected electricity demand is represented in two different fashions. First, actual hourly MW electricity supplied (MWh) on delivery day is used as a demand variable in the hourly RTM price regression. Second, the day-ahead hourly demand forecast data are utilized in the hourly DAM price model. Two explanatory variables (demand forecast error) from the actual electricity demand also are included: over-predicted demand and under-predicted demand as variables that could potentially impact the price. It is expected that the over-predicted demand should drive down prices, while under-predicted demand would create supply shortfall leading to increased prices.

Natural gas prices

Another factor influencing electricity prices is fuel costs. Previous empirical research, including Bunn and Chen (2013), Paraschiv et al. (2014), and Bunn et al. (2016), have demonstrated that fuel prices, including prices of coal and natural gas, are all underlying factors driving the electricity prices. Similarly, Jenkins (2018), in his analysis on the drivers of wholesale prices in the PJM market, showed that natural gas price is a dominant factor influencing supply offer from generators and electricity market prices. Natural-gas-fired generation contributes a considerable amount to the PJM (more than 30%). As a result, natural-gas prices can have an influence on electricity costs, with thermal technology whose cost relied on the price of natural gas having a supply-side effect (Woo et al., 2013). Therefore, natural gas price is included as exogenous variable driving wholesale electricity prices in the model.

Weather variables

Climate variances have a significant impact on specific segments of the economy. The electricity market has been identified as one of the most sensitive to this fluctuation because electricity demand is connected to several weather variables, specifically atmospheric temperature (Valor et al., 2001). Thus, variations in climate are potent drivers of price spikes in the electricity market. Temperature data are gathered from counties with the largest population in Texas and the PJM regions. A population-weighted average temperature index TI (°F) is created for each electricity market from the average daily temperature measure at five weather stations in each market region[18]. Counties population has been selected as a weighting criterion because weather motivates the electricity demand through people's response to climate conditions. The mean population-weighted temperature is obtained with the methodology developed in Valor et al. (2001) as:

$$\emptyset_t = \sum_{i=1}^{n} \bar{T}_{ti}\, \rho_{ti} \tag{4.1}$$

where $\emptyset_t$ represent the mean weighted temperature, $\bar{T}_{ti}$ represent the average daily temperature on each day *t* at a given weather station *i*. ρ_{ti} indicate the population weight of the location allotted to each weather station, and it is estimated, as shown in equation (4.2).

$$\rho_{ti} = \frac{\mu_{ti}}{\sum_{i=1}^{n} \mu_{ti}} \tag{4.2}$$

where ρ_{ti} is the total county population on day *t* allotted to weather station *i*.

Due to a non-linear relationship that exists between energy demand and temperature, showing two branches, it would be appropriate for further data interpretation to separate these two

[18] The weather stations utilized in the PJM region include Chicago (KORD), Cleveland (KBKL), Indianapolis (KEYE), Philadelphia (KPHL), and Pittsburgh (KACC). The weather stations selected in Texas are Austin (KATT), Dallas (KDAL), Fort Worth (KFTW), Houston (KMCJ), and San Antonio (KSAT).

branches (Valor et al., 2001). Thus, the weighted temperature data are divided into cooling and heating degree days (CDD and HDD). The concept of degree days is defined as the difference between a base temperature, usually 65^0 Fahrenheit (°F) in the United States, and the average daily temperature recorded for a particular location (EIA). The estimation of the CDD and HDD indices are achieved using the following equations:

$$\chi_{CDD} = \max(T - T^*, 0) \tag{4.3}$$

$$\chi_{HDD} = \max(T^* - T, 0) \tag{4.4}$$

where T^* represent the base temperature. Finally, the χ_{CDD} and χ_{HDD} variables are squared to account for non-linearities, as suggested by Valor et al. (2001).

<u>Unit revenues and value factors</u>

To quantify the influence of wind penetration on the market value of baseload generation (nuclear and coal-fired generation) versus non-baseload (natural gas) sources to that of wind power source itself, two dependent variables are used: daily unit revenues and value factors. Unit revenues are described as the weighted average prices received by baseload and non-baseload sources each day. The values are computed by applying the techniques the same as methods described in Clò and D'Adamo (2015) and López Prol et al. (2020) as:

$$UR_d^i = \frac{R_d^i}{\sum_{t=1}^{24} q_t^i} = \frac{\sum_{t=1}^{24} p_t q_t^i}{\sum_{t=1}^{24} q_t^i} \tag{4.5}$$

where UR_d^i represents the daily unit revenues from each baseload and non-baseload source. R_d^i stand for daily revenues from baseload and each non-baseload source. p_t represents the hourly RTM wholesale electricity prices, and q_t^i represents the hourly amount of electricity generation of each power source in MWh. i stands for wind, gas, and baseload sources (nuclear and coal), respectively.

The Value Factor index (VF^i) represents a relation between the unit revenues and the mean daily price $\overline{p_t}$ as:

$$VF^i = \frac{UR_d^i}{\overline{p_t}} = \frac{\sum_{t=1}^{24} p_t q_t^i / \sum_{t=1}^{24} q_t^i}{\sum_{t=1}^{24} p_t / 24} * 100 \tag{4.6}$$

4.5.2. Stationarity and multicollinearity test

Given that time-series data poses challenges that frequently need alteration of the data because the correlation of variables over time may lead to spurious regression results. Non-stationarity of the series is a widespread issue identified, implying that the mean and variance of such variation are not constant over time (Edward and Štefan, 2009). Therefore, before moving ahead to formal empirical analysis, I first test for the presence of a unit root by employing the augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) unit root tests with a constant and linear trend (see Table 4.1). The number of lags in each test is determined by the Akaike Information Criteria (AIC). Results from both the ADF and PP point in the same direction. While the ADF for the baseload share variable without trend failed to reject the null hypothesis, the PP test carefully rejects the null hypothesis of a unit root in the variable in both with and without trend at 1% significance level. Since the PP test is non-parametric and more robust to heteroskedasticity and autocorrelation in the disturbance procedure of the test equation, I, therefore, take the variables as stationary.

Table 4.1. Unit root tests

	Variables	ADF (levels)	ADF with trend	PP (levels)	PP with trend
PJM	DAM price	-18.810***	-19.289***	-90.673***	-89.034***
	RTM price	-22.849***	-23.558***	-187.081***	-185.097***
	Demand forecast	-14.145***	-14.572***	-38.123***	-38.332***
	Actual demand	-13.016***	-13.061***	-40.084***	40.093***
	Wind share	-18.362***	-20.043***	-29.294***	-29.050***
	Natural gas price	-5.914***	-6.532***	-6.162***	-6.822***
	Over predicted demand	-17.462***	-18.570***	-23.645***	-24.974***
	Under predicted demand	-25.294***	-25.479***	-41.956***	-41.701***
	Temperature	-6.464***	-6.459***	-7.687***	-7.685***
	HDD	-6.948***	-6.944***	-8.491***	-8.489***
	CDD	-9.987***	-9.998***	-11.384***	-11.441***
	Gas share	-4.235***	-5.773***	-4.959***	-9.707***
	Baseload share	-1.762	-3.979***	-6.231***	-14.329***
	Wind supply	-3.308***	-3.581***	-26.58***	-26.48***
	Gas supply	-3.738***	-4.477***	-6.936***	-10.386***
	Baseload supply	-3.792***	-4.092***	-6.102***	-6.699***
	Wind unit revenue	-8.198***	8.194***	-13.184***	-13.180***
	Gas unit revenue	-7.868***	-7.867***	-13.962***	-13.958***
	Baseload unit revenue	-7.686***	-7.685***	-13.646***	-13.642***
	Wind value factor	-6.253***	-6.278***	-37.731***	37.710***
	Gas value factor	-3.570***	-3.575**	-26.210***	-26.209***
	Baseload value factor	-2.895***	-2.293	-28.799***	-28.874***
ERCOT	DAM price	-24.992***	-25.031***	-124.656***	-124.511***
	RTM price	-31.716***	-31.859***	-106.861***	-106.599***
	Demand forecast	-7.668***	-8.441***	-36.903***	-38.766***
	Actual demand	-11.064***	-11.596***	-196.006***	-198.605***
	Wind share	-18.033***	-20.399***	-44.639***	-42.636***
	Natural gas price	-4.420***	-4.866***	-5.260***	-5.815***
	Over predicted demand	-13.206***	-17.431***	-256.080***	-191.403***
	Under predicted demand	-19.452***	-21.818***	-128.370***	-109.724***
	Temperature	-8.447***	-8.444***	-10.312***	-10.309***
	HDD	-13.695***	-13.696***	-17.300***	-17.304***
	CDD	-6.953***	-6.954***	-8.657***	-8.658***

Notes: ADF - augmented Dickey-Fuller; PP - Phillips-Perron. The null hypothesis for both tests is the presence of unit root in the data. *** , **, and * show rejected at the 1%, 5%, and 10% significance levels, respectively.

In multiple regression setting, multicollinearity has been a potential issue of concern, as it might wreak havoc on the analysis when it exists and thus restrict the research conclusions. To check whether this problem exists within the merit-order models' variables, multicollinearity tests are conducted using the variance inflation factors (VIFs) of all the predictor variables in a multiple regression model[19]. The resulting values are presented in Table 4.2. The upper panel of Table 4.2 shows the test results for RTM and DAM regressions in both market regions, and the lower panel is the test results for the market value regression for the PJM. Based on the upper panel results in Table 4.2, it is notable that none of the predictor variables is highly correlated since their variance inflation factor values are less than 5. Thus, confirming that multicollinearity among the variables is not a problem.

However, when considering the independent variables for estimating the market value of variable renewable in the PJM regional market, the baseload source is highly correlated with actual electricity demand (the two variables have a correlation coefficient of 0.84). The high correlation suggests that the inclusion of these two variables in the regression would raise an issue of multicollinearity (see the test results in the lower panel of Table 4.2). This higher connection is a consequence of the fact that the baseload source supplies the largest share of the electricity delivered in the PJM footprint and usually runs at almost constant power throughout the whole day, seven days a week. In this manner, if actual demand is excluded and incorporate the baseload source variable as a control variable in the model, baseload source may unsuitably be credited with the a positive effect on electricity prices that is, indeed, demand-driven as suggested by Clò and D'Adamo (2015). Thus, actual demand is used as a control variable in the unit revenue and value factor analysis.

[19] The variance inflation factor is a more rigorous and robust for collinearity than a correlation coefficient. Checking the correlations merely between the explanatory variables is restrictive, as it is likely that the pairwise correlations are little, and hitherto a linear dependence exists amongst two or more predictor variables.

Table 4.2. Multicollinearity test

Variable	Variance Inflation Factor			
	PJM		**ERCOT**	
	RTM	DAM	RTM	DAM
Actual demand (GWh)	1.64	-	2.76	-
Demand forecast (GWh)	-	1.75	-	3.12
Wind share (%)	1.30	1.30	1.40	1.40
Natural gas price ($/MMBtu)	1.39	1.39	1.49	1.49
Over predicted demand (GWh)	1.12	-	1.59	-
Under predicted demand (GWh)	1.15	-	1.71	-
HDD	1.43	-	1.31	-
CDD	1.63	-	2.30	-
Actual demand (GWh)	1.64	-	-	-
Wind share (%)	1.30	-	-	-
Natural gas price ($/MMBtu)	1.39	-	-	-
Wind supply	1.25	-	-	-
Gas supply	3.22	-	-	-
Baseload generator supply	**9.09**	-	-	-
Gas price	1.33	-	-	-
Actual demand	**11.11**	-	-	-

4.5.3. Summary statistics

Table 4.3 summarizes statistics on essential variables of the dataset used in the analysis for PJM and ERCOT. In 2019, aggregate energy generation in the PJM territory was 829,705 GWh, with wind share representing 2.9% of the aggregate generation. PJM markets uphold a diverse energy mix, with 36.1% of the aggregate generation coming from gas. Nuclear accounted for 33.6%, while 23.7% of the aggregate energy generated came from coal. During the 2011-2019 period, the average annual aggregate generation in ERCOT was 349,151 GWh, with wind energy accounting for 13.9%. Coal accounted for 30.9%, gas representing 37.8%, while 11.4% of the aggregate generation came from nuclear energy.

The statistics in Table 4.3 show that the real-time and day-ahead prices in the PJM have means of \$34.76 and \$35.72 that are marginally higher than the medians of \$28.72 and \$31.38, respectively, hence, signifying that the distribution of the price data is skewed towards left. The price distribution in the ERCOT region shows similar patterns in real-time and day-ahead have means of \$33.74 and \$31.73 above the medians of \$23.33 and \$24.56, respectively. Figures 4.A1 and 4.A2 in appendix present scatter plots of real-time and day-ahead prices against each market region's predictor variable. The plots designate similar arrangements – as the electricity generation via wind resources increases, the real-time or day-ahead prices decrease. Conversely, the higher the natural gas prices, the higher the electricity prices in real-time and day-ahead markets.

More importantly, looking at the skewness and the kurtosis results in both market regions, I can mention that the kurtosis coefficients of almost all covariates are higher than three, suggesting the unconditional distribution of the variables. Similarly, the outcomes of the skewness and kurtosis of the dependent variables show that their distribution is non-normal. Hence, a quantile regression approach produces more robust estimation results than conventional OLS regression analysis Koenker and Bassett (1978).

Table 4.3. Summary statistics - hourly averages in the PJM and ERCOT regions

Region	Variable	Unit	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
PJM	DAM price	$/MWh	35.72	24.35	3.43	932.00	10.48	220.77
	RTM price	$/MWh	34.76	31.54	-230.05	1840.75	16.39	625.75
	Demand forecast	GWh	91.26	17.25	51.68	157.16	0.68	3.29
	Actual demand	GWh	89.52	16.65	50.64	158.04	0.66	3.34
	Wind share	%	2.26	1.74	-0.02	11.23	1.06	3.86
	Natural gas price	$/MMBtu	3.18	0.80	1.49	8.15	0.77	4.87
	Over predicted demand	GWh	2.56	7.46	0.00	80.82	5.95	42.38
	Under predicted demand	GWh	-0.83	2.69	-55.97	0.00	-9.75	134.78
	Temperature	°F	52.96	18.93	-4.14	89.47	-0.28	2.13
	HDD		15.04	15.57	0.00	69.14	0.73	2.5
	CDD		2.99	5.11	0.00	24.47	1.57	4.29
ERCOT	DAM price	$/MWh	31.73	77.13	1.05	5008.13	29.56	1157.55
	RTM price	$/MWh	33.74	140.04	-45.96	9005.29	21.26	502.30
	Demand forecast	GWh	40.24	10.08	21.33	75.79	0.88	3.19
	Actual demand	GWh	39.79	9.49	22.37	74.54	0.87	3.27
	Wind share	%	13.87	10.01	0.02	59.02	1.00	3.64
	Natural gas price	$/MMBtu	3.18	0.80	1.49	8.15	0.83	4.74
	Over predicted demand	GWh	3.36	5.67	0.00	42.85	2.32	9.08
	Under predicted demand	GWh	-2.91	4.79	-35.26	0.00	-2.04	6.99
	Temperature	°F	70.57	14.34	22.28	95.26	-0.51	2.42
	HDD		3.81	7.09	0.00	42.72	2.07	6.93
	CDD		9.38	9.15	0.00	30.26	0.39	1.65

Note: Data cover hourly observations from 01/01/2011 – 12/31/2019

Table 4.4 reports summary statistics on daily average values by generating sources from January 2016 – December 2019 in PJM interconnection. On average, while daily wind revenues increased from $1.19 million in 2016 to $1.65 million in 2019, baseload generators declined from $42.87 million to $35.04 million over the same period in PJM territory. Interestingly, gas follows the same suit as wind, though much higher, increases from $15.06 million in 2016 to $22.54 in 2019. Unit revenues of all technology, including wind, declined between January 2016 and December 2019.

Meanwhile, the average wind value factor slightly increases from 96.92% in 2013 to 97.59% in 2019, while the value factor of both baseload generators and gas faintly decline over the same period (Figure 4.5). Wind-generated electricity was worth 2.8% less than the average unit of electricity sold in the PJM's wholesale electricity market within four years (2016-2019). Remarkably, the value factors for both baseload and gas generators are higher than that of wind over the study period. Moreover, the results show that all the dependent variables for market unit revenues and value factors are non-normal. Specifically, Wind, gas, and baseload unit revenues, gas value factor, and baseload value factor variables are positively skewed. At the same time, the wind value factor is skewed towards left.

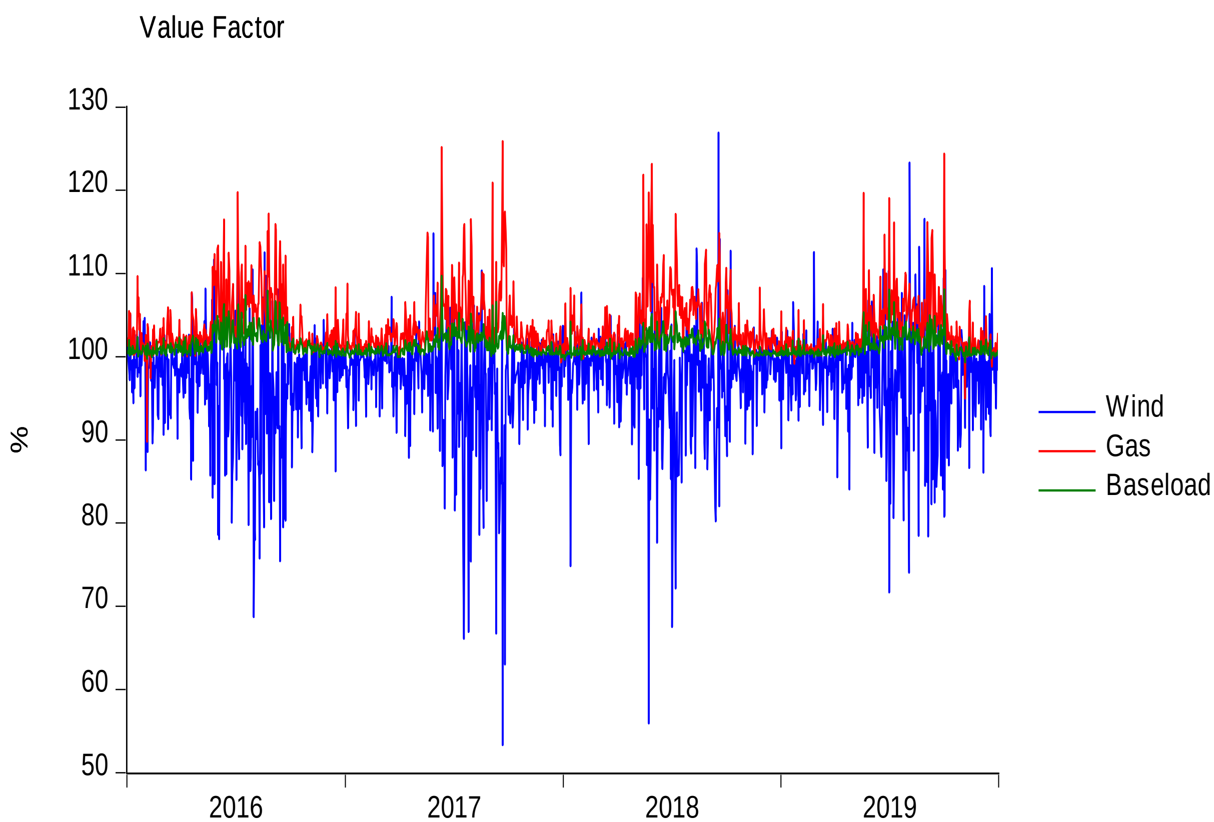


Figure 4.5: Value factors of generation sources in the PJM.

Table 4.4. Summary statistics - daily average values, by generator in the PJM region

	2016			**2019**			**2016-2019**		
Variable	Mean	Std.dev.	Skewness	Mean	Std.dev.	Skewness	Mean	Std.dev.	Skewness
Wind supply (GWh)	45.83	28.31	0.71	65.94	38.67	0.55	56.54	34.72	-0.03
Gas supply (GWh)	505.11	195.52	-0.55	820.13	162.78	0.58	651.13	199.81	0.67
Baseload supply (GWh)	1493.80	216.14	0.28	1304.00	170.14	0.61	1430.00	201.21	0.49
Actual demand (GWh)	2164.62	320.72	0.44	2156.51	286.60	0.47	2162.52	292.02	0.5
Natural gas price ($/MMBtu)	2.51	0.56	0.24	2.55	0.31	0.98	2.79	0.54	0.6
Wind unit revenue ($/MWh)	26.61	6.80	1.66	25.33	7.83	3.43	28.78	13.72	7.45
Gas unit revenue ($/MWh)	28.72	8.16	1.59	26.95	9.52	5.41	30.87	14.66	6.49
Baseload unit revenue ($/MWh)	28.04	7.44	1.43	26.38	8.65	4.66	30.08	13.98	6.93
Wind Share (%)	2.20	1.52	0.69	3.08	1.91	0.60	2.64	1.73	0.63
Gas Share (%)	22.82	7.25	-1.87	35.70	3.64	-0.24	28.78	6.81	-1.03
Baseload Share (%)	68.61	3.04	0.45	57.67	3.05	0.46	64.33	5.42	-0.19
Wind value factor (%)	96.92	6.41	-1.01	97.59	6.27	-0.61	97.20	6.47	-1.38
Gas value factor (%)	103.78	3.66	1.32	103.22	3.31	2.36	103.72	3.60	1.99
Baseload value factor (%)	101.63	1.41	1.60	101.29	1.22	1.94	101.36	1.24	1.81
Wind daily revenue (Mln $)	1.19	0.76	0.81	1.65	1.10	1.24	1.64	1.47	5.05
Gas daily revenue (Mln $)	15.06	8.87	1.34	22.54	10.72	4.06	20.54	12.30	3.27
Baseload daily revenue (Mln $)	42.87	16.62	1.53	35.04	15.07	3.61	44.26	28.34	7.27

Note: Data cover the period from 1st January 2016 to December 31st, 2019

4.5.4. Basic regression models

Supply and demand are fundamental components of the electricity market price model. To explore the effects of utility-scale wind generation on both DAM and RTM prices in the PJM versus ERCOT markets, following previous literature on this topic, I model electricity prices as a function of demand and supply variables, including wind generation share of total electricity supply, electricity demand, gas price, degree days variables, and demand forecast error. Specifically, this paper proposes a benchmark linear regression model estimated using OLS to examine the relationship between the dependent and independent variables to establish baseline results in order to compare with quantile regression results. More specifically, I follow a similar model specification as in Clò and D'Adamo (2015) and López Prol et al. (2020). I estimate the following regression equations:

$$\boldsymbol{RTMP_t} = \beta + \beta_1 wind\_sh_t + \beta_2 demand\_actual_t + \beta_3 gas\_price_t + \beta_4 over\_pred\_demand_t + \beta_5 under\_pred\_demand_t + \beta_6 CDD_t + \beta_7 HDD_t + \beta_8 CDD^2{}_t + \beta_9 HDD^2{}_t + \sum_{n=1}^{N} \beta_D Daily_{t,n} + \sum_{i=1}^{N} \beta_M Monthly_{t,i} + \sum_{i=1}^{N} \beta_Y yearly_{t,i} + \varepsilon_t \tag{4.7}$$

$$\boldsymbol{DAMP_t} = \theta + \theta_1 wind\_sh_t + \theta_2 demand\_forecast_t + \theta_3 gas\_price_t + \sum_{n=1}^{N} \theta_D Daily_{t,n} + \sum_{i=1}^{N} \theta_M Monthly_{t,i} + \sum_{i=1}^{N} \theta_Y yearly_{t,i} + \mu_t \tag{4.8}$$

Equation (4.7) shows the model built for hourly average wholesale electricity real-time prices, while Equation (4.8) is the model for hourly average electricity day-ahead prices. In equation 4.7 and 4.8, $RTMP_{ht}$ (\$/MWh) is the system-wide real-time market electricity price at hour t, $DAMP_t$ (\$/MWh) represent the system-wide the day-ahead market electricity price at hour t, respectively. $wind\_sh_t$ represent the share of wind generation on total electricity produced during hour t in the two models above, β_1 and θ_1 . The coefficients on the wind share for hour t are the parameter of interest. While the demand in Equation (4.7) is the actual electricity consumption, the demand in Equation (4.8) uses the day-ahead electricity demand forecast. gas_price, $over\_pred\_demand_t$ and $under\_pred\_demand_t$ are natural gas price, over predicted and under predicted electricity demand resulting from forecast error, respectively. CDD_t and HDD_t denotes cooling and heating degree days. CDD^2 and HDD^2 are squared of cooling and heating degree days, respectively. The next three binary variables are time fixed effects for every day of the week, every month of the year, and every year (To avoid singularity issue in regression modeling, one day, one month, and one year each was excluded). β and θ are the time-dependent intercepts, respectively, that aims to account for the residual price effect not captured by other RHS variables. Finally, ε_t and μ_t are the random error terms in the models, respectively.

The central hypothesis of this research is investigating whether increasing wind penetration is driving down wholesale electricity prices, implying that the estimated coefficient on the wind share is expected to be negative and statistically significant. The daily natural gas price marginal effect on the RTM and DAM prices are expected to be positive. Given that prices will increase as demand increases, the estimated coefficient of demand is expected to be positive.

In an attempt to understand how a rising penetration of wind-generated electricity is impacting the market value of baseload versus non-baseload sources and undermine its own market value, I estimate the following regression equation:

$$UR_t^i = \pi + \pi_1 wind\_gwh_t + \pi_2 gas\_gwh_t + \pi_3 baseload\_gwh_t + \pi_4 demand\_gwh_t + \pi_5 gas\_price_t + \eta' D_t + \varepsilon_t \tag{4.9}$$

$$VF_t^i = \phi + \phi_1 wind\_sh_t + \phi_2 gas\_sh_t + \phi_3 baseload\_sh_t + \phi_4 demand\_actaul_t + \phi_5 gas\_price_t + \eta' D_t + \mu_t \tag{4.10}$$

where UR_t^i and VF_t^i represent the unit revenues and value factor index[20], respectively, from baseload and each of the non-baseload sources, which will be the dependent variables of the models. i stand for wind, gas, and baseload, respectively. $wind\_gwh_t$, gas_gwh_t, and $baseload\_gwh_t$ represent the quantity of electricity in GWh from wind, gas, and baseload, respectively. $wind\_sh_t$, is the share of wind generation, gas_sh_t represent the share of gas, $baseload\_sh_t$ represent the baseload share, which is an aggregate share of nuclear and coal in the total electricity supplied. $demand_t$ is the actual quantity of electricity consumed. D_t represent the vector of daily, monthly, and yearly dummy variables that account for trends and various levels of seasonality. Finally, ε_t and μ_t are the error terms in the models. Using these models allows us to quantify how increasing market penetration of wind power impacts its unit revenues and value factor, as well as the impacts across technologies.

4.5.5. Quantile regression models

Moving forward, the OLS regression specified in equations (4.7), (4.8), (4.9), and (4.10) depict average relationships between the dependent variable (RTM and DAM prices, unit revenues, and value factors) and independent variables. OLS regressions, however, do not measure the linkages between the two variables in extreme market situations. Specifically, the traditional econometric methods involve certain assumptions as regards the distribution of the error terms, particularly for the standard OLS fixed effects technique, which relies on the independent and identical distribution (*iid*) of the error term and assumes a normal distribution. Regrettably, these assumptions may not hold in situations where the dependent variable shows highly skewed and heavy-tailed distribution (Koenker and Hallock, 2001). Therefore, to address the above limitation in the conventional OLS, I move beyond OLS regression analysis by employing the quantile regression

[20] The description of how these dependent variables are calculated is in section 4.5.1.

approach proposed by Koenker and Bassett (1978) to avoid biased estimates and account for the dependence structure of the variables under investigation for different market situations.

Quantile regression, as an extension of the OLS regression method, has two significant rewards. First, in contrast to the conventional OLS model, the quantile regression coefficient captures a more accurate and precise result of the dependent variables' conditional distribution, which permits differentiating the intensity of the impact of the explanatory variables across the distribution of the dependent variable. In other words, compared to traditional OLS, quantile regression estimates are more informative. Second, the quantile regression method estimates are less sensitive to heteroskedasticity, outliers, and skewness on the dependent variables (Koenker and Hallock, 2001). Thus, the quantile regression technique provides more precise and accurate estimation outcomes than its OLS regression counterpart. Following Koenker and Bassett (1978), the quantile regression method of Y_i given X_i is specified as follows:

$$Q_{y_i}(\tau|X) = \delta(\tau) + X_i'\rho(\tau) \tag{4.11}$$

In Equation (4.11), Y is the dependent variable (RTM and DAM prices), which is assumed to be linearly dependent on X. $Q_y\,(\tau|X)$ is defined as the τ-th conditional quantile of y_i and $0<\tau<1$. $\rho(\tau)$ is the quantile regression coefficient, $\delta(\tau)$ is the unobserved effects, and τ is a quantile (0,1). Contrary to the traditional minimization of the sum of squared errors as with OLS, the coefficients $\rho(\tau)$ are estimated by minimizing the weighted sum of absolute deviations between the electricity prices (RTM and DAM) and a linear combination of the explanatory variables as:

$$\hat{\rho}(\tau) = arg\min_{\rho(\tau)} \textstyle\sum_{i=1}^{N} \gamma_\tau(y_i - x_i'\rho(\tau) - \delta(\tau)) \tag{4.12}$$

where $\gamma_\tau(u) = u(\tau - 1(u < 0))$ is the check function, and $I(\cdot)$ is an indicator function $(u = y_i - x_i'\rho(\tau) - \delta(\tau))$.

To explore the merit-order effects of wind generation and other explanatory variables on wholesale electricity prices quantile wise, the following transformation on Equations (4.7) and (4.8) is presented as follows:

$$\boldsymbol{Q_{RTMP}}(\boldsymbol{\tau}|\boldsymbol{x}) = \beta(\tau) + \beta_1(\tau)wind\_sh_t + \beta_2(\tau)demand\_actual_t + \beta_3(\tau)gas\_price_t + \beta_4(\tau)over\_pred\_demand_t + \beta_5(\tau)under\_pred\_demand_t + \beta_6(\tau)CDD_t + \beta_7(\tau)HDD_t + \beta_8(\tau){CDD^2}_t + \beta_9(\tau){HDD^2}_t + \sum_{k=1}\beta_D(\tau)Daily_{t,k} + \sum_{m=1}\beta_M(\tau)Monthly_{t,m} + \sum_{i=1}\beta_Y(\tau)Yearly_{t,i} + \varepsilon_t \quad (4.13)$$

$$\boldsymbol{Q_{DAMP}}(\boldsymbol{\tau}|\boldsymbol{x}) = \theta(\tau) + \theta_1(\tau)wind\_sh_t + \theta_2(\tau)demand\_forecast_t + \theta_3(\tau)gas\_price_t + \sum_{k=1}\theta_D(\tau)Daily_{t,k} + \sum_{m=1}\theta_M(\tau)Monthly_{t,m} + \sum_{i=1}\theta_Y(\tau)Yearly_{t,i} + \mu_t \quad (4.14)$$

In Equation (4.13), $Q_{RTMP}(\tau|x)$ and $\beta(\tau)$ are the τth quantile regression parameters of the real-time market prices and constant, $\beta_1(\tau)$, $\beta_2(\tau)$, $\beta_3(\tau)$, $\beta_4(\tau)$, $\beta_5(\tau)$, $\beta_6(\tau)$, $\beta_7(\tau)$, $\beta_8(\tau)$, and $\beta_9(\tau)$ are the coefficient parameters of τth quantile of the explanatory variables. Likewise, in equation (4.14), $Q_{DAMP}(\tau|x)$ and $\theta(\tau)$ are the τth quantile regression parameters of the day-ahead market prices and constant, $\theta_1(\tau)$, $\theta_2(\tau)$, $\theta_3(\tau)$, are the coefficient parameters of τth quantile of the explanatory variables. The central focus here is on coefficients $\beta_1(\tau)$ and $\theta_1(\tau)$, estimating the merit-order effects. Each coefficient will be interpreted as the marginal change in price as a result of a marginal difference in the given regressor.

Similarly, to explore the effects of wind penetration and other explanatory variables on unit revenues and value factors quantile wise, the following transformation on Equations (4.9) and (4.10) is presented as follows:

$$\boldsymbol{Q_{UR}}(\boldsymbol{\tau}|\boldsymbol{x}) = \pi(\tau) + \pi_1(\tau)wind\_gwh_t + \pi_2(\tau)gas\_gwh_t + \pi_3(\tau)baseload\_gwh_t + \pi_4(\tau)demand\_gwh_t + \pi_5(\tau)gas\_price_t + \sum_{k=1}\pi_D(\tau)Daily_{t,k} + \sum_{m=1}\pi_M(\tau)Monthly_{t,m} + \sum_{i=1}\pi_Y(\tau)Yearly_{t,i} + \varepsilon_t \quad (4.15)$$

$$\boldsymbol{Q_{VF}(\tau|x)} = \phi(\tau) + \phi_1(\tau)wind\_sh_t + \phi_2(\tau)gas\_sh_t + \phi_3(\tau)baseload\_sh_t + \phi_4(\tau)demand\_gwh_t + \phi_5(\tau)gas\_price_t + \sum_{k=1} \phi_D(\tau)Daily_{t,k} + \sum_{m=1} \phi_M(\tau)Monthly_{t,m} + \sum_{i=1} \phi_Y(\tau)Yearly_{t,i} + \mu_t \tag{4.16}$$

In Equation (4.15), $Q_{UR}(\tau|x)$ and $\pi(\tau)$ are the τth quantile regression parameters of the unit revenues and constant, $\pi_1(\tau)$, $\pi_2(\tau)$, $\pi_3(\tau)$, $\pi_4(\tau), \pi_5(\tau)$ are the coefficient parameters of τth quantile of the explanatory variables. Likewise, in equation (4.16), $Q_{VF}(\tau|x)$ and $\phi(\tau)$ are the τth quantile regression parameters of the value factors and constant, $\phi_1(\tau)$, $\phi_2(\tau)$, $\phi_3(\tau)$, $\phi_4(\tau)$, $\phi_5(\tau)$ are the coefficient parameters of τth quantile of the explanatory variables. The central focus here is on coefficients $\pi_1(\tau)$ and $\phi_1(\tau)$, estimating the cannibalization and cross-cannibalization effects.

For this analysis, following Hagfors et al. (2016), equations (4.13), (4.14), (4.15) and (4.16) are estimated for nine different quantiles, namely, τ = (1%, 5%, 10%, 25%, 50%, 75%, 90%, 95%, 99%). Moreover, these nine quantiles are categorized into three groups: the lower quantiles τ = (1%, 5%, 10%, and 25%) represent extreme depressed price market conditions, the median quantile τ = (50%) denotes periods with moderate market demand, and high quantiles τ = (75%, 90%, 95%, and 99%) to represent high price market conditions. The standard errors of the coefficient estimates are estimated via bootstraps in order to correct for heteroskedasticity. The XY- pair bootstrapping method proposed by Buchinsky (1995) was used with 1000 replications.

4.6. Results and discussion

This section starts with a presentation of the main findings obtained from quantifying the effects of wind penetration on wholesale electricity market prices, known as the "merit-order effect". Next, results are presented that quantify the effects of wind penetration on the market values of wind power, baseload generation, and non-baseload sources, known as "cannibalization" and "cross-cannibalization" effects (López Prol et al., 2020). To enable these comparisons, equations (4.7), (4.8), (4.9), and (4.10) are estimated using OLS with heteroskedasticity and autocorrelation consistent (HC/HAC) standard errors. Breusch Pagan tests on these equations reject the null hypothesis of homoscedasticity for each regression model. Then, equations (4.13), (4.14), (4.15), and (4.16) are estimated with quantile regressions. All equations include other explanatory variables and controlling variables for daily, monthly, and yearly dummies.

There are three significant problems with the use of an OLS model. First, the OLS estimates are based on conditional mean, therefore, unable to determine the explanatory variables' differential impact on the conditional distribution of wholesale electricity prices. Second, the estimate assumes homoscedasticity, implying that the conditional variance in the error terms remains unchanged. Finally, the OLS is susceptible to extreme values and outliers.

4.6.1. Merit-order effect: Day-ahead price regressions

The upper and lower panels in Table 4.5 display the estimation results of the OLS and quantile regression in the PJM and ERCOT, respectively, for DAM price regression based on equations (4.8) and (4.14). From Table 4.5, the quantile regression results provide a reasonably different picture than the OLS estimates. Notably, the estimated results show that moving up the conditional distribution, wind generation impact on DAM prices varies in magnitude with wind supply having statistically significant, negative effects on the DAM price across all quantiles of electricity prices in both market regions. However, wind generation in ERCOT reduces wholesale prices more in high quantiles of DAM prices (above the 90^{th} percentile) than lower quantiles.

The negative relations between wind generation and electricity price increase in magnitude as it moves from the lower tail of the distribution to the upper tail, except at the uppermost tail (99^{th} quantiles) in the PJM market. In other words, the strength of the MOE impact increases at higher quantiles- which implies that as DAM price increases, the MOE from wind increases (i.e. a more negative impact resulting in larger price decreases). This indicates that wind is more successful in reducing the occurrence of positive price spikes in ERCOT than it does in PJM. This further means that at least part of the extremely negative price variation in these market regions can be linked to different price stability across quantiles.

More specifically, holding everything else constant, the coefficient estimates of hourly wind supply indicate that each additional expected increase in PJM's hourly wind generation's share by one percentage point reduces DAM prices across the wholesale price distribution that range from $0.39/MWh to $0.60/MWh, about 1.1% to 1.7% of mean prices across quantiles. The same size of hourly wind generation increase in the ERCOT market region is estimated to reduce DAM prices across all quantile of the price distribution by amounts that range from about $0.28/MWh to $0.54/MWh, which are about 0.9% to 1.7% of mean prices across quantiles.

Table 4.5. Estimation results for impacts of wind energy penetration on the day-ahead market (DAM) wholesale electricity prices

Region	Variable	Low quantiles				Median		High quantiles			
		Q1	Q5	Q10	Q25	Q50	Q75	Q90	Q95	Q99	OLS
PJM	Wind supply	-0.426***	-0.442***	-0.477***	-0.500***	-0.501***	-0.522***	-0.584***	-0.599***	-0.385***	-0.724***
	Demand forecast	0.391***	0.380***	0.391***	0.444***	0.537***	0.661***	0.834***	0.100***	1.520***	0.755***
	Gas price	3.410***	3.567***	3.771***	4.132***	4.658***	5.775***	7.679***	8.361***	9.852***	8.445***
	Constant	-15.638***	-13.662***	-14.135***	-17.893***	-25.106***	-35.020***	-33.465***	-7.752***	47.483***	-46.157***
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Pseudo R^2 (%)	40.23%	40.00%	38.93%	39.65%	40.79%	39.51%	38.39%	41.24%	53.50%	38.56%
ERCOT	Wind supply	-0.311***	-0.286***	-0.280***	-0.284***	-0.320***	-0.391***	-0.501***	-0.535***	-0.512***	-0.349***
	Demand forecast	0.155***	0.141***	0.147***	0.171***	0.269***	0.556***	1.058***	1.548***	3.800***	1.253***
	Gas price	2.926***	3.578***	4.096***	4.929***	5.619***	6.571***	7.397***	8.406***	13.153***	7.225***
	Constant	2.211***	2.628***	2.973***	2.321***	0.168	-8.520***	-22.203***	-37.771***	-111.659***	-28.918***
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Pseudo R^2 /R^2(%)	27.74%	22.85%	20.41%	19.78%	16.89%	15.70%	13.78%	13.27%	24.41%	4.44%

Note: Pseudo R-squared has a similar interpretation as the conventional R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

These results are in tandem with merit-order theory which show that an increase in the near-zero marginal cost of renewable energy sources such as wind power will reduce wholesale electricity prices. Furthermore, these results support and consistent with the recent findings of Westgaard et al. (2021), Maciejowska (2020), Sirin and Yilma (2020), Sapio (2019), and Do et al. (2019), who verified the negative distribution impacts between renewable energy penetration and DAM electricity prices in California, German, Turkish, and Italian electricity markets. These authors employed a quantile regression model to analyze the MOE and show that conditional wholesale electricity prices react differently to renewable power penetration at different quantiles. For example, Sapio (2019) showed that solar power's merit order effect is discovered predominantly in the price distribution body and the lower quantiles when the prices were already relatively low. Sirin and Yilma (2020) show in the Turkish electricity market that the estimated merit-order of wind technology ranges between 0.01% and 0.15% and conclude that the variation between quantiles varies within hours of the day.

All other fundamental drivers' of DAM wholesale electricity prices had highly statistically significant (at the 1 % level of significance) coefficients. In both market regions, electricity demand forecasts and natural gas prices positively affect wholesale electricity prices. Coefficient estimates of the natural gas price show that a \$1/MMBtu rise in natural gas price increases the DAM prices in the PJM region from \$3.13/MWh to \$9.85/MWh. These results indicate an 8.8% to 27.6% increase in mean DAM prices across quantiles. Similarly, a \$1/MMBtu increase in natural gas price causes DAM prices in the ERCOT market to increase in an amount that ranges from \$2.93/MWh to \$13.15/MWh depending upon the price quantile, a 9.2% to 41% increase in the mean DAM prices across quantiles.

The electricity demand forecast coefficient estimates imply that a one GWh increase in PJM's electricity demand is projected to increase DAM price that ranges from about \$0.10/MWh to \$1.52/MWh. The same size of electricity demand forecast increase in the ERCOT region is estimated to increase DAM price by an amount ranging from about \$0.17/MWh to \$3.80/MWh depending upon the price quantile.

4.6.2. Merit-order effect: Real-time price regressions

Table 4.6 presents the RTM estimation results for the OLS and quantile regressions in the PJM and ERCOT based on equations (4.7) and (4.13). The quantile regression coefficient estimates act as a supplement the OLS regression results and paint some different pictures. Indeed, the OLS regression produces only a mean estimate, providing only minimal information about the merit-order effect. By comparison, a series of conditional quantile regressions offer a much more detailed statistical information on the functional relationships between dependent and explanatory variables. As the regression results show, most of the variables differ in their estimated coefficients compared to the OLS estimates and change distinctively in magnitude across quantiles.

Across all quantiles of the RTM price distribution, wind generation has statistically significant coefficients with expected negative impacts on price in the PJM region. In the ERCOT market, the merit order effect of wind power penetration is confirmed at the median and higher quantiles of the electricity price distribution. The lower quantiles' differing results show positive impacts, failing to support the merit order price-dampening hypothesis, which is somehow difficult to explain. On the one hand, one immediate conclusion to be drawn is that forecast imbalance between wind output and actual electricity demand (load) might be responsible for the RTM estimate to deviate from the DAM values. The differing results imply that the deviation of the RTM merit-order effect from the DAM estimates is supply-side driven. On the other hand, this result may be partly due to trading inefficiency in ERCOT's DAM price, as noted by (Zarnikau et al., 2014).

At the 50% quantile and higher, the relationship between wind generation and RTM prices are found to be stable, negative, and statistically significant. This finding suggests that a mean coefficient estimate can conceal valuable results. Specifically, the real-time electricity price for the

PJM region decreases in the range of $0.52/MWh to $0.80/MWh for each percentage point increase in wind generation. The same percentage point increase in wind generation share reduces real-time electricity price by roughly $0.05/MWh to $2.13/MWh in the ERCOT market. The results from the ERCOT suggests more significant uncertainly in the real-time market as a result of increasing wind generation mainly results in low prices under bearish condition.

Other fundamental drivers of RTM price include the estimated impact of actual demand on price distribution being positive, as expected, and statistically significant across all quantiles in both regions. The results vary substantially across quantiles. Precisely, RTM prices for the PJM region rise across the price distribution ranging from $0.40/MWh to $1.80/MWh for each additional GWh of actual electricity demand. In the ERCOT region, each additional GWh of actual electricity demand leads to an increase in real-time price by price distribution that ranges from around $0.03/MWh to $1.13/MWh.

Table 4.6. Estimation results for impacts of wind energy penetration on real-time market (RTM) wholesale electricity prices

Region	Variable	Low quantiles				Median		High quantiles			OLS
		Q1	Q5	Q10	Q25	Q50	Q75	Q90	Q95	Q99	
PJM	Wind supply	-0.677***	-0.541***	-0.524***	-0.535***	-0.588***	-0.690***	-0.638***	-0.664***	-0.811***	-0.540***
	Actual demand	0.587***	0.424***	0.400***	0.406***	0.468***	0.624***	0.875***	1.114***	1.795***	0.861***
	Gas price	3.661***	3.472***	3.438***	3.597***	3.984***	4.410***	4.279***	4.315***	2.501***	4.590***
	Over predicted demand	-0.015*	-0.018***	-0.021***	-0.011***	0.006***	0.034***	0.054***	0.068***	0.005	0.096***
	Under predicted demand	-0.004	-0.004	-0.018***	-0.077***	-0.311***	-0.944***	-3.318***	-5.517***	-12.100***	-0.630***
	CDD	-0.918***	-0.270***	-0.239***	-0.287***	-0.363***	-0.755***	-2.030***	-3.205***	-6.984***	-1.715***
	HDD	0.113***	0.042***	0.033***	-0.028***	-0.137***	-0.519***	-1.553***	-2.350***	-4.450***	-1.343***
	CDD squared	0.017***	0.000	0.003***	0.008***	0.012***	0.031***	0.103***	0.170***	0.434***	0.080***
	HDD squared	-0.004***	-0.001***	-0.001***	0.001***	0.003***	0.014***	0.043***	0.066***	0.125***	0.032***
	Constant	-38.396***	-19.773***	-16.410***	-15.619***	-19.642***	-28.301***	-33.589***	-39.130***	-51.489***	-41.309***
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Pseudo R^2 (%)	36.27%	37.77%	38.11%	37.39%	34.99%	32.54%	35.32%	39.63%	48.47%	32.16%
ERCOT	Wind supply	0.135***	0.139***	0.135***	0.030***	-0.054***	-0.208***	-0.594***	-0.915***	-2.131***	-0.017
	Actual demand	0.204***	0.055***	0.028***	0.054***	0.090***	0.187***	0.292***	0.116***	1.125***	0.204***
	Gas price	1.104***	1.410***	1.787***	2.003***	2.147***	3.061***	3.098***	3.692***	4.082***	4.193***
	Over predicted demand	-0.047***	0.022***	0.026***	-0.029***	-0.044***	-0.054***	-0.076***	0.293***	16.277***	0.724***
	Under predicted demand	-0.246***	-0.097***	-0.042***	0.012***	-0.004***	-0.031***	-0.037***	0.170***	1.366***	0.284***
	CDD	-0.052*	-0.011	0.055***	0.112***	0.111***	0.260***	0.002	-0.182***	-1.528***	0.044
	HDD	0.048*	0.103***	0.131***	0.132***	0.024***	-0.027***	-0.146***	-0.298***	-0.601*	-0.039
	CDD squared	-0.006***	-0.002***	-0.004***	-0.003***	-0.001***	-0.002***	0.008***	0.008***	0.116***	0.008
	HDD squared	-0.003***	-0.003***	-0.005***	-0.005***	-0.001***	0.000	0.000	0.002	0.001	0.002
	Constant	13.622***	12.196***	11.292***	15.346***	20.959***	26.768***	31.807***	25.527***	-20.601***	8.117**
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Pseudo R^2 (%)	4.54%	2.59%	2.50%	2.61%	1.85%	1.54%	1.58%	1.32%	8.60%	0.90%

Note: Pseudo R-squared has a similar interpretation as the conventional R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Natural gas price has a positive impact on real-time price, as expected in both market regions. Estimates of the impact of natural gas price are all statistically significant at 1% level of significance throughout the entire spectrum of quantiles of the price distribution. More specifically, the coefficient of natural gas price for the PJM indicates that a $1/MMBtu rise in gas price tends to raise real-time electricity prices by $2.50/MWh - $4.41/MWh. The same price increase in gas price raises the RTM price in the ERCOT region by approximately $1.10/MWh to $4.08/MWh. Intuitively, these results agree with Jenkins's (2018) claim, whose analysis suggests that recent declines in natural gas prices dominantly contribute to the decreasing wholesale electricity prices in the PJM market region. While natural gas prices have been declining in recent years due to shale fracking and horizontal drilling boom in the U.S, this result suggests that these prices may increase if shale gas experience any shortfall in its production. Further, these results show that natural gas price impacts on electricity prices tend to be more pronounced on DAM than the RTM prices.

Turning to the impact of demand forecast error (over-predicted demand and under-predicted demand) on real-time prices, the results are mixed across quantiles and counterintuitive in both market regions. For example, over-predicted demand tends to decrease prices only at the lower tails of the price distribution (1%, 5%, 10%, and 25% quantiles). Simultaneously, it causes the price to rise in the median and upper quantiles in the PJM region. Under-predicted demand results in the price decline, which is untenable. Thus, it is difficult to draw any conclusions based on the overall effects of over-predicted and under-predicted demand on RTM prices. Further, the weather variables (HDD and CDD) show non-linear impacts on RTM prices in both market regions.

4.6.3. *Quantile regression coefficients tests*

While the estimated coefficients obviously differ across quantile levels reported in Tables 4.5 and 4.6, some conditional quantile functions are superimposed on the results. To further clarify these differences, formal tests for the hypothesis of quantile slope equality are more convincing.

Thus, quantile slope equality test proposed by Koenker and Bassett (1982) are used to evaluate whether the wind supply changes' estimates have heterogeneity between the median quantile and the other quantiles statistically. These tests use the following null hypotheses:

$$\begin{cases} \beta_{k,\tau=0.01} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.05} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.10} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.25} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.75} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.90} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.95} = \beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.99} = \beta_{k,\tau=0.5} \end{cases} \qquad \text{where k = 1, 2…8.}$$

The results of the F-test slope equality are presented in Tables 4.7 and 4.8. A rejection of the null hypothesis indicates that slopes significantly differ across quantiles. The results are presented for lower quantile versus the median, higher quantile versus the median, and lower quantile against higher quantile. According to the results, the null hypothesis is uniformly rejected on the wind supply variable's coefficients at different quantile distributions for both real-time and day-ahead models. The test results in both regions (PJM and ERCOT) and both markets model (RTM and DAM) suggest that the estimated coefficients are not constant and that the conditional quantiles are not identical. The test results further show the caveat about relying on using the median or average level of the data to analyze renewable energy's merit-order effect on electricity prices.

Table 4.7. Quantile slope equality test results for the day-ahead market (DAM) model reported in Table 4.5

Region	Variable	Q0.01 = Q0.50	Q0.05 = Q0.50	Q0.1 = Q0.50	Q0.25 = Q0.50	Q0.50 = Q0.75	Q0.50 = Q0.90	Q0.50 = Q0.95	Q0.50 = Q0.99
PJM	Wind supply	0.075***	0.058***	0.024	0.000	0.021	0.083***	0.098***	-0.115
	Demand forecast	-0.146***	-0.157***	-0.146***	-0.092***	-0.124	-0.297***	-0.463***	-0.983***
	Gas price	-1.248***	-1.091***	-0.887***	-0.526***	-1.117***	-3.021***	-3.703*	-5.193***
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ERCOT	Wind supply	0.009	0.033***	0.039***	0.035***	0.072***	0.182***	0.216***	0.192***
	Demand forecast	-0.114***	-0.128***	-0.121***	-0.098***	-0.287***	-0.789***	-1.279***	-3.531***
	Gas price	-2.693***	-2.041***	-1.523***	-0.689***	-0.952***	-1.778***	-2.787***	-7.534
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4.8. Quantile slope equality test results for the real-time market (RTM) model reported in Table 4.6

Region	Variable	Q0.01 = Q0.50	Q0.05 = Q0.50	Q0.1 = Q0.50	Q0.25 = Q0.50	Q0.50 = Q0.75	Q0.50 = Q0.90	Q0.05 = Q0.95	Q0.50 = Q0.99
PJM	Wind supply	-0.089**	0.047**	0.064***	0.053***	0.102***	0.049	0.075**	-0.074**
	Actual demand	0.118***	-0.044***	-0.069***	-0.063***	-0.156***	-0.406***	-0.646***	-1.352***
	Gas price	-0.323**	-0.512***	-0.546***	-0.387***	-0.427***	-0.294***	-0.346	-0.248
	Over predicted demand	-0.021	-0.025***	-0.027***	-0.018***	-0.028***	-0.048***	-0.061***	0.110***
	Under predicted demand	0.307***	0.307***	0.293***	0.234***	0.633***	3.007***	5.207***	13.884***
	CDD	-0.554***	0.093***	0.124***	0.077***	0.391***	1.666***	2.841***	6.067***
	HDD	0.250***	0.179***	0.169***	0.108***	0.382***	1.416***	2.212***	4.564***
	CDD squared	0.005	-0.011***	-0.008***	-0.003***	-0.019***	-0.092***	-0.158***	-0.068***
	HDD squared	-0.007***	-0.005***	-0.004***	-0.003***	-0.010***	-0.039***	-0.062***	-0.042***
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ERCOT	Wind supply	0.189***	0.193***	0.188***	0.084***	0.154***	0.541***	0.861***	2.267***
	Actual demand	-0.113***	0.036***	0.063***	0.036***	0.097***	0.202***	0.026	-1.329***
	Gas price	-1.492***	-0.738***	-0.361***	-0.144***	-0.913***	-3.733***	-6.517***	-18.133***
	Over predicted demand	-0.002	0.066***	0.070***	0.015***	0.009	0.031	-0.337	-16.324***
	Under predicted demand	0.025	0.079***	0.108***	0.108***	0.027***	0.033	-0.172	-1.612***
	CDD	-0.242***	-0.093***	-0.038***	0.016	-0.148***	0.109	0.294	1.477
	HDD	-0.163**	-0.122***	-0.056***	0.000***	0.051***	0.170***	0.322	0.649
	CDD squared	-0.005*	-0.001	-0.003***	-0.003***	0.001	-0.008***	-0.008**	-0.122
	HDD squared	-0.002	-0.002***	-0.003***	-0.003***	-0.002**	-0.002	-0.003	-0.004
	DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4.9. Symmetric Quantile Test for the day-ahead market (DAM) model reported in Table 4.5

Region	Variable	Quantiles			
		5^{th}	25^{th}	75^{th}	95^{th}
PJM	Wind supply	0.468***	0.084***	0.084***	0.468***
	Demand forecast	0.166***	0.026***	0.026***	0.166***
	Gas price	-0.796***	0.100	0.100	-0.796***
	Over predicted demand	-0.170***	-0.022***	-0.022***	-0.170***
	Under predicted demand	-0.178**	-0.026*	-0.026*	-0.178**
	CDD	-2.679***	-0.294***	-0.294***	-2.679***
	HDD	-1.735***	-0.201***	-0.201***	-1.735***
	CDD squared	0.175***	0.018***	0.018***	0.175***
	HDD squared	0.055***	0.007***	0.007***	0.055***
	DMY dummies	Yes	Yes	Yes	Yes
ERCOT	Wind supply	-0.415***	-0.063***	-0.063***	-0.415***
	Demand forecast	0.711***	0.132***	0.132***	0.711***
	Gas price	-1.402***	-0.212***	-0.212***	-1.402***
	Over predicted demand	-0.039	-0.051***	-0.051***	-0.039
	Under predicted demand	-1.139***	-0.208***	-0.208***	-1.139***
	CDD	-1.489***	-0.058***	-0.058***	-1.489***
	HDD	-1.056***	-0.027	-0.027	-1.056***
	CDD squared	0.088***	0.002***	0.002***	0.088***
	HDD squared	0.066***	0.004***	0.004***	0.066***
	DMY dummies	Yes	Yes	Yes	Yes

Notes: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4.10. Symmetric Quantile Test for the real-time market (RTM) model reported in Table 4.6

Region	Variable	Quantiles			
		5th	25th	75th	95th
PJM	Wind supply	-0.124	-0.069***	-0.069***	-0.124
	Actual demand	0.629***	0.098***	0.098***	0.629***
	Gas price	-0.793	0.052	0.052	-0.793
	Over predicted demand	-0.032***	0.008**	0.008	-0.032***
	Under predicted demand	-5.327***	-0.381***	-0.381***	-5.327***
	CDD	-2.748***	-0.315***	-0.315***	-2.748***
	HDD	-2.033***	-0.273***	-0.273***	-2.033***
	CDD squared	0.147***	0.015***	0.015***	0.147***
	HDD squared	0.019***	0.002***	0.002***	0.019***
	DMY dummies	Yes	Yes	Yes	Yes
ERCOT	Wind supply	-0.668***	-0.070***	-0.070***	-0.668***
	Actual demand	0.010	-0.061***	-0.061***	0.010
	Gas price	5.779***	0.769***	0.769***	5.779***
	Over predicted demand	0.403***	0.006	0.006	0.403***
	Under predicted demand	0.082*	-0.010	-0.010	0.082*
	CDD	-0.415***	0.148***	0.148***	-0.415***
	HDD	-0.243***	0.057***	0.057***	-0.243***
	CDD squared	0.007*	-0.004***	-0.004***	0.007*
	HDD squared	0.001	-0.001*	-0.001*	0.001
	DMY dummies	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Apart from the established evidence that the slope coefficients of the variables are not constant across quantiles, the symmetry of the electricity price-wind generation association for the quantiles above the median relative to those below the median is also of interest. Specifically, conditional symmetry testing was employed (Newey and Powell (1987)) with the following restrictions:

$$\begin{cases} \beta_{k,\tau=0.75} + \beta_{k,\tau=0.25} = 2\beta_{k,\tau=0.5} \\ \beta_{k,\tau=0.95} + \beta_{k,\tau=0.05} = 2\beta_{k.\tau=0.5} \end{cases} \qquad \text{where k = 1, 2, 3 4.}$$

This test calculates a Wald statistic to determine whether or not the two sets of coefficients for symmetric quantiles around the median will equal the coefficients' median value. The null hypothesis for this test is that the distribution is symmetric. Tables 4.9 and 4.10 present the results of the conditional symmetry tests for $\tau = 0.05, 0.95,$ and $\tau = 0.25, 0.75$. The Wald tests' overall p-value in the DAM and RTM models in both market regions are less than 0.05, signifying the rejection of the null hypothesis that the distribution is symmetric. Furthermore, the individual restriction test values are statistically significant, thereby proving strong evidence of asymmetry. The results further prove that the slope parameters, estimates between lower quantiles, medians, and the upper quantiles, consistently differ in magnitude.

4.6.4. Market values effects

This subsection now turns to the presentation of the results obtained from quantifying the effects of wind generation on the market value of baseload generation versus non-baseload sources to that of wind energy sources itself, what is known as "cannibalization" and "cross-cannibalization" effect (López Prol et al., 2020). Equations (4.15) and (4.16) are estimated for the PJM region in terms of unit revenues and value factors impacts of wind generation using OLS with heteroskedasticity and autocorrelation consistent (HC/HAC) standard errors and quantile regressions over the sample from 2016 until 2019. All equations include other explanatory variables and controlling variables for daily, monthly, and yearly dummies.

4.6.5. Unit revenues regressions

The results from the OLS regression in Table 4.11 show that wind supply is negatively correlated with wind unit revenue but statistically insignificant. However, quantile regression results show wind supply coefficient estimates to be consistently negative and statistically significant across all quantiles of the unit revenue distribution. This result confirms that in the PJM market, the increasing penetration of wind power undermines its unit revenues. More specifically, each additional GWh increase in electricity produced from wind is associated with a fall in its unit revenues across quantiles by an amount that ranges from approximately $0.01/MWh to $0.06/MWh.

The graphical description of the quantile regression, as displayed in Figure 4.6, demonstrates the unit revenue impacts across quantiles, the variance of the slope of each regression coefficient. The vertical axis measures the regression coefficient magnitudes and the horizontal axis contains the various quantiles. The solid blue line in each quintile shows the estimate of the quantiles' regression coefficient; the two solid orange lines present the confidence bands of the coefficients at 95%. In addition, the quantile slope equality test further confirms that wind unit revenue coefficients are different at each quantile (Table 4.12). This unit revenue dampening evidence of wind penetration is consistent with the negative impact findings by López Prol et al. (2020). Nevertheless, the resultant values found in this research are lower than the average value observed for the California electricity market.

Table 4.11 Estimation results for wind penetration effect on unit revenues.

Variable	Low quantiles				Median		High quantiles			OLS
	Q1	Q5	Q10	Q25	Q50	Q75	Q90	Q95	Q99	
A.	**Dependent variable: Wind unit revenues**									
Wind supply	-0.010**	-0.009**	-0.010***	-0.013***	-0.012***	-0.013***	-0.010*	-0.027*	-0.065***	-0.003
Gas supply	0.002	0.002	0.002*	0.002**	0.001	-0.002	0.001	-0.018	-0.047**	-0.005**
Actual demand	0.013***	0.015	0.014***	0.014***	0.018***	0.026***	0.033***	0.051***	0.084***	0.039***
Gas price	3.875***	3.490***	3.391***	3.480***	2.784***	2.783***	1.673	-1.482	-11.368**	1.673
Constant	-18.598***	-20.874***	-17.988***	-17.833***	-21.107***	-33.696***	-26.703**	-12.659	-10.735	-53.114***
DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R2 (%)	40.49%	36.46%	34.91%	32.71%	31.71%	31.24%	34.88%	43.35%	69.14%	37.83%
B.	**Dependent variable: Gas unit revenues**									
Wind supply	-0.015***	-0.017***	-0.021***	-0.028***	-0.027***	-0.020***	-0.025**	-0.043***	-0.064***	-0.020**
Gas supply	-0.000	0.003**	0.005***	0.003**	0.004***	0.005*	0.008	-0.026	-0.041*	-0.004*
Actual demand	0.015***	0.015***	0.015***	0.017***	0.021***	0.029***	0.037***	0.065***	0.089***	0.042***
Gas price	3.669***	3.390***	3.327***	3.064***	3.068***	3.008***	1.804	-3.754	-10.981***	1.977
Constant	-19.988***	-19.209***	-18.620***	-22.631***	-27.218***	-40.715***	-35.456***	-37.327**	-37.809*	-60.182***
DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R2 (%)	42.00%	36.58%	35.25%	34.48%	33.53%	33.37%	35.60%	42.72%	65.42%	39.22%
C.	**Dependent variable: Baseload unit revenues**									
Wind supply	-0.016***	-0.018***	-0.022***	-0.026***	-0.027***	-0.026***	-0.025***	-0.035**	-0.049**	-0.019**
Gas supply	0.001	0.004***	0.004***	0.002*	0.003***	0.006**	0.003	-0.031*	-0.025	-0.004**
Actual demand	0.016***	0.014***	0.015***	0.016***	0.020***	0.026***	0.034***	0.064***	0.081***	0.040***
Gas price	3.784***	3.205***	3.266***	3.083***	3.110***	3.272***	2.212	-3.491	-11.616***	1.832
Constant	-22.775***	-18.249***	-18.725***	-20.138***	-25.712***	-36.591***	-31.768***	-33.643*	-20.477	-55.347***
DMY dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R2 (%)	43.17%	37.76%	35.85%	35.06%	33.85%	33.34%	35.43%	42.95%	67.78%	38.95%

Note: Pseudo R-squared has similar interpretation as the conventional R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Interestingly, increased wind penetration also reduces the unit revenues of gas and baseload generations (Table 4.11). The estimated coefficients for the wind supply variable are negative and statistically significant for both the OLS regressions and across all quantiles for both gas unit revenues and baseload unit revenues. Each additional GWh of electricity produced from wind is associated with a decrease in gas unit revenues across quantiles ranging from $0.02/MWh to $0.06/MWh. Similarly, an additional GWh of wind penetration is associated with a reduction in baseload unit revenues across quantiles ranging from $0.02/MWh to $0.05/MWh. These results confirm the cross-cannibalization impact of wind penetration among generation technologies. They are consistent with previous findings for the California market by López Prol et al. (2020) and the Italian power market by Clò and D'Adamo (2015)[21]. Specifically, Clò and D'Adamo (2015) find that each additional GWh of electricity supplied from solar reduced solar unit revenues by 0.36 €/MWh and gas unit revenues by 0.12 €/MWh, respectively. Similarly, López Prol et al. (2020) find that each percentage point increase in electricity generated from wind and solar leads to a fall in wind and solar unit revenues by $0.838/MWh and $1.295, respectively in California Market.

[21] Although the studies by López Prol et al. (2020) and Clò and D'Adamo (2015) make use of an econometric approach that only measure the average value in their estimations. In contrary, I employed a quantile regression method which allows identifying the impact of wind penetration not only on their market values but also on the shape of the distribution.

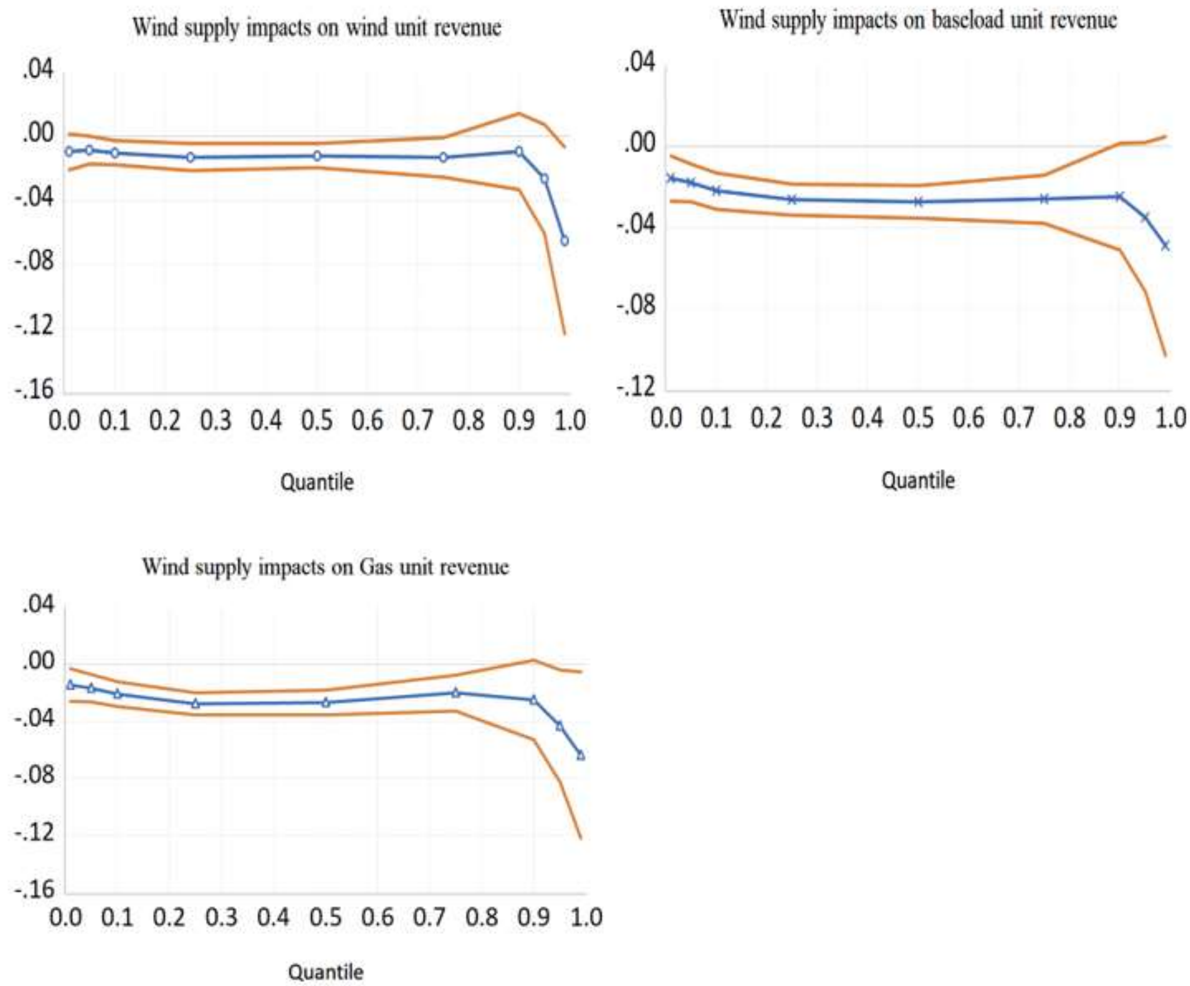


Figure 4.6: Quantile regression estimates for unit revenues with 95% confidence band

Table 4.12. Quantile slope equality test results for wind unit revenue model reported in Table 4.11

	Variables			
	Wind supply	Gas supply	Actual demand	Gas price
Q0.01 = Q0.50	0.002	0.004	-0.004***	1.092**
Q0.05 = Q0.50	0.003	0.005	-0.003**	0.706
Q0.10 = Q0.50	0.002	0.001	-0.004***	0.607
Q0.25 = Q0.50	-0.001	0001	-0.003***	0.696**
Q0.75 = Q0.50	0.001	0.003	-0.008***	0.001
Q0.90 = Q0.50	-0003**	0.001	-0.016*	1.111
Q0.99 = Q0.50	0.053**	0.048***	-0.066***	14.152***
Q0.05 = Q0.95	0.015**	0.019	-0.035***	4.266
Q0.01 = Q0.99	0.055***	0.0449**	-0.070***	15.244*

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Focusing on other control variables included in the models, as expected, the actual electricity demand is positively correlated with unit revenues of different technologies and is always statistically significant across quantiles of the distribution. This positive impact has been verified by the merit-order analysis in prior merit-order literature. Hence, it is directly reflected in the technology-specific unit revenue. Further, this observation is echoed more recently by López Prol et al. (2020). However, estimated coefficients of gas price faintly deviate from the established evidence from the literature. Natural gas price has uneven impacts on wind unit revenues, and the magnitude of the coefficients varies along quantiles. While gas prices are positively correlated with unit revenues of specific technologies at almost all quantiles of the distribution, negative and statistically significant effects are found in the upper tails (99^{th} percentile) of the distribution. At the same time, negative relations are found at the 95th, but are statistically not relevant across the technologies.

4.6.6. Value factor regressions

The OLS regression results fail to lend support for the cannibalization effect for the wind power value factor. Wind share has a positive impact on wind share value factor in panel A of Table 4.13. However, a different picture emerges with the results from quantile regressions. These results show that the cannibalization effect occurs only at the upper tails of the distribution (above the 90^{th} percentile). At these upper tails of the distribution, an increase in the share of wind by one percentage point eventually leads to a marked reduction in wind market value from 0.03 to 0.28 percentage points (pp). These results of wind penetration are well below those average values reported by Clò and D'Adamo (2015) for the Italian market (- 2.23 pp) and (López Prol et al., 2020) for the California electricity market (-0.84 pp). At the lower quantiles and median quantiles, however, wind share of the electricity generation is positively associated with wind market value as measured by its value factor. More specifically, one percentage point increase in wind share leads to marked increases in market value ranging from 0.32 to 2.10 pp.

Figure 4.7 display the graphical representation of quantile regression coefficients of wind supply across quantiles from wind, gas, and baseload value factor regressions. These graphs show how coefficient vary throughout the value factor quantiles. These reveal that these impacts are not constant across different ranges of the technology-specific value factor. The results of the quantile slope equality tests in Table 4.14 further confirm these arguments, particularly for wind share variable.

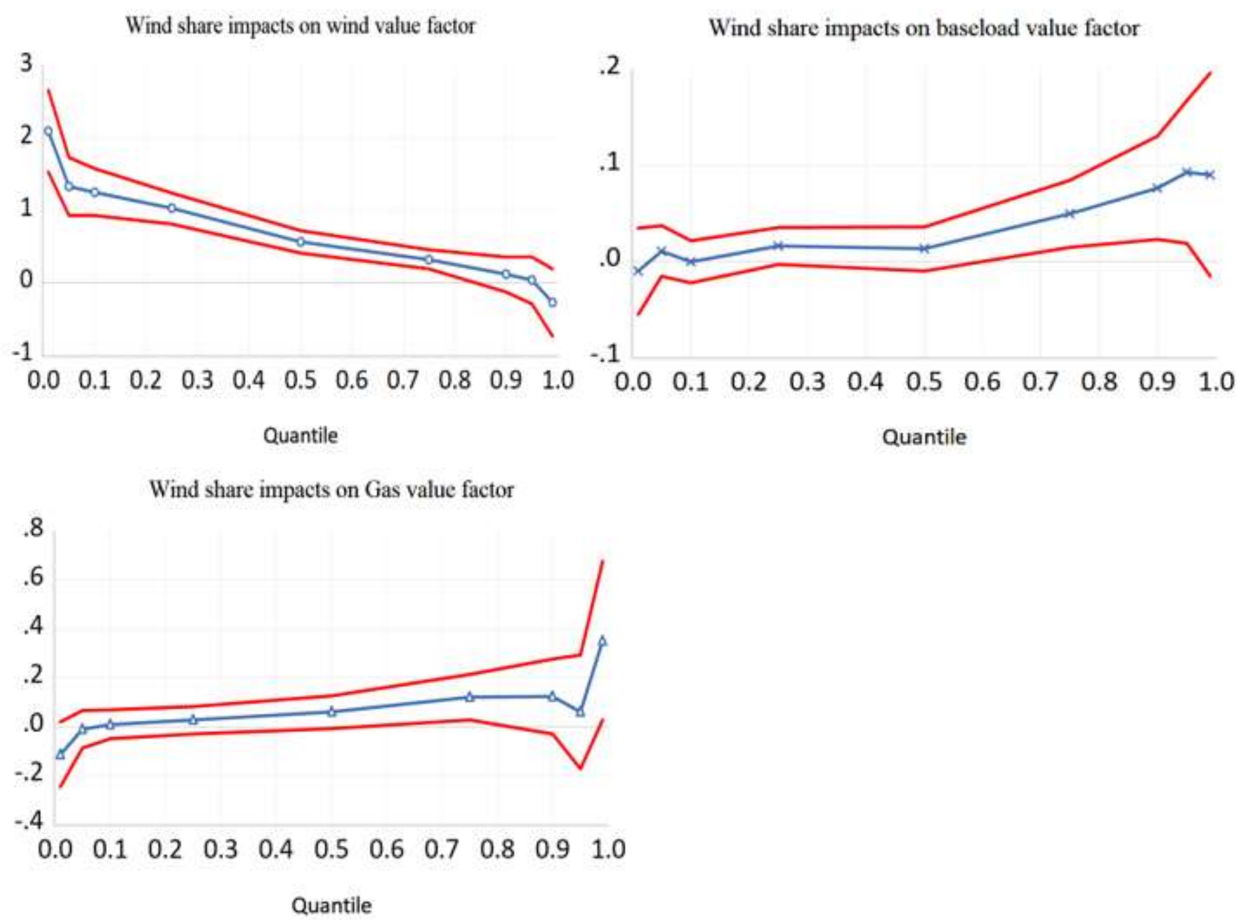


Figure 4.7: Quantile regression estimates for value factor with 95% confidence bands

Table 4.13. Estimation results for wind penetration effect on the value factor in the PJM region.

Variable	Low quantiles				Median	High quantiles				OLS
	Q1	Q5	Q10	Q25	Q50	Q75	Q90	Q95	Q99	
A.	**Dependent variable: Wind value factor**									
Wind share	2.103***	1.330***	1.252***	1.030***	0.564***	0.323***	-0.115*	-0.033***	-0.275***	0.924***
Gas share	0.102	-0.246***	-0.223***	-0.144***	-0.062***	-0.025	-0.014**	0.016	0.153***	-0.119***
Actual demand	-0.005***	-0.003**	0.003*	0.004	0.003	0.008**	0.003***	0.004***	0.001	-0.001
Gas price	1.967***	0.971**	0.580	0.222	-0.058	-0.150	-0.580	-0.982*	-1.994***	-0.187
Constant	89.759***	97.297***	98.911***	93.605***	97.384***	98.614***	98.502***	97.595***	111.444***	97.82***
DMY dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R^2 (%)	38.96%	28.58%	24.63%	16.16%	6.36%	2.70%	7.91%	13.03%	24.57%	12.77%
B.	**Dependent variable: Gas value factor**									
Wind share	-0.116*	-0.013	-0.008	-0.025**	-0.058*	-0.120***	-0.121***	-0.005**	0.350***	0.090*
Gas share	0.181***	0.080***	0.055***	0.54***	0.067	0.076***	0.031	0.009	0.123*	0.098***
Actual demand	0.004	0.005**	0.009***	0.003***	0.003***	0.004***	0.005***	0.005***	0.006***	0.004***
Gas price	0.101	-0.004	0.052	-0.015	0.036	0.244	-0.226*	-0.125*	0.875**	-0.088
Constant	96.055***	98.280***	97.892***	96.833***	95.222***	93.185***	93.483***	95.647***	92.418***	91.200***
DMY dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R^2 (%)	19.13%	15.27%	17.55%	21.50%	28.00%	33.78%	37.74%	38.85%	43.06%	42.78%
C.	**Dependent variable: Baseload value factor**									
Wind share	-0.011	-0.010	-0.008**	-0.016**	0.012	0.049***	0.076***	0.092***	0.090**	0.030*
Gas share	0.017**	0.019***	0.017***	0.015***	0.012***	0.018***	0.026***	0.025*	0.020	0.023***
Actual demand	0.002*	0.002*	-0.001	0.002*	0.003***	-0.008***	0.001***	-0.009***	0.001**	0.009***
Gas price	-0.025	-0.045	0.009	-0.011	-0.089***	-0.153***	-0.134**	-0.093	-0.271	-0.075
Constant	99.069***	99.593***	99.967***	100.025***	100.180***	99.650***	99.462***	99.544***	100.478***	98.764***
DMY dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1461	1461	1461	1461	1461	1461	1461	1461	1461	1461
Pseudo R^2 (%)	19.95%	17.79%	20.15%	26.52%	33.58%	37.56%	39.82%	40.45%	41.81%	48.13%

Note: Pseudo R-squared has a similar interpretation as the conventional R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4.14. Quantile slope equality test results for wind value factor model reported in Table 4.13

	Variables			
	Wind share	Gas share	Actual demand	Gas price
Q0.01 = Q0.50	1.539***	0.164	-0.05*	2.025*
Q0.05 = Q0.50	0.766***	-0.184	-0.004	1.029
Q0.10 = Q0.50	0.688***	-0.161**	-0003**	0.638
Q0.25 = Q0.50	0.466***	-0.082***	0.001	0.280
Q0.75 = Q0.50	0.241***	-0.037	-0.005	0.091
Q0.90 = Q0.50	0.449***	-0.048	-0.002**	0.522
Q0.99 = Q0.50	0.840***	-0.215***	-0.001	1.936***
Q0.05 = Q0.95	0.531***	-0.079	-0.004**	0.923*
Q0.01 = Q0.99	1.988***	0.116	-0.008**	2.547**

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

The results for wind share on value factors are inconsistent with that of unit revenues. There may be several explanations for this result. The differences could be attributed to the intermittency of wind energy resources, as it is practically impossible to selectively include wind energy to meet electricity demand during high price periods. While wind impact on value factor reflects the quantity of electricity supplied, however, unit revenues strictly reflect prices. On the one hand, if the value factor is low, that implies that the prices that have been received by wind power are low relative to the average daily prices. Thus, additional GWh of wind still increases the value factors relative to average price in terms of unit revenue. On the other hand, high-value factors for wind mean that high price levels are generated for wind relative to the average daily price; however, additional wind power during these periods drives down the value factor by decreasing prices.

Turning the attention to the cross-cannibalization effects, the results here are less compelling. First, looking at the gas value factor, while wind penetration is negatively correlated with gas value factor at almost all the quantiles of the distribution (5^{th} – 95^{th}), statistically significant evidence of cross-cannibalization effect is only found in the median quantiles (25^{th} – 75^{th}). This result implies that the relations between wind penetration and the value factor of the gas source are not constant across quantiles and may depend on wind penetration level and market conditions. More interesting, the relations between wind penetration and baseload market value are not constant across the distribution quantiles. Mainly, statistically significant evidence of the cross-cannibalization effect from wind penetration to baseload generators is found only at the 10th percentile of the distribution. While at high quantiles, there is a positive impact from wind on baseload value factors.

4.7. Conclusions

This study provides a new perspective and empirical evidence on the impact of the increasing wind penetration on wholesale electricity market prices, known as the "merit-order effect" in PJM and ERCOT markets. The study also provides evidence on the impact of the increasing wind penetration on its market values (cannibalization effect) and that of baseload and gas generating sources (cross-cannibalization effects) in the PJM regional market. Although the effect of renewable generation on electricity prices in the U.S. markets has been studied exhaustively in the literature (e.g., Jenkins, 2018; Quint and Dahlke, 2019), most studies agree that renewable generation tends to reduce wholesale electricity prices. However, these studies focus mainly on the price aspect alone.

In contrast, this study has demonstrated how increasing wind power penetration is driving down prices and showing how it is prone to negatively impact revenues to and values from different generators within wholesale electricity markets. Existing studies only focus on estimating the average impact of renewable generation on wholesale prices by using OLS regressions. Further, these existing studies do not anticipate that the wind generation's impacts on the wholesale electricity prices might vary with electricity market conditions. To address these previously unaccounted phenomena, quantile regression is used to analyze the wholesale prices and market values impacts of wind power supply, which provides more reliable and efficient estimates as it allows us to cover a comprehensive spectrum of conditional quantile distributions of electricity prices. The values obtained from quantile regressions, in particular, indicate that wind generation has unequal impacts on wholesale prices and market values, which have statistically different impacts across quantiles, reinforcing the need for this type of analysis.

A summary of research findings is as follows: First, increasing penetration of wind power significantly reduces the wholesale electricity price in both market regions examined. The empirical analyses confirmed the merit-order effect across different quantiles of the conditional distribution of wholesale prices for both DAM and RTM, implying that the increasing deployment of wind power for electricity generation significantly suppresses the wholesale electricity prices in the PJM market. Contrary to the PJM estimations, merit-order effects are confirmed across quantiles of wholesale prices for only the DAM in the ERCOT market. However, the analyses confirmed the merit-order effect at the median quantile and higher in ERCOT market for the RTM. The differing results occur at the lower quantiles by showing positive impacts of wind power on wholesale prices, failing to support the merit order price-dampening hypothesis. Explanations for this result include forecast imbalance between wind output and actual electricity demand (load) in this market and trading inefficiency in ERCOT's DAM price as noted by (Zarnikau et al., 2014).

Second, other control variables included in the analysis, particularly natural gas price and electricity demand, have statistically significant effects electricity prices across different quantiles of the conditional distribution of wholesale electricity prices. Third, these research findings show that as wind penetration grows within the market, the revenue earned by wind power producers reduces across different quantiles of unit revenue conditional distribution. Specifically, each additional GWh increase in electricity produced from wind is associated with a fall in its unit revenues across quantiles by an amount that ranges from approximately $0.01/MWh to $0.06/MWh. These results suggest that increasing wind power deployment in the PJM region undermines its market values in terms of unit revenues.

On the contrary, there is much weaker evidence of the cannibalization effect of increasing wind supply in terms of its value factor. The results also confirm the cross-cannibalization among other generators. In particular, each additional GWh increase in electricity produced from wind is associated with a decrease in gas and baseload generator unit revenues across quantiles by amounts that range from approximately \$0.02/MWh to \$0.06/MWh and \$0.02/MWh to \$0.05, respectively. These reductions in revenue earned from gas and baseload generators from wind penetration suggest that an increasing expansion of wind capacity may create revenue uncertainty for other generators, both current and future.

It is important to note that this research assumes that both regions (PJM and ERCOT) act as a single unified market to estimate the impact of wind generation, electricity demand, natural gas prices, and other control variables on unit revenues and value factors. However, the estimated effect of wind generation may exhibit geographic variation. For example, the vast majority of wind turbines in the PJM regions are located in the western zones of PJM. This geographic variation might have an essential role in increasing wind power penetration on wholesale electricity prices. Thus, future research could utilize a semi-parametric approach employed in this analysis to address the issue by disaggregating wind generation at the ISO level.

Regardless of the above limitation, the empirical findings from this research have relevant insight and policy implications for market participants, wind developers, and energy policymakers. First, market participants could use this study to understand the market fundaments that drives extreme price movement and the impact of growing renewable generation on electricity prices distribution in PJM and ERCOT markets. Consequently, market participants could optimize their trading strategies on real-time markets and day-ahead markets to minimize their investment exposure to risk. Second, since the results from this analysis prove that renewable power, particularly wind, reduces negative externalities from electricity generation and results in possible cost savings for PJM and ERCOT's electricity consumers. Therefore, if the policy interest is to reduce electricity prices for consumers' benefit, albeit emission externalities reduction, more policies supporting further investments in green energies should be designed and implemented, including the current tax credits.

This study's results, however, also suggest that increasing penetration of variable renewable sources, particularly wind power, in the electricity market creates revenue uncertainty, undermines future profitability, and potentially decreases the reliability of the electricity generation system. In terms of policy implications of these findings, given the recent debate on resource adequacy, reliability, and grid resilience (Aryani et al., 2020; Liebensteiner and Wrienz, 2020), policymakers should be conscious of the negative impacts of renewable power on returns to conventional power plants. Thus, this research suggests the need for a reform of the existing system by launching a well-structured 'coordinated incentive mechanism' for both conventional and renewable sources that would simultaneously meet multiple objectives: achieve adequacy, resilience, and environmental issues targets. Some possible policies to address these negative impacts include: (1) providing a 'resiliency fee' for baseload generators in addition to wholesale market prices, and (2) a return to greater vertical integration of generation, transmission, and distribution within the electricity system.

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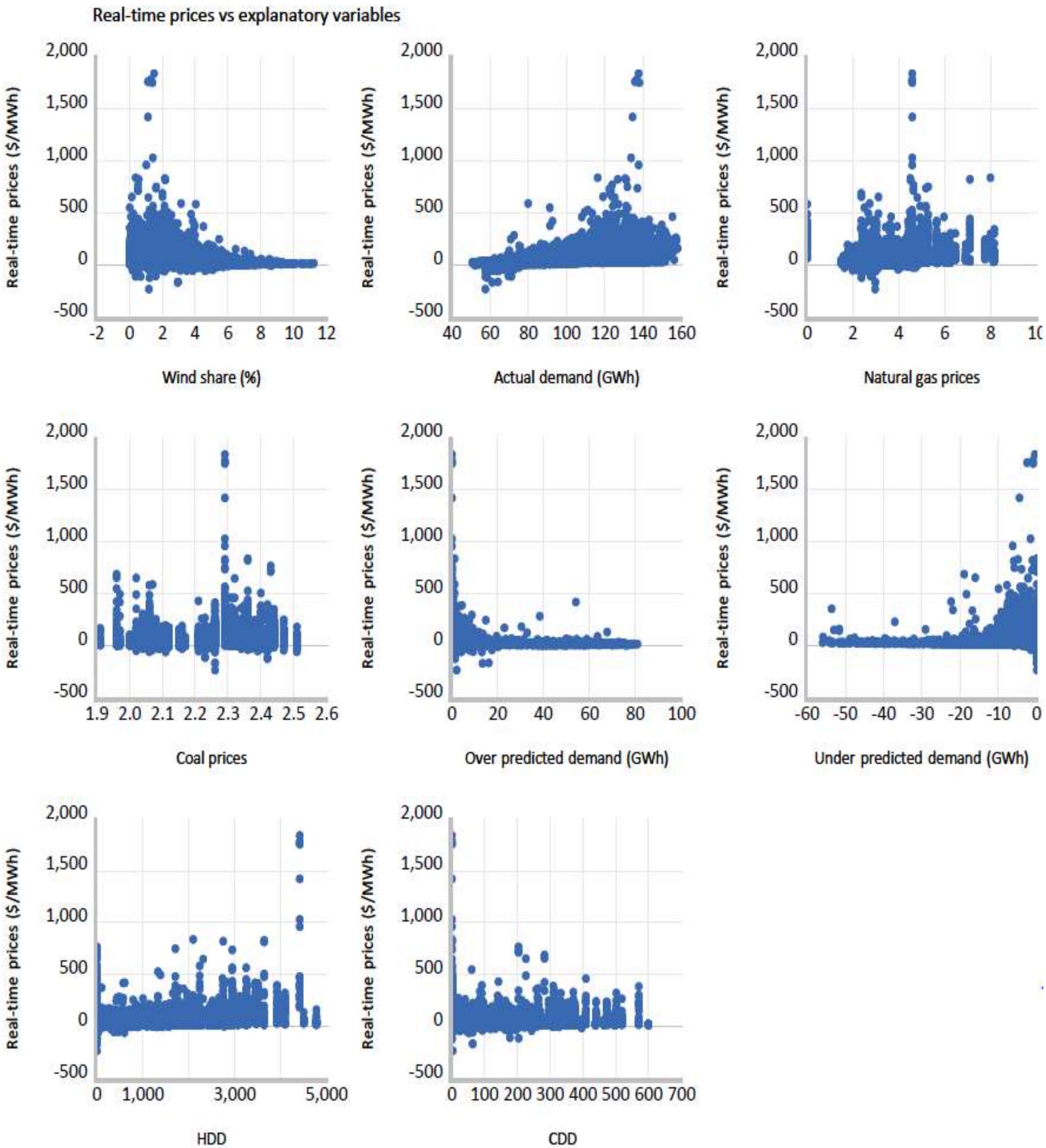
Appendix 4.A: Figures



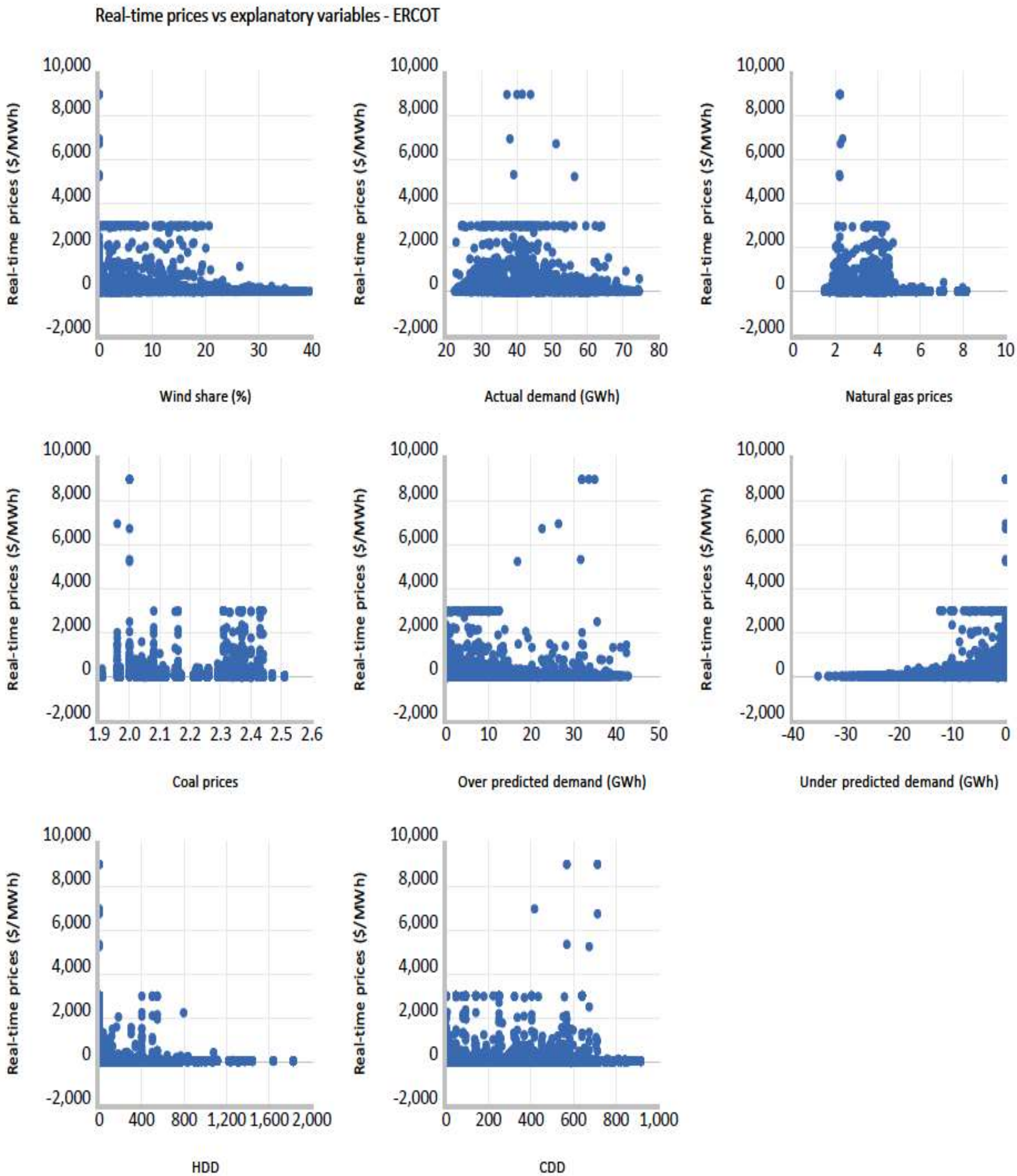
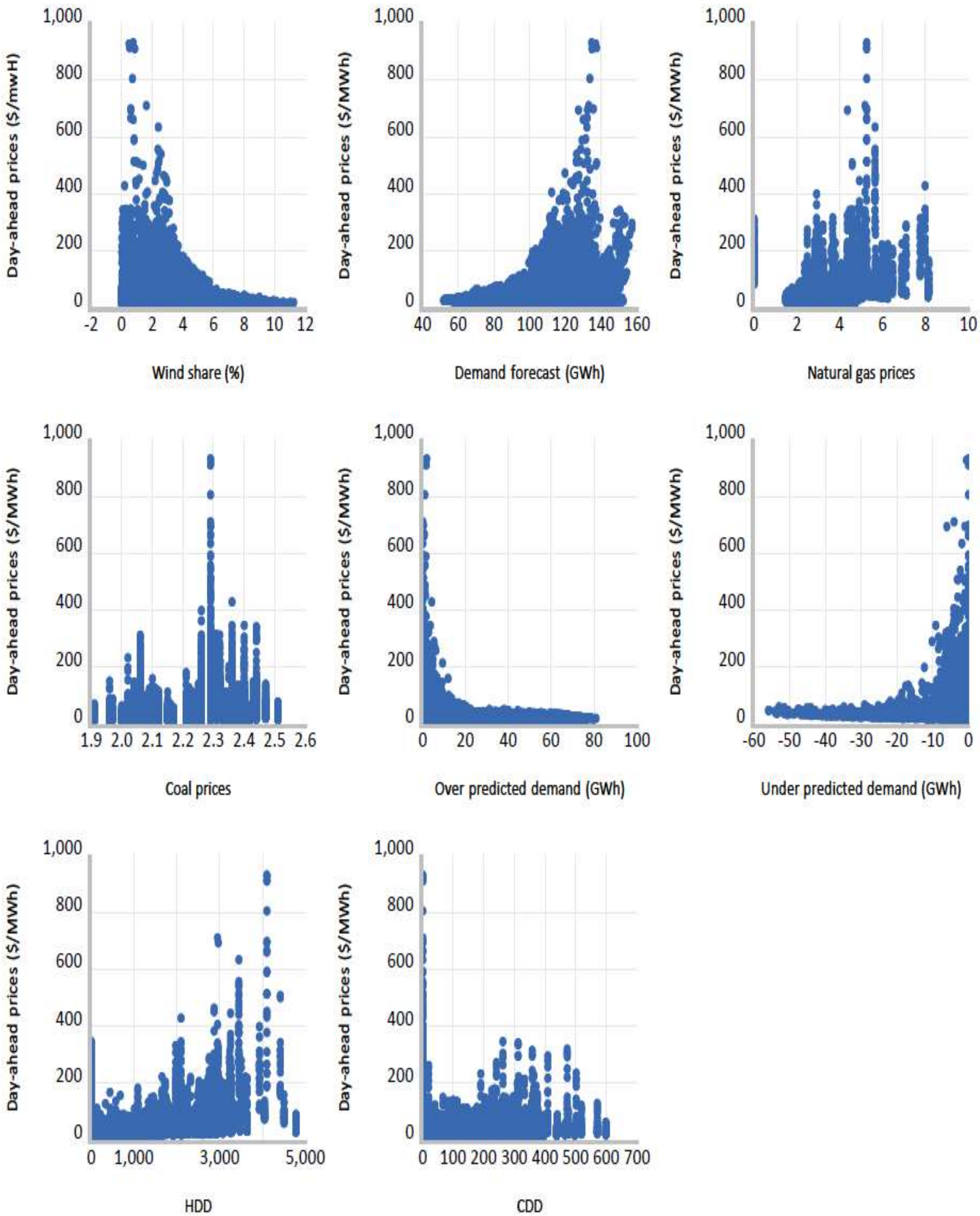


Figure 4.A1: Scatter plots of real-time price and predictor variables in the PJM and ERCOT markets, respectively

Day-ahead prices vs. explanatory variables- PJM



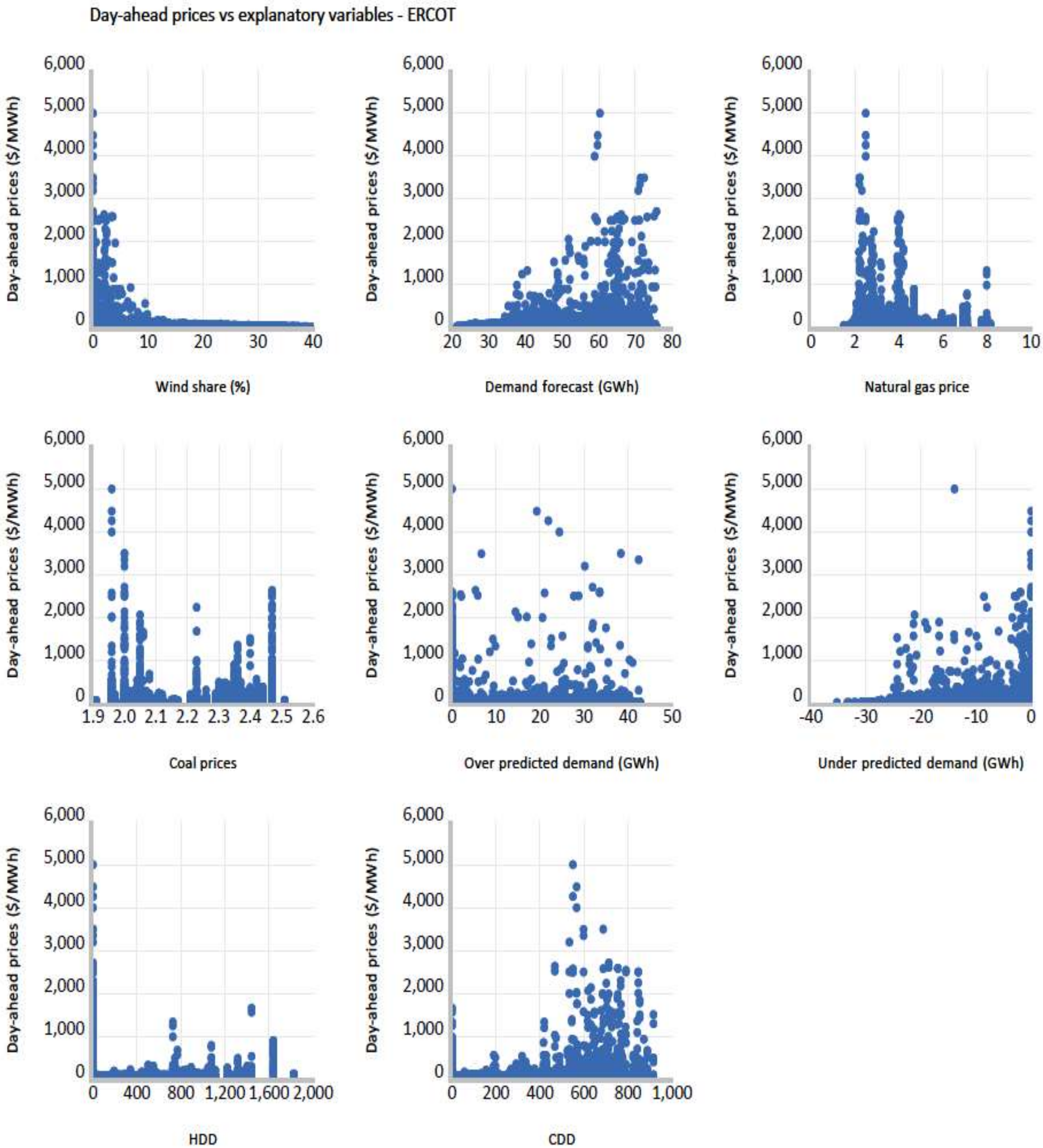


Figure 4.A2: Scatter plots of day-ahead price and predictor variables in the PJM and ERCOT markets, respectively

CHAPTER 5

Summary and Conclusions

This dissertation empirically provides clarification for the impact of economic growth on environmental quality (deforestation), creates a spatial analysis framework for utility-scale wind farms development, and better understands the role of wind energy penetration on the wholesale electricity market.

5.1. Study summary

In the first essay, a dynamic panel data methodology is utilized to estimate the impact of economic growth (GDP per capita) and other explanatory variables on net deforestation to test the validity of the EKC hypothesis for deforestation in 45 African countries. Specifically, I adopt the dynamic panel system GMM estimator to overcome potential endogeneity problems from reverse causality. Results from the generalized method of moments (GMM) estimation confirm the EKC hypothesis's validity. These results support an inverted U-shaped EKC relationship between GDP per capita and net deforestation in Africa. These results imply that economic development can provide environmental protection if such growth is close to or beyond the turning point. In this essay, a turning point of US $3,000 per capita GDP for African countries is estimated, which is higher than the GDP per capita in about half of the 45 countries utilized in this study. This turning point conforms with previous literature by Bhattarai and Hammig (2001) . This result indicates that significant damage may happen to forests in these countries before an EKC turning point is reached, as is demonstrated with the country Tanzania. Finally, a Granger causality test identified a unidirectional Granger causality from GDP per capita to net deforestation. This one direction of causality implies that GDP changes impact net deforestation but not the other way around.

The second essay provides a modeling approach that incorporates expert opinions of siting criteria to determine potential locations for wind farms in the state of West Virginia. The essay involved a two-stage, holistic approach: (1) a multi-criteria decision analysis – AHP, and (2) GIS assessment of sites. These analyses identified and evaluated environmental, economic, social, and technical factors for site suitability modeling for utility-scale wind farms in West Virginia. By incorporating expert opinions on weights for ten siting factors, this study identified about 70,000 hectares of land as 'highly suitable' for wind power development throughout the state of West Virginia. This area represents the potential to yield an estimated 29,000 MW of wind generating capacity. At this capacity, wind power can provide electricity output in the range of 64.20-terawatt hour (TWh) to 105.29-terawatt hour (TWh) per year when assuming capacity factors between 25% - 41%. These power output levels compare favorably to the current annual coal dominated electric power generation of 73.4 TWh in West Virginia.

In the third essay, a new approach is presented to evaluating the increasing wind penetration on the wholesale electricity market. Specifically, I demonstrate how increasing wind power penetration drives down wholesale electricity market prices and show how wind power negatively impact revenues to and values from different generators within wholesale electricity markets. The results show that increasing wind power penetration significantly reduces the wholesale electricity price, particularly for DAM in both the PJM and ERCOT market regions examined. Furthermore, these research findings show that as wind penetration grows within the market, the revenue earned by wind power producers reduces across different quantiles of unit revenue conditional distribution.

In the following sub-section, I will explain each essay's policy implication based on the results.

5.2. Policy implications

The first essay's empirical findings showed that EKC exists for net deforestation for a group of 45 nations in Africa. Thus, these countries should concentrate on effective economic development policy formulation and implementation in tandem with forest conservation policies. The study further suggests that those countries still in the development stage where the quest for higher economic progress may negatively impact forest resources, adequate enforcement of forest policy and environmental laws must be taken as a priority in these nations to reduce forest conversion and improve environmental qualities. Following the Granger causality test results in this first essay, it is suggested that African nations could deter and reverse deforestation through proper land-use and trade of forest products policies such as quantitative restrictions, and the consequences of these policies would not impact their economic growth. Finally, in general, developing countries should not wait for economic growth to obtain the deforestation benefits from the EKC turning point before deriving the gains of effective forest conservation and other environmental policies to lessen the pressure of forest resources.

Findings from the second essay showed that there is an outstanding potential for future utility-scale wind power generation in West Virginia. However, several requirements and policy instruments can strengthen the development of wind power in the state. These include but are not limited to policies of: 1) the guaranteed purchase of electricity, 2) establishment of regulations or tariffs that will ensure fixed cost recovery for power produced from wind power plants, and 3) the development of a stable electricity market for renewable energy to encourage wind power developers to assume the liability of the capital cost required in the establishment of wind farms. The second essay further suggests that the state's repealed Renewable Portfolio Standard (RPS) could be reconsidered for new legislation that would not be a burdensome mandate on utilities to increase renewable energy production from wind.

The third essay's findings have relevant insight and policy implications for market participants, wind developers, and energy policymakers. Following this study's results, market participants could optimize their trading strategies on real-time markets and day-ahead markets to minimize their investment exposure to risk. The results from this third essay prove that renewable power, particularly wind, reduces negative externalities from electricity generation and results in possible cost savings for PJM and ERCOT's electricity consumers. Consequently, if the policy interest is to reduce electricity prices for consumers' benefit, albeit emission externalities reduction, more policies supporting further investments in green energies should be designed and implemented, including the current tax credits. Finally, The negative impacts of wind power on gas and baseload generators demonstrate the need for corrective policies. Some possible policies to address these negative impacts include: (1) providing a 'resiliency fee' for baseload generators in addition to wholesale market prices, and (2) a return to greater vertical integration of generation, transmission, and distribution within the electricity system.

5.3. Study limitations and future research

Several limitations are identified in this research. In the first essay, although I had included several socioeconomic factors that may impact forest resources, including income, population, political institutions, there are other possible important explanatory variables, including agriculture and forestry taxes, afforestation policies, export price index, technological development, debt, and trade openness that could have been included in this analysis, however, data were not available for all the countries analyzed. Second, previous research has documented that deforestation could show another turning point, less pronounced than the first one, reflecting the maximum reforestation rate stage Caravaggio (2020). Therefore, one suggestion for future research is changing the classic quadratic functional form to incorporate a third order of the GDP, consequently including the second turning point. However, the data available for this study only covered a 27-year period, which was judged not to be adequate in length to incorporate several changes for long-lived resources like the forest.

The FAO-sourced forest cover data used in this analysis also is not without shortcomings. According to the FAO (2011), statistics for emerging countries are difficult to collect, and expectations and assumptions differ greatly, resulting in a degree of potential unreliability. Thus, future research could utilize satellite data to provide a more accurate forest cover measure to determine deforestation.

In the second essay, an important limitation is related to bird and bat habitat data utilized in this research. The state of West Virginia serves as an important migratory bird route. However; this research only incorporates defined bird and bat habitats in critical habitat but lacks data on migratory routes of other bird species. The Audubon Society's important bird areas data utilized in this study do not include bats and other endangered species habitats specifically. Although efforts were made to obtain information on bat hibernacula locations in the state from West Virginia Department of Natural Resources, these records in the state were considered extremely sensitive and these data could not be shared with other researchers. Finally, the pairwise comparison survey and questionnaire lacks bird and bats experts, including wildlife resource managers, ornithologists, or wildlife biologists in the analysis.

Other limitations in essay two included the wind potential data utilized for this analysis are estimated, not measured. Therefore, the application of energy output maps requires further validation in the field with wind speed measurement at particular locations identified in this research. Another impediment not accounted for in this essay is the ownership category (private or public) of the land located on highly suitable sites. Therefore, a future study could be considered, including incorporating other criteria such as bird and bat migratory paths if data becomes available, land ownership status, and land use in the suitability modeling process.

For the third essay, the market regions investigated were assumed as a single unified market to estimate the impact of wind generation, electricity demand, natural gas prices, and other control variables on unit revenues and value factors. Nevertheless, the estimated effect of wind generation may exhibit geographic variation. This geographic variation might have an essential role in increasing wind power penetration on wholesale electricity prices. Consequently, future research could utilize a semi-parametric approach employed in this analysis to address the issue by disaggregating wind generation at the ISO level.

5.4. References

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