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Winds of Change. An analysis on the initial integration of wind power on price volatility in European energy markets.

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PREFACE AND ACKNOWLEDGEMENTS

Writing this thesis has been one of the most difficult academic and personal challenges I have faced. I would like to firstly thank my family for their consistent support and motivation throughout, I do not believe I would have been able to succeed in writing this without them. I would also like to thank my initial supervisor Dr. Judy Chalabi for allowing me to undertake a topic I was passionate about but, also Dr. Ronald Huisman for agreeing to take over supervising this thesis along with his invaluable guidance and knowledge on the subject. I would lastly like to thank my grandmother, Florence. Although she is unable to see the conclusion of my academics, her encouragement to expand my knowledge and horizons is something I will continue to carry with me the rest of my life.

ABSTRACT

As a result of countries' policies in Europe to decarbonise energy sectors, wind power has been increasingly used as a source of electricity generation. In contrast to fossil fuels, wind is a partially dispatchable source of electricity. Therefore, this paper seeks to understand whether, during this initial integration, wind power increases volatility in electricity prices. A sample of 12 countries with low levels of wind power integration is analysed through a panel study relating volatility in wind power generation to volatility in Day-ahead prices. Volatility in wind power is not found to be significant in affecting volatility of Day-ahead prices in this study however, the amount of diversification of the electricity sector is. It is concluded that to consider that there is no relationship between the level of wind power is risky and that greater study is required as this integration continues to higher levels.

Keywords:
[panel study, wind power, day-ahead prices, price volatility, Europe]

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1 Introduction

Europe has been a leader in installing wind power technology as a form of renewable energy generation, and it is expected to provide the largest contribution to achieving renewable energy targets in the coming decades. By 2020, in the European Union (EU), wind power accounted for 220 gigawatts of generating capacity providing 16% of the bloc's electricity demand (Wind Europe, 2021). In 2004 15.9% of gross electricity consumption was from renewable sources, rising to 34.1% in 2019. This increasing reliance on wind power, as a form of electricity generation, highlights the shift towards renewable forms of electricity by countries inside the bloc.

The integration of wind power, along with other renewable energy sources, into EU countries' power mixes has been motivated by the primary aim of decarbonising a historically fossil fuel intensive industry. In contrast to fossil fuels that have been historically used to generate electricity wind power has near zero running costs. Wind power plants can supply power exchanges at lower prices than conventional fossil fuel driven power plants thus, reducing electricity price levels. Wind power is however a partially-dispatchable, variable source of renewable energy (VRE), dissimilar to fossil fuels plants that are dispatchable and able to generate electricity to meet market demands. The varying nature of wind, where from hour to hour generating capacity can fluctuate, means it is unable to provide a constant source of electricity. The ability of wind power to lower prices in power markets, combined with its inherent variable nature, poses the problem as to whether this can, in theory, increase price volatility in power exchanges.

European countries willingness to integrate wind power, as previously stated, offers the opportunity to study this problem and to observe that whether with this initial integration of wind power, there has been an observable increase in price volatility as a result. The central research question for this paper is therefore,

Does the initial integration of wind power into European countries' electricity power mixes increase volatility in electricity power prices?

The following intention of this paper is therefore to answer this central research question. A panel-based model, will be used to observe whether the initial integration of wind power increases electricity power prices, studying a sample of 12 countries in the EU is therefore used. This paper intends to contribute to existing literature by conducting a multi-country analysis, in contrast to the singular analysis of countries in current literature, focusing specifically on countries that have gone from low levels of wind power integration to comparatively higher levels. It will also further contribute by using an alternative measure of volatility to measure used in previous literature on this topic.

Following this section, an overview of existing literature will be provided. Explaining in more detail the underlying theory and current literature on the topic to be covered in this paper. Thereafter, the methodology for data collection and modelling and testing the research question will be presented, followed by an overview of the data used in the model. The results will then be presented and discussed with concluding remarks.

2 Literature Review

2.1 Theoretical Overview

2.1.1 Merit Order Effect Theory

The Merit Order Effect is a theory initially proposed by Sensfuß et al. (2008). The theory proposes that the increased integration of renewable forms of energy reduces prices in power markets, where supply is ordered and organised by a system of merit order. In a merit order based electrical exchange, grid operators rank power plants by their offered cost of production, where the cheapest offering is the starting point of supply. Where demand for electricity meets supply, a market clearing price is established, a price all participants in the market either buy or sell electricity at. Renewable power plants, including wind power plants, offer significantly lower operating costs due to the near zero marginal production cost they face when producing electricity. Offering lower production prices to grid operators, they are ordered at the beginning of the merit order supply curve. Therefore, the integration of renewables has the theoretical possibility of reducing prices (Merit Order Effect) as more expensive forms of energy production are not required to meet demand, with this instead being met by relatively inexpensive renewable energy production plants.

Sensfuß et al. (2008) observed this effect through analysis of electricity spot prices in Germany. Using a simulation-based model they measure the size of the Merit Order Effect in the German electricity market, observing that in 2006 there was a 7.83 €/MWh reduction in the average market price from the integration of renewables. More recent studies have further observed the Merit Order Effect. Clò et al. (2015), Gelabert et al. (2011) both observe this effect, to varying significance and degree of effect, in Italy and Spain respectively.

These studies indicate that the theory of the Merit Order Effect, introduced by Sensfuß et al., is observable for renewables sources including wind power. As discussed in the previous section, although wind power has the capacity to reduce prices in power markets, it is variable in its generating capacity. Figure 1 illustrates this effect in the framework of a merit order supply curve. When the generating capacity of wind power is higher the supply curve shifts to the right, lowering prices. However, if the capacity for generation by wind power drops, due to a change in conditions the supply curve shifts leftwards, raising prices and reducing the Merit Order Effect. These shifts in the supply curve, and resulting price volatility, can theoretically be observed in day-ahead spot, markets for electricity. In these markets power plants offer energy to the exchange for the day-ahead by the hour. For wind power plants their offerings are dependent on expectations of generating capacity based on weather conditions. In analysing the interaction of wind power with this market, research in this paper analyses whether the hourly variations in wind power are significant in driving hourly changes in the market clearing price. A sub research question is therefore formed:

Are changes in the variation of a country's hourly day-ahead electricity prices driven by a change in the rate of wind power plants expected hourly generating capacity?

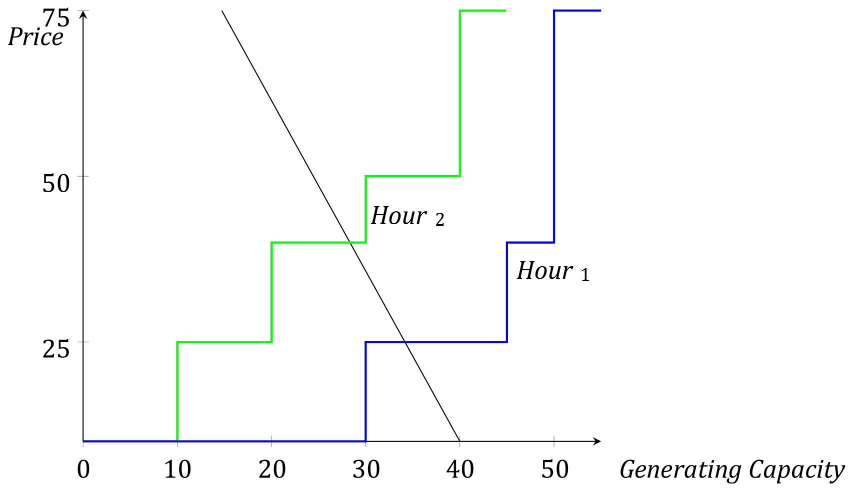

Figure 1: Varying Renewable Capacity

2.1.2 Merit Order Effect Theory - Sensitivities

Renewable sources of electricity supply constitute only a partial amount of the merit order supply curve in countries that are undergoing an initial integration of renewables. The magnitude of the Merit Order Effect, and in turn price volatility, is therefore sensitive to the structure and dynamics of the remaining suppliers in the supply curve. In countries where the structure of the merit order supply curve contains suppliers with low generating capacity at high costs, their supply curve will be steeper. In comparison when a country has a larger generating capacity among suppliers with comparatively lower costing, they exhibit a shallower supply curve. Figure 2 illustrates this comparison. The top graph displays a shallower supply curve, demand can be met by cheaper forms of power production causing the market clearing price to be lower than the graph below. This displays a country exhibiting a steep merit order supply curve where demand is not met by cheaper forms of power production and supply must be met by more expensive, peaking power plants.

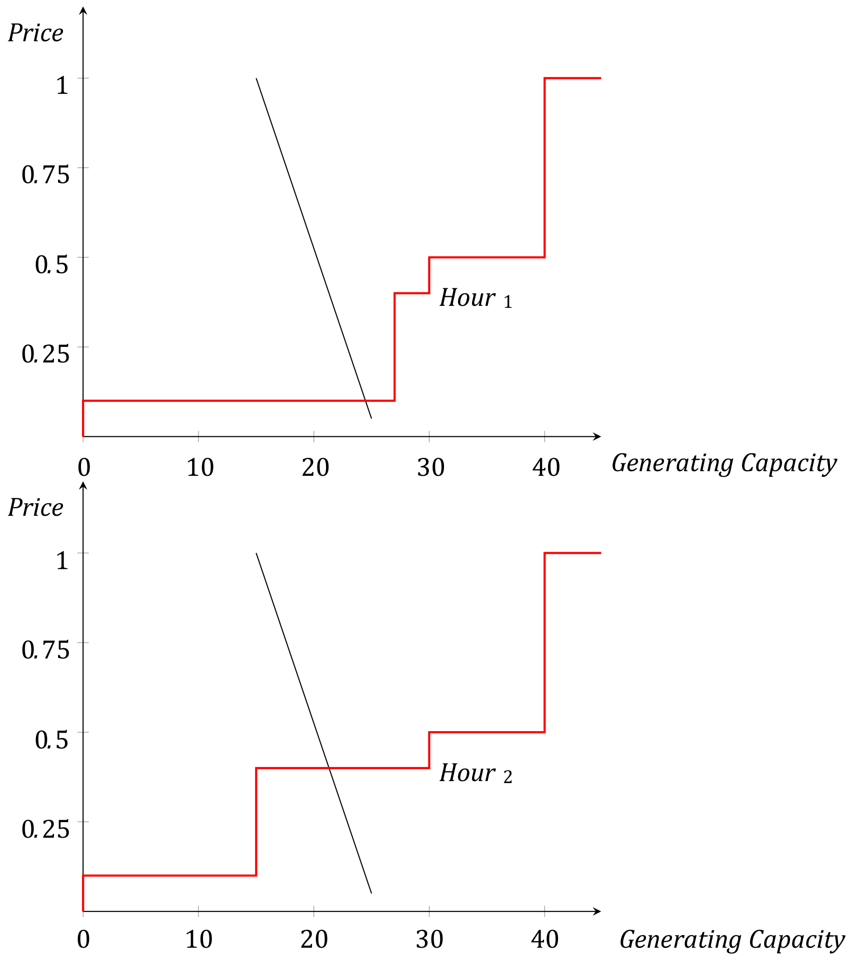

Figure 2: Merit Order Supply Curve Comparison

This merit order supply structure is important when considering the theory of the Merit Order Effect and price volatility. Theoretically, a country that has a shallower supply curve will have a better ability to offset variations in renewable energy production. When the generating capacity is reduced and the supply curve shifts left, a shallower supply curve will exhibit less variation in prices than a steeper supply curve that is more reliant on expensive forms of power production. Another sub research question is formed,

Does diversification in the supply of generating capacity affect price volatility in electricity markets?

Non-renewable energy sources that constitute the remainder of the merit order supply curve are also exposed to variations in the costs of supply for power plants to operate. Sensfuß et al. (2008) consider this in their original article on the Merit Order Effect. In their analysis they considered both fuel prices and carbon prices. Gas and coal prices were analysed, due to their price setting nature in the German energy market, and observations of their affects differed. Reductions in the price of gas price decreased the size of the Merit Order Effect while coal price reduction increased the effect. A simulated rise in carbon prices also reduced the size of the Merit Order Effect, this was explained to be cause by the volume of the Merit Order Effect being largely dependent on the steepness of the supply curve. We therefore ask the further question,

Do higher supply costs for non-renewable power production increase price volatility in electricity markets?

2.2 Empirical Studies

2.2.1 Renewable Energy Impact on Price Volatility

Research on the impact of variable renewable energy on price volatility in electricity markets has increased in recent years, in part due to the increasing desire by researchers to understand the effects that increasing integration of renewables has on electricity markets price dynamics. Literature on this topic is relatively new, with various methods and modelling techniques having been proposed to study intermittent renewables effects on price volatility. In these studies, many come to a similar conclusion, that to varying extents intermittent renewables increase price volatility in electricity markets.

Woo et al. (2011), motivated by Texas' growing wind generating capacity, conducted a salient study on the impact of wind power generation on electricity spot market prices in the state. The authors sought, in part, to predict the increase of wind power generation on price volatility based on the results of a partial-adjustment linear regression model with price as the dependent variable (The partially adjusted nature arising from the lagged price variable). Wind power generation is an explanatory variable in their modelling method, based on 15-minute generation statistics from the ERCOT database. Seasonality in price is also considered by use of dummy variables in their regression and, possible endogeneity of variables leads the authors to omit fossil fuel production instead using proxies like gas price. The error in the model is assumed to follow a stationary AR(1) process, which is validated. Estimating the values resulting from this regression and applying to a forecast variance formula proposed by Feldstein (1971), price variance increased, to varying amounts, in all the Texas zonal markets. GARCH modelling processes were also modelled but the authors concluded, that because in these models rising nuclear energy increased market prices, they were considered inappropriate for quantifying effects of wind integration. This contrasts with studies, to be discussed later in this section, that use this modelling method.

Clò et al. (2015) further the modelling approach of Woo et al. (2011), using a similar method to analyse the Italian energy market, their study motivated by the desire to understand the effect of VRE on consumer surplus. Using hourly day-ahead prices, the authors instead choose to convert to a daily average for observation, reducing the intra-day price volatility of prices intentionally. Wind power and seasonality are modelled as explanatory variables in the regression in a similar process to Woo et al. (2011). They also follow a first-order autoregressive process in their model which is validated for all regressions. Furthermore, they perform robustness test to their regressions by also performing ARCH and GARCH tests that show minor differences in their results, but of a similar pattern. Their study also concludes that for the Italian electricity market, higher volatility of day-ahead prices will occur with increased integration of wind power, using the Feldstein (1971) method.

Jónsson et al. (2010), in contrast, use a non-parametric model to assess the effects of wind power forecast on price behaviour in the Day-Ahead Danish DK1 zonal market. Prices for the DK1 zone are collected from the Nord Pool Day-Ahead Markets. In this study analysis is driven by forecast analysis simulating wind power forecasts where actual load is a function of predicted load and a randomly distributed error. Wind power forecasts are then modelled by the impact on price by its percentage of total load demand, the authors refer to this as wind penetration. Prices are defined as being dependent on a vector of explanatory variables derived from wind power forecasts and hours of the day indicators. Based on their observations of wind power penetration at varying levels, with its ability to reduce prices to near zero, this means that price volatility would increase as prices become more dependent on the stochastic nature of wind power forecasts. The authors also observe that the relationship between wind power penetration and price has some non-linear effects, implying that the ability to scale the current market and make future predictions is not possible, contrary to the methodologies of Woo et al. (2011) and Clò et al. (2015).

Ketterer (2014) partially expands on the Jónsson et al. (2010) modelling approach, studying German electricity prices but approaching the price volatility dynamic using a GARCH model. In this model prices are regarded as a function of seasonality and stochastic parts. Seasonality is therefore accounted for in the data, rather than the regression, by Ketterer where data on prices is adjusted to account for this process. Ketterer follows Jónsson et al. (2010) wind power penetration methodology to model the relationship between wind power and prices. Under a GARCH modelling process, prices are regarded as being dependent on the previous price period's value and volatility, testing for the significance of this model finds it to be present and significant. Ketterer therefore uses a GARCH (1,1) model. This expands on the simpler AR(1) process used by other literature in this field that do not consider the volatility of the previous price period. Based on previous literature, their GARCH model also includes a mean-reverting parameter as previous studies have observed this effect to be present. The results of the paper observe an increase in volatility in the studied period of German electricity prices, confirming the alternative modelling results of Woo et al. (2011) and Jónsson et al. (2010).

Mauritzen (2010) takes a different approach to Jónsson et al. (2010) in analysing Danish price volatility relationship with wind power generation. Maurtizen considers both bidding areas in Denmark (DK1 and DK2), modelling to test for daily, weekly and monthly volatility. Hourly prices for these areas are calculated to find the standard deviation in intra-day prices, then further calculated for weekly and monthly data. Mauritzen tests for further autoregressive features in the data, finding AR(2) or AR(3) processes to be significant in explaining price dynamics. Seasonality is considered in the regression with a weekly moving average term. The results of modelling undertaken by Mauritzen suggest that intra-day volatility in system price is reduced by wind power but, when tested by zonal area, this effect is marginally stronger in the western DK1 zone. Maurtizen theorises this is due to the fact wind power plants are mainly located in this zone. However, weekly and monthly volatility is observed as increasing with wind power production. Mauritzen theorises this is because daily price fluctuation over longer periods increases volatility.

Rintamäki et al. (2017) follow the methodology of Mauritzen (2010) providing more recent analysis on Danish as well as German electricity markets. In contrast Rintamäki et al. separate the Danish energy zones in their analysis. Maurtizen's methodology is expanded by also assessing the impact of peak hours of demand on intra-day price volatility, hypothesising that these peak time effects that cause volatility to fall in intra-day prices. Hourly data for forecasted wind power production and day-ahead prices are used for both systems. Rintamäki et al. follow the same methodology for calculating standard deviation in prices but chooses to use Jonsson et al. methodology of wind power penetration for their wind variable. Seasonality is again considered inside the regression using a seasonal weekly moving average while AR(1) and AR(2) processes are considered for auto-regression in prices. Their results show contrasting results for the two countries in intra-day markets. In both Danish area markets higher wind penetration reduces intra-day price volatility, in contrast German price volatility is instead increased. Testing for the effects of peak hours on volatility, they observe that in Denmark wind is more likely to blow during peak hours, reducing volatility, while in Germany wind is more likely to blow on off-peak hours in turn increasing volatility. Weekly price volatility is observed to increase in both countries aligning their results with Jónsson et al. (2010), Mauritzen (2010) and Ketterer (2014).

The modelling considerations of the empirical literature referenced in this section have been explained in detail because they are important in creating a model that can create more accurate and representative results. This thesis will expand on existing literature by furthering the study of wind power’s impact on price volatility into a panel regression, a technique that has not yet been observed in empirical literature. Furthermore, the study will also focus on a select period of integration, the initial integration, in contrast to previous studies that have not provided any focus on this aspect. The empirical literature also allows for expectations and hypotheses to be created and tested for in the model, these are as follows:

H0: Wind penetration does not affect volatility in day-ahead electricity prices

H1: Wind penetration increases volatility in day-ahead electricity prices

2.2.2 Merit Order Supply Elasticity

There has been considerable research on supply curves shifts caused by the introduction of renewable energy, this is evident in most of the literature discussed in the previous section. Less research has been undertaken to studying the elasticity structure of the merit order supply curve itself and, how the steepness/shape of this can affect the magnitude of the Merit Order Effect and in turn price volatility.

Clò et al. (2015) consider the impact of VRE penetration depending on the merit-order supply curve shape and elasticity, performing a direct comparison between two contrasting Italian energy markets. They find that for a simulated increase in renewable energy production the change in the market clearing price is dependent on the slope of the supply curve and where it intersects with demand. Furthermore, they observe that market concentration plays a role in the shape of the supply curve, theorising that more concentrated markets exhibit a larger Merit Order Effect than comparatively less concentrated markets, as the ability for renewables to undercut producers price setting behaviour is greater. Research into the effect of peaking hours on price can also provide an indication on how supply structure may impact the Merit Order Effect. Nicholson et al. (2010) observe that during the day the marginal effect of renewables is larger than at night, this being due to the steeper supply curve during the day. Rintamäki et al. (2017) observe a reverse of this effect in Germany. They observe that with a larger wind power generating capacity during off-peak hours than on-peak hours greater price reduction and variation occurs. This literature allows us to form the expectations:

H0: Merit Order supply curve elasticity does not affect volatility in day-ahead electricity prices

H1: Merit Order supply curve elasticity affects volatility in day-ahead electricity prices

By considering and integrating supply elasticities into this thesis' model, this thesis will expand on previous literature by considering the effect of wind power on price volatility as part of the wider scope of the merit order supply curve's dynamics.

2.2.3 Non-Renewable Supply Costs on Merit Order Effect

Studies on the effect of fuel costs have been more apparent in literature than merit order supply structure. This is in part because they have been included as a proxy for non-renewable power plants to avoid the problem of endogeneity. As noted already, Sensfuß et al. (2010) observe differing results for a rise in price of Coal and gas prices while also observing a rise in the cost of carbon credits reducing the Merit Order Effect. Woo et al. also consider the effect of fuel prices in their paper observing that increases in natural gas prices cause prices to also rise. Although this analysis is not focused on price volatility it does indicate that changes in gas prices effect the cost of production and in turn the steepness of the merit order supply curve. Clo et al. (2015) also observe that gas increases daily average price. This allows us to form the hypotheses:

H0: The costs of production for non-renewable power plants does not affect on volatility in day-ahead-electricity prices

H1: The costs of production for non-renewable power plants increase volatility in day-ahead electricity prices

3 Methodology

Outlined in the section of this paper is the methodology intended to be used to analyse the initial integration of wind power into European energy markets, the focus for this paper. Specifying a model that can effectively analyse this is therefore necessary. Furthermore, variable specification is considered, this is important to coherently answer hypotheses proposed in the previous section and support the model specification.

3.1 Model Specification

To provide effective analysis for the research in this paper the regression used must be able to factor in the following components: analyse multiple countries over a time period in a single regression and, perform multivariate analysis to answer the hypotheses that have been proposed. For this study a panel model is therefore proposed, conducting a panel study provides a single regression, for multiple countries, that analyse the listed components above. To test if a fixed or random effect regression is appropriate for the data in this study a Hausman Specification Test is conducted. The value of this test is significant (further details in 1A) meaning a fixed-effect model is the appropriate model to employ for this panel study.

The following regression outlines the panel regression this thesis intends to use:

$$Price\_Volatility_{i,t} = \beta_0 + \beta_1 Wind\_Penetration_{i,t} + \beta_2 Diversification\_Index_{i,t} + \beta_3 Gas\_Price\_Variance_t + \beta_4 Coal\_Price\_Variance_t + \beta_5 Emissions\_Price\_Variance_t + \mu_i$$

In this regression, where subscript *i* is used, it defines the country being used for the variable. Due to likely occurrence of a Type 1 error creating a false positive if the time period is too large, such as days over multiple years, the subscript *t* represents the yearly time period for the coefficients being analysed. In the variable specification that follows further information is given on how daily data is transformed into a yearly average allowing the data to be effectively used in a panel regression.

The model will be run three times where the variables being tested for the different hypothesis being added each time. Performing this modelling technique allows for a greater understanding of how the secondary explanatory variables effect the primary variable of interest.

3.2 Variable Specification

For this study, day-ahead prices form the core in studying price volatility in electricity markets. Information that may influence price is fixed as all prices for a 24-hour period are decided in one bidding session, in contrast to intra-day prices any information. Changes that occur after the prices have been set will not influence day-ahead prices. This makes assessing how variation in elements of interest like fuel and emissions prices, and their subsequent effect on price volatility, are difficult to measure. To create a model that can reflect this changing information, and its effect on price volatility, daily changes are used. This allows us to understand how information and supply structure changes drive changes in electricity price volatility. Converting this to a yearly average and fitting into a panel model subsequently allows us to understand how the initial integration of wind power effects price volatility in our European Sample.

The dependent variable in this model is Price Volatility ($Price\_Volatility_{i,t}$), this is calculated using Li and Flynn's (2004) methodology. This method expresses the daily average rate of hourly change in price as a fraction of the average price in the period. This is referred to as daily velocity based on overall average price (DVOA). The following equation outlines how $DVOA_{c,i}$, is the calculation of the described method for country "c" on a given day i. .

$$DVOA_{\mathrm{c},i} = \frac{1}{M}\left\{\left[\left(\sum_{j=1}^{M-1}\left|p_{i,j+1} - p_{ij}\right|\right) + \left|p_{i-1,M} - p_{i,1}\right|\right]/\bar{p}_{.,.}\right\}, \quad i = 1,2,\ldots,N$$

Where, the value M is equal to hours in the day (24), given day $i = 1, 2 \ldots\ldots N$ and, j is the index of the hourly time period $j = 1, 2 \ldots\ldots M$. Price is p_{ij} at jth time period on the given day i.

The coefficient $\bar{p}_{.,.}$, represents the overall average price of the studied period, for this study the period is equal to all days in a calendar day year:

$$\bar{p}_{.,.} = \frac{1}{M \times N} \sum_{i=1}^{N} \sum_{j=1}^{M} p_{i,j} \qquad i = 1,2,\dots,N$$

Consequently, using this technique, a value of 0.2, for example, means that on that given day electricity prices in this countries market move at 20% of the long-term average price. As described in the introduction to this section, daily values of DVOA for a country are used to create a daily average change for volatility for an entire year in a country's day ahead electricity market (Further information on the data calculation and descriptive statistics are available in 2A).

$$Price\_Volatility_{i,t} = \frac{\sum \frac{DVOA_{c,i+1} - DVOA_{c,i}}{DVOA_{c,i}}}{n}$$

The primary independent variable of interest in this study is wind power ($\beta_1 Wind\_Penetration_{i,t}$). Jonsson et al. (2010) formula of wind penetration is used in this methodology. Wind penetration is measured by calculating forecast wind power generation with relation to the predicted load, relating wind generating supply to the total supply in this way allows us to understand it's effect on the merit order supply curve.

$$V_t^{(p)} = \frac{V_t}{L_t}$$

Where $V_t^{(p)}$ defines the wind penetration, V_t is defined as the forecast in wind and L_t is the load demand forecast. To understand how varying wind penetration effects price volatility, an average of the standard deviation in hourly prices is taken for each day and, then differencing these averages day by day. Observing the effect of this measurement on price volatility allows the studying of the wind power hypotheses proposed in the literature section of this paper (Further information on the data calculation and descriptive statistics are available in 2A).

The additional two hypotheses proposed are studied with further variables. The variable $\beta_2 Diversification\_Index_{i,t}$ is used to test the second hypotheses proposed in this paper that the elasticity of supply influences price volatility. This is measured using a Herfindahl-Hirschman Index measurement, where s_n represents the yearly market share of each form of electricity production:

$$HHI = s_1^2 + s_2^2 + \ldots s_n^2$$

This diversification metric is used to avoid the problem of endogeneity in market participation in contrast to measuring production statistics of power plants, where other variables may affect a power plants decision to offer electricity generation.

To test for the final hypothesis in this paper variables are included for Gas, Coal and Emissions Prices (variables β_3, β_4 and β_5 respectively). A yearly weighted average based on daily price change is used to represent these variables. By calculating the daily price change we can observe indications of whether the changing price effects price volatility through changing the shape of the supply. Furthermore, by weighting these price movements to a country's reliance on these inputs allows us to differentiate countries rather than repeating the same value (more detail in Appendix). If the resulting coefficient is positive, then this would suggest positive changes in daily prices results in higher price volatility in the following day. As is described in the following section, the data for these figures are based on both Spot and Forward prices, it is understood that suppliers will likely hedge and have a larger amount of information when considering their input costs in production. However, these measures provide a useful representation of the information available to them and the resulting effect on price volatility.

4 Data

The following section intends to describe the data and where it is collected from while also providing justification for the sample of countries intended to be used for analysis.

4.1 Data Descriptions

To examine the dependent variable and primary independent variable of interest, price volatility and wind penetration respectively, The European Network Transmission System Operators for Electricity (hereafter ENTSO-E) Transparency Platform is used to provide data. ENTSO-E provides fundamental information of generation, load, transmission and balancing for European Member States and other markets outside the European Union. Publication of this fundamental was mandatory for member states in the European Union from the beginning of 2015 onwards where the data is consistently uploaded and accessible according to regulation publication guidelines.
Specifically for the variables this study is interested in this database provides day-ahead prices for every hourly market time unit in each bidding zone from power exchange owners. Furthermore, day-ahead wind power generation and total load forecasts are provided from this platform for our wind penetration variable. Wind generation is presented in Megawatts both in quarterly hour intervals and hourly intervals for different bidding zones. However, for the purpose of this study quarterly hour intervals are converted into hourly intervals to create a homogenous dataset. Generation forecasts for wind are also differentiated by onshore and offshore forecasted generation, as this study is not concerned with the location of wind generation these are summed together to find the total forecasted production. Day-ahead total load forecasts are also presented in varying sub-hourly intervals where again these are converted into homogenous hourly intervals for all bidding zones.

To observe electricity market diversity in countries data from the European Statistical Office (Eurostat) database is used. Eurostat provides statistical information for member countries in the European Union. Part of its purpose is to provide homogenised data collection and statistical methodology from its member states. This is particularly useful for analysing electricity market diversity as many countries internally produced statistics for these figures often use different methodology and collection techniques. Eurostat provides annual data for production of electricity in gigawatt-hours by type of fuel, which is used for this study. This production data for each fuel type is divided by the total production for each year, providing a value that can be used for the diversification index method presented in the previous section.

The European Energy Exchange (EEX) provides data for EU carbon emissions allowances on along with indexed prices for natural gas. The EEX is a large energy exchange based out of Leipzig in Germany, it serves a variety of commodity markets and contracts for power, natural gas, and emission allowances. EEX exists as common auction platform for carbon emission allowances on behalf of 25 EU member states. The daily settlement price, available through Refinitiv Datastream, at the close of trading days is used as the variable for carbon emissions in our regression. EEX's European Gas Index (EGIX), which corresponds to the current market price for gas deliveries in the next month, provides the data for natural gas prices.

Lastly, the Intercontinental Exchange (ICE) database on coal futures is used to provide data for the Coal variable in our regression. The ICE is a platform that provides databases and expertise for energy markets worldwide. Through Refinitiv Datastream, settlement prices for API2 Rotterdam Coal Futures, from ICE, are used to provide data representing the price of coal for electricity suppliers in markets.

4.2 Sample Selection

Analysing the initial integration of wind power in Europe requires a sample of countries that have integrated wind power at a similar pace. For this study a sample will be assessed on the period of 2015-2019, this is due to the constraints of the data that is accessible for this study. Reliable figures on day-ahead prices and market production measures used in variables are accessible between these dates. In selecting a sample of countries, the initial integration of wind power is considered first. Measuring annual figures on wind generation as a percentage of total generation is used to find figures on countries annual wind generation penetration. This is used in contrast to figures like that of installed capacity at the beginning of a year as it is assumed that with power plant's ability to curtail or install greater generating capacity this would be unrepresentative of countries true integration of wind. In selecting countries to be used those that have generated more than 30% of their power in a single year from wind are not considered. This is based on Jonsson et al. (2010) that finds a significant decrease on prices when this occurs in contrast to lower levels of penetration.

Furthermore, countries included in the sample must also have national bidding zones only for the period of 2015-2019 (Germany and Austria, for example, shared a joint bidding zone from 2015-2017). This is because analysing country specific coefficients across a time period where day-ahead bidding zones are partially cross-border could lead to spurious results that do not reflect the true nature of what causes price volatility. As a result, we are left with 12 countries that will be used for analysis in this study.

Belgium
Estonia
France
Greece
Netherlands
Spain
Portugal
Belgium
Finland
Romania
UK
Italy

Table 1: Country List

4.3 Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
$Price\_Volatility$	overall	.1504485	.1481972	.0289506	.6711262	N = 60
	between		.1391407	.0484988	.4404485	n = 12
	within		.0625687	-.0392028	.3811262	T = 5
$Wind\_Penetration$	overall	.2942515	.0709856	.1256959	.4732314	N = 60
	between		.0592149	.1655016	.3703041	n = 12
	within		.0420745	.2179457	.4272955	T = 5
$Diversification\_Index$	overall	.2990266	.1276359	.1584374	.6360263	N = 60
	between		.1278426	.1687706	.561261	n = 12
	within		.0324846	.1143652	.373792	T = 5
$Emissions\_Price\_Variance$	overall	.8125731	.872065	.0069926	3.80455	N = 60
	between		.4744723	.021929	1.491163	n = 12
	within		.7420485	-.1875873	3.12596	T = 5
$Coal\_Price\_Variance$	overall	1.055353	1.186729	0	5.383786	N = 60
	between		.9875833	.0033851	2.85057	n = 12
	within		.7064909	-.0005019	3.747516	T = 5
$\beta_3 Gas\_Price\_Variance$	overall	.5595205	.4480533	.0032717	1.880604	N = 60
	between		.3998103	.0057561	1.233401	n = 12
	within		.2274656	.0775143	1.206724	T = 5

Table 2: Descriptive Statistics

5 Results

This section will first restate hypotheses proposed to answer the core and sub-research questions in this paper. Results are then presented with analysis of the regression modelling.

5.1 Restated Hypotheses

The first hypotheses proposed in this paper is the primary variable of interest, seeking to understand if changes in hourly day-ahead prices are driven by hourly variation in wind generating capacity.

H0: Wind penetration does not affect volatility in day-ahead electricity prices

H1: Wind penetration increases volatility in day-ahead electricity prices

The second hypotheses proposed relates diversification in the electricity generating sector to the Merit Order Effect and whether it effects price volatility and furthermore if it changes the level of effect wind power has on price volatility under this initial period of integration.

H0: Merit Order supply curve elasticity does not affect volatility in day-ahead electricity prices

H1: Merit Order supply curve elasticity affects volatility in day-ahead electricity prices

The final hypotheses focus on non-renewable fuel price (and costs) and, again on whether variation in these costs of production effect prices in country's electricity markets as well as the accommodation of wind power.

H0: The costs of production for non-renewable power plants do not affect on volatility in day-ahead-electricity prices

H1: The costs of production for non-renewable power plants increase volatility in day-ahead electricity prices

5.2 Results

Table 3 provides the results for the three regressions run to test the hypotheses for this paper with the coefficients and standard errors for the variables analysed.

Table 3: Panel Study Regression: Price Volatility Analysis

PriceVol	(Model 1)	(Model 2)	(Model 2A)	(Model 4)
$Wind\_Penetration$	.087	.040		.091
	(.216)	(.210)		(.224)
$Diversification\_Index$		.572**	.577**	.565*
		(.272)	(.268)	(.282)
$Gas\_Price\_Variance$				-.006
				(.019)
$Coal\_Price\_Variance$				-.010
				(.014)
$Emissions\_Price\_Variance$				-.010
				(.105)
$Constant$	.125	-.032	-.022	-.042
	(.0643)	(.097)	(.081)	(.105)
Observations	60	60	60	60

standard error in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As outlined previously the primary variable of interest, Wind Penetration, is positively correlated in all three models where used. This means positive daily variations in wind penetration variation drives higher daily variation in price volatility. This result is consistent with Jonsson et al. (2010) study on wind penetration and total load. However, in none of the models are the results for this variable significant. As can be observed in the Appendix, the p-value in all models for the variable was distant from the minimum critical value of 0.1. There is, therefore, insufficient evidence to reject the null hypothesis for the first research question in this paper and the results indicate that wind power penetration does not affect volatility in day ahead electricity prices.

H0: Wind penetration does not affect volatility in Day Ahead Electricity Prices

In this study Sweden and Italy are analysed as part of the panel regression, each of which have four and two bidding zones respectively. It is possible that these differing dynamics discussed in Mauritzen's paper may provide spurious results, so a regression is run to exclude these two countries. However, when these regressions are re-run excluding these two countries there is no meaningful change in the values or significance of the coefficients analysed and therefore altering the model in this way provide no value to this study.

Rintamäki et al. (2017) also provides an explanation as to the lack of a significant result for the wind penetration coefficient. As noted earlier in this paper, they observe differing effects of wind penetration volatility on price volatility in Germany and Denmark in peak and off-peak hours. As the panel study that has been undertaken in the models above is based on hourly data at a daily perspective it is again possible that the panel model used fails to capture the idiosyncratic differences in countries as shown by Rintamäki et al..

The second variable of interest, Diversification, is also positively correlated to price volatility. This result suggests that as a country's energy generating capacity becomes less diversified and more concentrated to a smaller number of inputs (moving towards the value of 1) price volatility increases. In Model (2) and Model (3) this affect is significant to 5% and 10% respectively. A further model (Model 2A) is run where Diversification is the only independent variable, again this is significant at a 5% level. This result indicates that there is sufficient evidence to reject the null hypothesis that merit order supply curve elasticity affects Price Volatility.

H1: Merit Order supply curve elasticity affects Price Volatility

These results of this coefficient are consistent with Clo et al. (2015) theory that the market concentration plays an important role in determining the shape of the supply curve and in turn the Merit Order Effect.

The final variables of interest, ETS Price, Coal Price and Gas Price, present differing results with respect to price volatility. ETS Prices, which measures variation in daily ETS price weighted to the usage of fossil fuels in a country, show no relation to price volatility in Model (3). Coal Price and Gas Price variables show differing coefficients. Coal Price has a marginally positive correlation to Price Volatility and, Gas price has a negative correlation to Price Volatility. For the final hypotheses, it can be concluded that there is insufficient evidence to reject the null hypothesis and one can assume that the costs of production for non-renewable power plants do not affect price volatility.

> *H0*: The costs of production for non-renewable power plants does not affect on volatility in day-ahead-electricity prices

The differing coefficients for these final variables of interest analysed are similar to Sensfuß et al. (2010) study that observed a similar phenomenon. However, the approach used in this theses to transform and quantity the data into a value that can relate the price of these variables to a country's dependence on them could be better improved. A simple relationship of country's usage of coal, gas or fossil fuels to the cost of their inputs may not effectively explore and explain the relationship at the hourly and daily level in markets.

6 Concluding Remarks

The resulting evidence from the panel regressions modelled in the previous section indicate both an answer to the hypotheses and research question proposed in this paper but also the difficulty in modelling and analysing price volatility and renewable integration.

The primary variable of interest ($Wind\_Penetration$) was insignificant in all the models run. This may be because during this initial integration of wind power the level of penetration in the total load is at too low a level to be significant in driving price volatility. Research that observes increasing wind power penetration with increased price volatility, Mauritzen (2010) and Jónsson et al. (2010), analyse Denmark, an area with high levels of wind power integration. The second hypothesis and corresponding variable studied, diversification in electricity generation, was the only significant variable of interest in this study. It indicates that with increased wind and renewable power integration in countries in Europe and the rest of the world, the concentration of the electricity sector and resulting elasticity of supply at a micro level must be considered in analysis and decision making when integrating renewables. The final hypotheses consider fuel inputs price variation on price volatility. The varying results and lacking significance highlight the difficulty in measuring the effect wholesale international prices have on domestic markets and, in turn, modelling such a relationship.

The results of the models used in this paper to answer the hypotheses and the core research question,

Are changes in the variation of a country's hourly day-ahead electricity prices driven by a change in the rate of wind power plants expected hourly generating capacity?

indicate that in the sample of 12 countries analysed in this paper, the initial integration of wind power into European countries' electricity power mixes is not significant in increasing volatility in electricity power prices. This lack of a significant positive relationship between increased wind penetration and price volatility, at a daily level, may be observed by some as a positive outcome. With wind power continuing to be seen as an attractive source of electricity generation for countries transitioning to a decarbonised energy sector, not observing a significant positive relationship provides a positive reason to continue the integration of wind without sacrificing energy security. However, with the initial levels of integration in the sample analysed being so low in comparison to countries like Denmark, and, with the desire of some of the sample countries to reach levels of wind integration at a similar level this insignificant relationship may become more significant in the future.

The results of this study also highlight the complexity and limitations of this study along with suggestions for focus in future research on the integration of renewable forms of energy. The complex nature of mapping long periods of hourly price and wind data into yearly data, that allows for a picture to be built of all countries in the sample analysis, is one that may be more effectively analysed. Ketterer's (2014) GARCH modelling process is an effective model in mapping and observing hourly data over long periods. Future modelling with a Panel GARCH Model may prove to be more effective at observing the micro levels of interaction between variations in wind power and price levels. Furthermore, performing a panel study also highlights the question as to whether domestic market idiosyncrasies are so important to driving market dynamics that, although techniques of analysis should be similar, these demand modelling countries individually to consider domestic idiosyncrasies?

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APPENDIX

7 Model Specification Test

7.1 Hausman Test

Table 1A: Hausman Test Results

	-----Coefficients-----			
	(b) fixed	(B) random	(b-B) Difference	(B) random
Wind_Penetration	.0912748	.2447888	-.153514	.049948
Diversification_Index	.5648734	.3376532	.2272202	.1963718
Gas_Price_Variance	-.0056173	-.0003715	-.0052458	.
Coal_Price_Variance	.0067344	.0036922	.0030422	.0036305
Emissions_Price_Variance	-.0097764	-.0567966	.0470202	.0214963

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic
chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 23.43
Prob>chi2 = 0.0003
(V_b-V_B is not positive definite)

8 Variables

8.1 Price Volatility – Data Computation and Descriptive Statistics

Data available from the ENTSO-E Transparency provides consistent data for most of the period of 2015-2019. There is however some consistent data entry error for this database. As presented in Table 2A, empty hour values are replaced with a repeated value of the hour preceding. For hours where there were two values the second value is deleted. For more specific data gaps in country's data the daily value differences are computed using the last available full day of data.

Empty Hour	**Double Hour**
29/3/15 02:00-03:00	25/10/15 02:00-03:00
27/3/16 02:00-03:00	30/10/16 02:00-03:00
26/3/17 02:00-03:00	29/10/17 02:00-03:00
25/3/18 02:00-03:00	28/10/18 02:00-03:00
31/3/19 02:00-03:00	27/10/19 02:00-03:00

Table 2A: Hour Errors in ENTSO-E Database

8.2 Wind Penetration

The variable for wind penetration uses data from ENTSO-E in it's variable calculations, wind forecast and load forecast data. These suffer from errors in hourly data as in Table2A, therefore the same approach is used to replacing the data. Furthermore, where longer periods of data aren't available, again, the last full day of data is used for daily percentage change calculations

8.3 Diversification

Data for diversification, available from Eurostat, is presented at two levels of specification in the database. Both at a general level of Solid Fossil Fuels, Natural Gas, Renewables etc. and at a more specific level e.g. Bituminous Coal, Wind etc. For this study all areas of electricity production are taken at their general level apart from renewable sources of power that are used at their specific levels. This is done to allow wind to be its own specific value of diversification rather than a value of renewables generally

9 Regression Models

9.1 Model 1

Fixed-effects (within) regression		Number of obs =	60
Group Variable: Country		Number of groups =	12
R-sq:		Obs per group:	
within =	0.0034	min =	5
between =	0.2125	avg =	5.0
overall =	0.1233	max =	5
		F(1,47) =	0.16
Corr(u_i, Xb) =	0.3471	Prob > F =	0.6890

$Price\_Volatility$	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval	
$Wind\_Penetration$	.0871957	.2165415	0.40	0.689	-.3484297	.522821
$\_cons$	.124791	.064355	1.94	0.059	-.0046746	.2542566
sigma_u	.1368375					
sigma_e	.06998201					
rho	.79267269	(fraction of variance due to u_i_)				

F test that all u_i=0: F(11, 47) = 16.81 Prob > F = 0.0000

Table 3A: Model 1 Regression Results

9.2 Model 2

Fixed-effects (within) regression		Number of obs =	60
Group Variable: Country		Number of groups =	12
R-sq:		Obs per group:	
within =	0.0905	min =	5
between =	0.0560	avg =	5.0
overall =	0.0575	max =	5
		F(2,476) =	2.29
Corr(u_i, Xb) =	-0.2791	Prob > F =	0.1129

$Price\_Volatility$	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval	
$Wind\_Penetration$	.0402315	.2102981	0.19	0.849	-.3830766	.4635395
$Diversification\_Index$	.5715498	.2723808	2.10	0.041	.0232756	1.119824
$\_cons$	-.0322983	.0972957	-0.33	0.741	-.2281445	.1635478
sigma_u	.1412037					
sigma_e	.06757824					
rho	.81363958	(fraction of variance due to u_i_)				

F test that all u_i=0: F(11, 46) = 17.77 Prob > F = 0.0000

Table 4A: Model 2 Regression Result

9.3 Model 3

Fixed-effects (within) regression		Number of obs =	60
Group Variable: Country		Number of groups =	12
R-sq:		Obs per group:	
within =	0.0898	min =	5
between =	0.0499	avg =	5.0
overall =	0.0520	max =	5
		F(1,47) =	4.64
Corr(u_i, Xb) =	-0.2903	Prob > F =	0.0365

$Price\_Volatility$	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval	
$Diversification\_Index$	.5770955	.2680437	2.15	0.036	.0378612	1.11633
$\_cons$	-.0221185	.0806159	-0.27	0.785	-.1842968	.1400599
sigma_u	.14217855					
sigma_e	.06688205					
rho	.81881003	(fraction of variance due to u_i_)				

F test that all u_i=0: F(11, 47) = 16.81 Prob > F = 0.0000

Table 5A: Model 2A Regression Results

9.4 Model 4

Fixed-effects (within) regression		Number of obs =	60
Group Variable: Country		Number of groups =	12
R-sq:		Obs per group:	
within =	0.1082	min =	5
between =	0.0736	avg =	5.0
overall =	0.0758	max =	5
		F(5,43) =	1.04
Corr(u_i, Xb) =	-0.2357	Prob > F =	0.4049

$Price\_Volatility$	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval	
$Wind\_Penetration$	.0912748	.2243463	0.41	0.686	-.3611627	.5437122
$Diversification\_Index$	.5648734	.2820094	2.00	0.052	-.0038528	1.1336
$Gas\_Price\_Variance$	-.0056173	.015817	-0.36	0.724	-.0375153	.0262807
$Coal\_Price\_Variance$	.0067344	.0135656	0.50	0.622	-.0206233	.0340921
$Emissions\_Price\_Variance$	-.0097764	.0514242	-0.19	0.850	-.1134832	.0939304
$\_cons$	-.0423941	.1046304	-0.41	0.687	-.2534014	.1686132
sigma_u	.1381609					
sigma_e	.06921285					
rho	.79938657	(fraction of variance due to u_i_)				

F test that all u_i=0: F(11, 43) = 10.95 Prob > F = 0.0000

Table 6A: Model 4 Regression Results