Spatial Analysis of the Merit-Order Effect of Wind Penetration in New Zealand

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Abstract

The study applies a new approach-spatial Durbin Model (SDM) to examine the merit-order effect (MOE) of wind generation after accounting for both spatial and seasonal effects. Negative and significant direct and indirect effects are associated with increases in both types of neighbourhood wind penetration, suggesting that the higher wind penetration in node *i* leads, not only to a reduction in nodal prices in node *i*, but also to those in neighbourhood node *j*. The stronger MOE is found during peak times and the weakest MOE occurs during the night. Our results show that disregarding spatial spill-overs leads to an underestimation of the MOE of wind penetration on nodal prices. The ability of spatial regression models to provide quantitative estimates of spill-over magnitudes and allowance for statistical testing for the significance of these represents the value of the contribution of spatial regression models to the understanding electricity prices.

Keywords: merit-order effect, spatial analysis, wind penetration, nodal price
JEL Classification: Q41, Q42, C21

1. Introduction

The New Zealand Government aims to lift the share of electricity generated from renewable resources from 80% to 90% by 2025. Due to the limited expansion of hydro capacity expected in the future, wind power could contribute as much as 20% if this target is to be achieved. According to the NZWEA, wind power will continue growing and reach to at least 3,500 MW capacity by 2030. Long run marginal cost for wind is decreasing with the large, mature and growing wind industry. The amount of wind generation is predictable. The zero cost of fuel for wind and the increasing cost for fossil fuel provide wind with a comparative advantage in the long run for the wind power developer.

New Zealand's electricity market would face a bigger challenge when integrating intermittent wind into the power system than Nord pool electricity market due to NZ's special geographical feature. The electricity is consumed within the country, and there are no electricity imports and exports to and from other nations. Unlike the Nordic electricity market, the surplus or shortage of electricity can be exported or imported within the Nord pool electricity market (Denmark, Finland, Sweden, Norway, Estonia and Lithuania).

Understanding the behaviour of nodal prices when adding wind is crucially important for valuation and risk management of real assets and financial claims. The non-storability of electricity, the characteristics of demand and supply and the structure of the market and the market power of the generators all contribute to the observed high volatility of electricity prices (Escribano et al., 2011). Electricity generation in New Zealand is hydro-dominated, with around 57% of electricity having been generated by hydro during the 2011-2014 period. The average electricity percentage generated from thermal sources was 21%, geothermal 15%, wind 5% and cogeneration 3% (ENZ, 2016). New Zealand lacks significant capacity for water storage to provide reliable hydro generation. This makes the New Zealand electricity system vulnerable to dry periods. During dry periods, HVDC provides the South Island consumers with access to the North Island's thermal generation capacity. During wet periods, the HVDC transfers surplus South Island hydroelectric power northwards to the North Island.

The impact of wind generation on electricity prices via the MOE has been examined in Germany (Sensfuss et al., 2008), Spain (de Miera et al., 2008) and Denmark (Munksgaard & Morthorst, 2008). However, policies in these countries directly support renewable energy sources, see Haas et al. (2008). Moreover, both Nicholson et al. (2010) and Pöyry (2010) found that the MOE is stronger during the day than in the night. The impact on price depends on the generation mix and availability of flexible conventional capacity. Furthermore, the majority of countries give priority to renewable energy plants in terms of network access and dispatching. In contrast, the electricity market in New Zealand is open and supply technologies can opt to bid in each 30 minute trading period. When the market closes, the system operator dispatches supply at least cost. As no subsidies are offered in New Zealand for the promotion of renewable resources, this provides an ideal opportunity for examining the MOE of wind penetration.

To the best of our knowledge, to date, no journal articles have been published on MOE in New Zealand. Therefore, in addition, there are no studies that have applied spatial models to MOE studies. Spatial models have been extensively used in urban and regional science studies, such as, knowledge and innovation (Anselin et al., 1997; Boschma, 2005; Carlino et al., 2007), cities and clustering (Duranton, 2007; Ellison et al., 2010), and labour and land markets (Faggian and McCann, 2009; Mellander et al., 2011). The issue of local geographic spill-overs between nodal price and wind generation is our particular area of interest, especially when studying the NZEM, which is characterized by nodal connections and geographic spread.

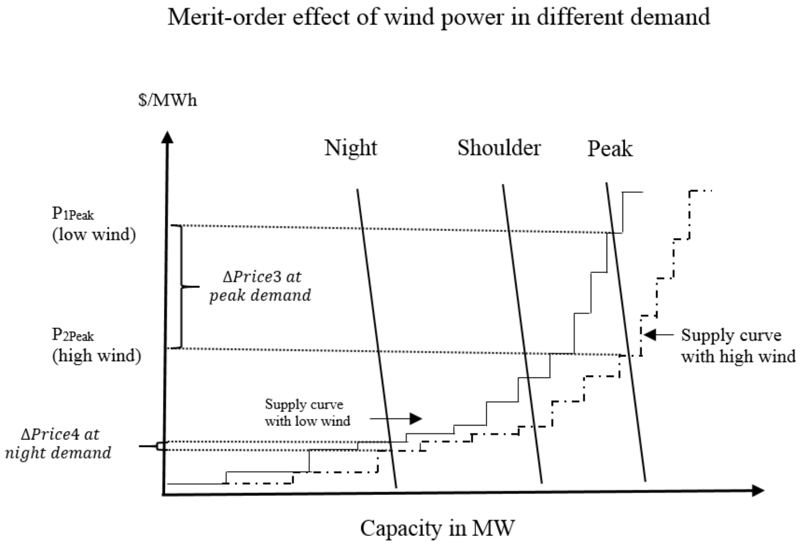
Inspired by the first law of geography: "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970), we apply a spatial model to examine the MOE of wind penetration. We hypothesise that the MOE of wind penetration is not only influenced not by factors at the grid injection point, but also by factors at its neighbouring nodes. We also estimate the MOE by season and demand segments.

Our paper aims to extend the literature by investigating the MOE in general in the New Zealand electricity market (NZEM) based on spatial models. We are interested in the evaluation of the extent of the MOE of wind penetration hourly, weekly and seasonally. By establishing the geographical location of wind farms we estimate the spatial impact of wind generated electricity at neighbouring nodes, again, controlling for competing sources of electricity. The findings are expected to provide important evidence for acquiring security of supply management to stabilise the balance between wind capacity and conventional capacity, the balance between electricity supply and demand. This innovative approach can be applied to assessing the MOE in any electricity system that is influenced by generation or regulatory factors in neighbouring countries.

The paper is structured in the following way. Section 2 reviews the literature. Section 3 provides the background to the NZEM, data and empirical analysis. Sections 4 and 5 describe the methodology and the empirical results. Section 6 concludes this paper.

2. Literature review

A number of studies have assessed the MOE of wind power on spot prices. The papers reviewed cover a wide range of MOE of wind power penetration across countries. Although each of the papers reviewed has adopted different assumptions and methods, similar conclusions were drawn. One of the general conclusions pertains to reduced spot power price due to increased wind power penetration.



Source: own illustration

Fig.1. Impact of wind generation on nodal prices in different segments of electricity demand

Fig. 1 illustrates the supply merit-order curve under two scenarios. When more low-cost wind capacity is added, this shifts the merit-order curve to the right and pushes out the most expensive generators. This results in the reduction of the wholesale electricity price at a given level of demand. During peak demand, after most of the cheaper technologies have been committed, demand is satisfied by relatively more expensive sources of electricity. Consequently, the MOE of wind generation is larger in peak demand conditions than in other circumstances. In contrast, the MOE is smallest during periods of off-peak demand.

Morthorst (2007) conducted a structural analysis by decomposing the data on wind power from the West Denmark area into five separate categories. 0 – 150 MW equals “No Wind” reference. There are four further categories starting from “Low Wind” through to “Storm”. The last category covers wind power greater than 1500 MW. The hourly data for wind power production and the corresponding power price were used. Seasonal variations were accounted for by choosing four different months during 2004 and 2005. The Author concluded that wind power has a “significant” effect (no statistical tests provided) on spot power prices. It was reported that power consumers witnessed a decreased spot power price of approximately 4-6% in 2004 and 12-14% in 2005. It was not possible to perform a complete analysis on all the relevant influencing factors e.g. data pertaining to trade with Germany.

Following the liberalization of the Danish electricity market in 1999, investment in new wind power installations declined in the country. Munksgaard and Morthorst (2008) investigated the impact of the re-designed feed-in tariff (FIT) on power price and its impact on the incentives to invest in new wind power capacity. They examined the economic impact of the measures on both wind power producers and electricity consumers. A comparison of the revenue from wind power production and the cost of production provided evidence as to whether there was an incentive to invest in wind power. The researchers concluded that it was not the tariff itself, but a combination of problems, e.g. spatial planning, high risk aversion of new wind investors and the more favourable support schemes offered in other countries, that were the cause of the recession in new wind power installation. By using data from 2000 to 2007, a decreased spot price of 12-14% in West Denmark and 2-5% in East Denmark were found during extreme weather scenarios, in which wind power production exceeded 1,500 MW. The electricity consumers pay a subsidy to wind-power producers, and the subsidy is to some extent remunerated by the MOE of low marginal costs of wind power.

Jónsson, et al. (2010) developed a non-parametric regression model to examine how spot prices in West Denmark were affected by wind power forecasts between 2006 and 2007. They found that the ratio between the wind generation forecast and the load forecast had the strongest effect on spot prices. An example illustrates that when the forecast wind penetration was less than 4% there was little or no effect on spot prices; with a forecast exceeding 11%, the spot prices gradually decrease. On average prices had dropped by 17.5% when wind power penetration was more than 4%. Wind power had a non-linear effect on prices, thus implying that the current market situation could not be scaled directly in order to analyse future circumstances. The impact of wind power generation on day-ahead spot pricing was substantial. The large price variation is due to the high wind penetration in a relatively small size electricity market. They concluded that 40% of the electricity price variation can be allocated to wind power.

In Germany, grid operators are required by law to buy electricity generated by specified renewable energy sources (RES) at a guaranteed FIT. Electricity supply companies must purchase electricity generated by the RES in advance; this has the effect of reducing the number of purchases from other sources. Consumers pay for the additional cost of the FIT. This arrangement impacts the MOE. Sensfuss, et al. (2008) carried out an analysis by using the calibrated agent-based model, PowerACE, which simulated the electricity market prices from 2001 to 2006. Bid prices were based on variable cost and start-up cost. The model includes fossil fuel (Nuclear, coal, gas, and oil) prices, capacity scarcity, and carbon prices. The MOE varies with the price of fuel. Gas and hard coal price has a significant impact on the MOE because gas and coal are the price setting units in Germany. Raising the renewable capacity 40% led to a 31% increase in the MOE. A premium that is added to the bid price is known as the scarcity mark-up, this increased the volume MOE by about €0.7 billion over the 2005-2006 period. The researchers found that the volume of MOE was largely dependent on the steepness of merit-order curve. In hours of peak demand, the simulated impacts of RES on spot price were found to range from 0 €/MWh to 36 €/MWh. In 2006 the reduction of the unweighted average price resulted in 7.8 €/MWh. The price effect was claimed to be similar to the impact of wind energy on market prices in Denmark (Morthorst, 2007) in which the author claimed that reductions in the order of 12-15% were observed.

Further, Weigt (2009) analysed the potential of wind energy to replace fossil fuel capacity, in addition to the cost savings it would be likely to bring. A static optimisation market model was employed with the objective of meeting demand with minimal production cost. Results for small scale generation from solar, biomass and other fuel types are not shown in the model. The export and import of electricity was not considered. Wind generation was found to have a downward impact on both price and generation cost. The price impact depended on the time of day (varying load levels) and was explained in terms of the MOE of the electricity markets. On average, there was around a 10 €/ MWh reduction in price after adding wind generation to the sources of power. There was a significant impact of increased wind generation on price reduction during peak hours, while there was only a small impact during off peak hours. The results were explained by the shape of the merit curve that showed a relatively flat supply curve at the start and a steep slope at the peak-load level.

Moreover, Ketterer (2014) examined the effect of wind generation on the level and the volatility of the electricity price in Germany based on a GARCH model and found that intermittent wind power reduces the price level but increases its volatility.

In Spain, de Miera et al. (2008) studied the reduction in the wholesale price of electricity as a result of the increase in renewable energy sources (RES-E) generation being fed into the Spanish electricity market grid. The results show that wind generation reduced the wholesale electricity price to 7.08 €/ MWh in 2005, 4.75 €/MWh in 2006 and 12.44 €/MWh in 2007. They concluded that the reduction in electricity prices stemmed from the change in the merit order caused by wind generation. There was an absolutely negative correlation between wind electricity promotion (the FIT) and the wholesale market price. The amount of price reduction was greater than the increase in cost for the consumers. Therefore, a consumer would benefit from a net reduction in the retail electricity price. The short/medium-term reduction in the wholesale price would be offset by the increase in the costs of RES-E support. The findings provided the policy implication that there are three objectives of RES-E deployment. A reduction in CO2 emissions and more moderate consumer prices can be accomplished instantaneously.

In Ireland, O’ Mahoney and Denny (2011) applied an hourly time series OLS regression model to estimate the MOE of wind generation in 2009 in the Irish electricity market. They found an increase of one MW of wind on the Irish system reduced price by 0.0099 € per MWh. The total costs to the market would have been 12% higher without wind output.

Except the discussed studies from European countries, in the United States, Woo et al. (2011) applied the method of maximum likelihood to study the four Electricity Reliability Council of Texas (ERCOT) Zonal market-price. The results showed that a 10% increase in the installed capacity of wind generation reduced the price by 2% in the non-Western zones and around 9% in the Western zone, but increased in a price variance of less than 1% in the non-Western zones and 5% in the Western zone. They concluded that rising wind generation is likely to reduce the spot prices but also to increase spot price variance.

In Australia, Cutler, et al. (2011) assessed the interaction of regional wind generation, electricity demand and spot prices over a two-year period from September 2008 to August 2010 in the South Australian (SA) region. With limited interconnection with other regions in the Australian National Electricity Market (NEM), SA’s wind energy represents an interesting example in order to study the impact of wind penetration on spot price. The researchers found that electricity demand dominates spot price, in comparison with other factors, has the greatest influence on spot pricing. Wind power has a significant secondary impact on spot pricing. There is a tendency for spot prices to be lower when there is a high level of wind power generation. Uncertain demand and various contingencies, as well as generator bidding strategies, were expected to influence price.

Raising wind into an electricity system tends to reduce spot prices via the MOE. The impact of MOE is greater when the system approaches its capacity limits (e.g. during peak load). A consistent conclusion has been found in many countries. With the reduction of installation and capital cost of photovoltaic (PV), many countries have increased the deployment of PV. Therefore, more attention is focussed on the studies of the MOE of solar (e.g. McConnell et al., 2013 in Australia, Cludius et al., 2014 in Germany, Clò et al., 2015 in Italy, Welisch el al., 2016 in Germany, Spain and Denmark, and Luňáčková el al., 2017 in the Czech Republic).

In their study of the effect of distributed photovoltaic generation on the Australian electricity market, McConnell et al. (2013) built a model based on historic bids in 2009 and 2010 and modelled the installation of distributed photovoltaic generation between 1 GW and 5 GW of capacity. They found the value of a 5 GW installation due to the MOE was 1. 2 billion, representing over 12% of the total value traded on the Australian pool market. The implication of their findings for FIT policies, is that, they could deliver savings to consumers, contrary to prevailing criticisms that they are a regressive form of taxation.

Cludius et al. (2014) used time-series regression analysis on the effect of wind and PV, on the German electricity spot price; separately, over the period 2008-2016, they found that the estimated MOE ranged from -0.94 to -2.27€/MWh for wind and from -0.84 to -1.37€/MWh for PV. The analysis on the redistributive effects of the

German Renewable Energy Sources Act (Erneuerbare Energien Gesetz, EEG) suggests that the distributional assessments should be taken into account for equity issues when designing and implementing a policy.

In Italy, Clò et al. (2015) applied a multivariate linear regression model to examine the impact of solar and wind generation on national wholesale electricity prices via MOE for the years 2005 to 2013 in the Italian power market. They found that by adding additional 1GWh to the hourly average solar and wind production, electricity prices would be reduced by 2.3€/MWh and 4.2€/MWh, respectively, and prices' volatility would be increased. Interestingly, the higher monetary savings from solar production, rather than from wind generation, are not sufficient to offset the cost of the related supporting schemes; and this results in the reduction of the consumer surplus. Estimates of savings from wind production present the opposite results.

Welisch el al. (2016) re-examined the MOE in Germany, Spain and Denmark by adding the solar power into the analysis. Results showed the consistent, negative impact of renewable energy sources (wind or solar photovoltaics-PV) on electricity spot market prices in all countries. In addition, the magnitudes of these impacts differed over countries. In Spain, a relatively high MOE was visible in the relatively low market value for wind and PV in comparison with other European countries. In Denmark, the small average MOE with high market value for wind power was found to be due to a more flexible demand-side management that accommodates large shares of renewable electricity into the heating system. In Germany, a stable in-feed pattern of renewable electricity was assumed to be obtained from a balanced mix of renewables by referring to generation profiles. By combining the MOE analysis with the market values of renewables, the study provides strategic insights for policy makers to integrate large shares of renewables into different electricity markets.

Based on the data for the Czech electricity spot market from 2010 to 2015, Luňáčková el al. (2017) examined the MOE as the elasticity of electricity spot price with respect to change in supply of electricity from renewable sources. The MOE of solar power and other renewable sources (mainly water and wind) were examined separately. The researchers found the MOE existed for other renewables, rather than for solar and concluded that promoting solar energy, rather than other renewable energy sources, may be suboptimal in the Czech Republic.

Low electricity prices driven by the large share of renewable technologies would reduce the unit revenues of the RES technologies (without considering subsidies) more than would the revenues from traditional sources. In this regard, Haas et al. (2013) found that increased PV directly reduces the electricity price when solar power is available, conversely, conventional power plants tend to increase the market price when RES are scarce. In this way, traditional sources would partially cover the loss of revenue in those hours when market price reduces due to RES penetration. On the contrary, RES producers cannot take on a similar strategic behaviour; the MOE of RES depends on the degree of market competition and on the shape of the merit-order function, in particular, the elasticity of supply.

The reviewed papers investigate the MOE of wind generation across countries. Each study has found a negative impact of wind generation on electricity price, but the extent of MOE varies across countries. This could arise from the differences in the models' assumptions, types of renewable sources, frequency of data, or variations across regions and countries. The most important variable for determining the MOE is the marginal cost of conventional technology that is being displaced.

Conclusions from the above studies drawn from the impact of wind power on electricity prices are conditional on the RES policies implemented (such as FIT, bearing in mind that not all FIT policies are equal) and the institutional structures in place to encouragement development, trading opportunities across countries, rules within countries (such as Sweden, where the system operator attempts to equalise prices across spot markets), within thermal profiles of country, and their transmission constraints.

The papers most relevant and important for the purposes of this study are summarised in Table 1. Two conclusions are of interest. First, and probably the most obvious, is that the impact on electricity prices is directly linked to wind conditions, and time of day (Morthorst, 2007; Weigt, 2009). Second, the impact on electricity prices depends on the penetration of wind (threshold effect) in the market (Jónsson, et al., 2010; de Miera et al., 2008).

[Table 1 here]

None of these studies has examined the MOE of wind penetration by using panel data with a spatial model that includes the generation mix and electricity demand in the NZEM. This study contributes to the literature by examining the direct and spill over MOE after controlling time and space. In New Zealand, wind and solar PV do not receive any direct government subsidies. The installed capacity of gird-connected solar power is 34.5 MW in 2015 (EA, 2016). Compared to the 10 GW total installed electricity capacity, the small portion of solar PV plays only a trivial role in nodal pricing. Therefore, we focus on the MOE of wind penetration in a competitive market.

3. Background, Data and Empirical Analysis

3.1 Background

Since 2004, the wholesale electricity market has operated a compulsory pool market in which all generated and consumed electricity is traded. Bilateral and other hedge arrangements are available, despite functioning as separate financial contacts. Each generator offers generation to the Independent System Operator (ISO) in the form of offer stacks. Bids (purchaser/demand) and offers (generator/supply) are uploaded into the wholesale information and trading system (WITS) by electricity market participants. Transpower, a state owned enterprise, owns the National Grid and is the Independent System Operator (ISO). The ISO ranks offers in order of price and selects the lowest-cost combination that satisfies demand. Prices on the spot markets are calculated every half hour and vary depending on supply and demand, and location.

There are 11743 km of high-voltage transmission lines in New Zealand. The transmission grid contains about 250 nodes over 450 links. Currently, both electricity generation and retail are open markets, but transmission and distribution are natural monopolies. Five major generators (Contact, Trustpower, Genesis Energy, Meridian Energy and Mighty River Power) operate 179 out of 200 power stations and produce 95% of New Zealand's electricity. Each generator has its own retailing business. With no subsidies for the promotion of renewable resources, New Zealand's deregulated market provides an ideal opportunity for the examination of the MOE of wind.

Annual average electricity demand continues its flat trend with an amount varying between 40,000 GWh and 42,000 GWh. Total installed electricity capacity in New Zealand is approximately 10GW. In 2015, approximately 81% of electricity was generated by renewables (MBIE, 2016). The fraction of power generated from wind is growing in New Zealand. In 2015, the combined installed capacity reached 690 MW and electricity generated by wind accounted for about 6.4% or 2,333 GWh. Currently, there are 19 wind farms. The majority of the existing wind farms are located in the Waikato, the Manawatu, Wellington and Southland.

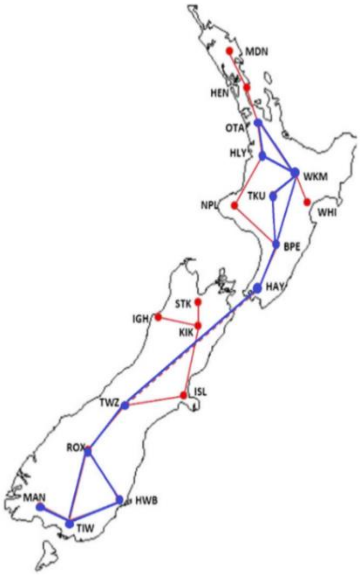
3.2. Data

Data used in this study are taken from the New Zealand Electricity Authority's Centralised Dataset (CDS) 2012, which provides details of actual generation, pricing, and demand data. The sample is restricted to a balanced panel for 2012. There are a number of reasons for the choice of 2012. First, 2012 was a dry year. As a hydro-dominated electricity system, in a dry year, the opportunity cost of using water is expected to increase; wholesale prices are expected to rise and thermal plants are expected to increase generation, this will lead to more price spikes in comparison with wet years due to greater uncertainty during periods of drought. We are interested in examining the MOE of wind penetration during dry and wet seasons. Second, there was a minimal increase in installed capacity over the period of 1993-2003. In 2011, there was a relatively large increase in installed capacity, reaching 623 MW; it remained at 623 MW until 2014 when installed capacity increased by 66 MW. Third, wind energy accounted for 5% of energy generation in 2012 compared to 4% in 2011. The decrease in hydro generation from 58% in 2011 to 53% in 2012 is associated with an increase in thermal generation from 23% in 2011 to 28% in 2012. Thus, 2012 provides an ideal platform with which to analyse the MOE.

After excluding nodes that contribute less than 1% of annual demand, we use 11 of the 19 nodes, which is simplified version of New Zealand's 244 node network (Browne et al., 2012). In 2012, more than 90% of the total demand was supplied from these nodes. A map of the 11 nodes (blue colour) is depicted in Fig.2. The location for these nodes and associated generation plants are reported in Table 2. Tararua, Te Rere Hau and Te Apiti wind farms are aggregated into one node, BPE. The Tararua wind farm, with a capacity of 264 MW, is

New Zealand's largest wind farm, both in terms of the number of turbines and output. The HLY node has both wind and thermal generation which allows us to analyze the relationship among wind, thermal and prices.

[Table 2 here]



Wind generation at Nodes BPE, HAY and HLY

Aggr. node	Type	Plant	Inst. Cap. [MW]	Typ. output [GWh/yr]	Share of supply (Typ.out/Total production 42900 GWh/yr)
BPE	**wind**	Tararua Stage 2	36.3	147	
	wind	Tararua Stage 1	31.7	128	
	wind	Tararua Stage 3	93	375	
	wind	Te Rere Hau	48.5	160	
	wind	Te Apiti	90.75	258	
BPE (Total)			**263.95**	**1068**	**0.025**
HAY	**wind**	West Wind	**143**	**550**	**0.013**
HLY	**wind**	Te Uku	**64.4**	**225**	**0.005**
	thermal		**1453**	**8105**	**0.189**

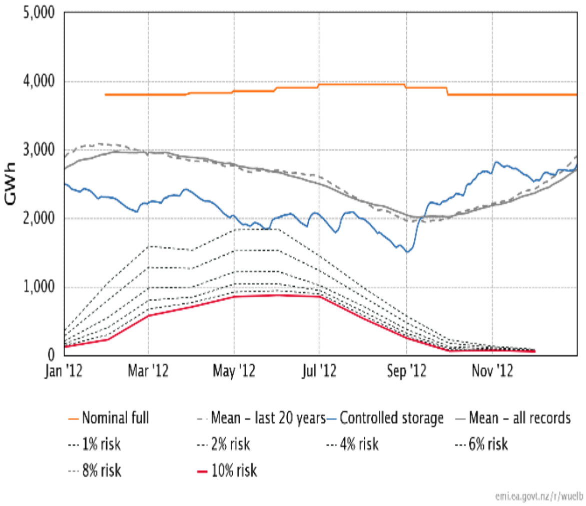
Fig.2. Simplified Nodes and Nodes in the study (Blue)

3.3. Hydro Storage

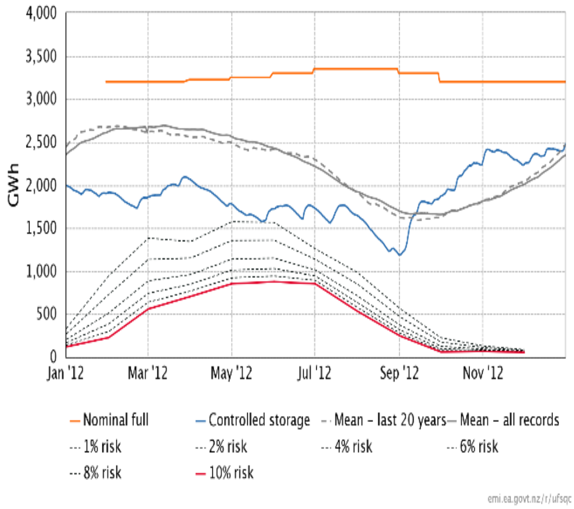
In a hydro-dominated electricity system, hydro storage reflects the hydro power availability to generate electricity. Fig.3 shows that hydro inflows with storage were far below average for the most of winter (May, June and July). They hit 1% hydro risk curve[1] in May, and continued falling. They recovered in mid-September when controlled storage was closer to mean and eventually hit mean storage. After this point, storage remained above mean storage for the rest of the year. The storage in the North Island is the subtraction of storage in New Zealand from the storage in the South Island. The same shapes for the two previously mentioned figures imply that, prior to September 2012, the North Island had had stable hydro storage and the South Island had experienced dry seasons.

[1] Hydro risk curve is a measure of the probability of forced electricity cuts.

(a) New Zealand



(b) South Island

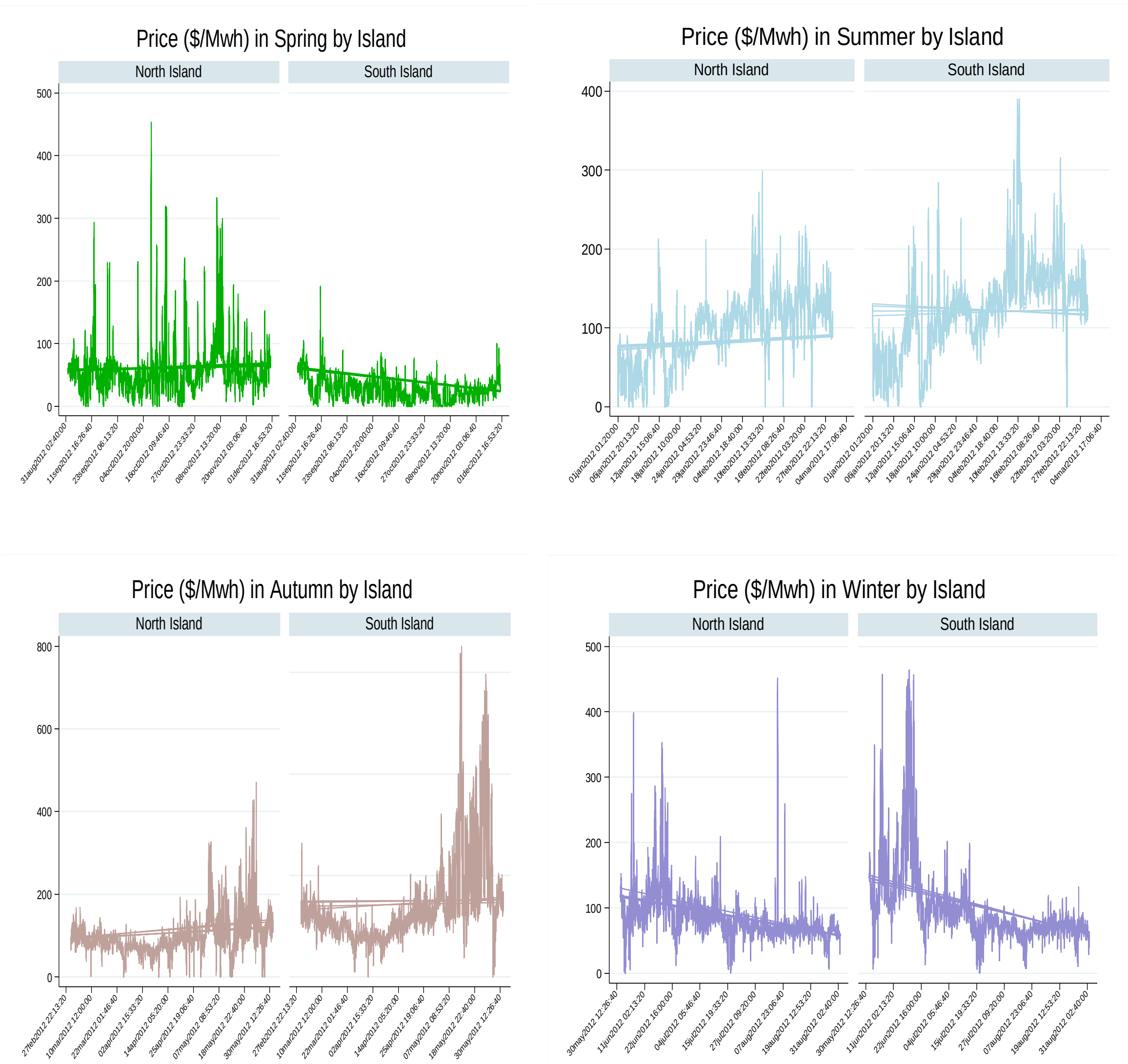


Source: Electricity Authority-Electricity Market Information (EA-EMI)

Fig.3. Historical Hydro Risk Curves 2012

3.4. Nodal Prices by season and Island

Nodal prices were further investigated by season and island. As shown in Fig.4, it was found that nodal prices varied by season and island. In spring, when hydro was high in the South Island, the nodal price was lower than in the North Island. More price spikes were found in the North Island than in the South Island. The rest of figure implied that nodal pirces rised during dry periods, and prices were higher in the South Island than the North Island when HVDC transferred surplus North Island thermal power southwards to the South Island. When adding more thermal generation, more price spikes occurred.



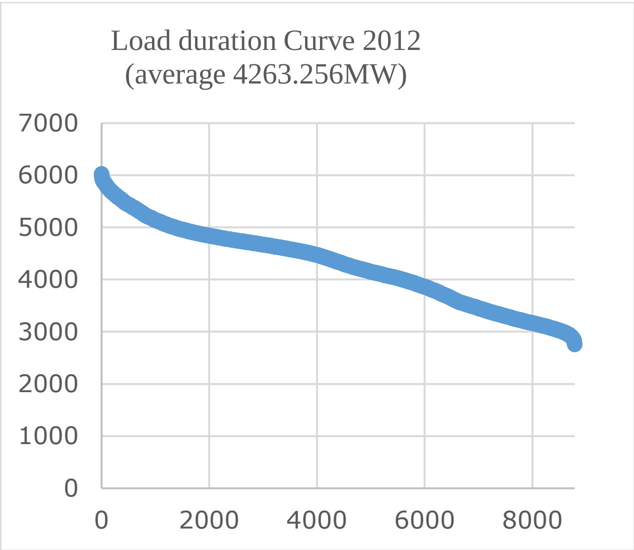
Source: Electricity Authority (EA), Centralised Dataset.

Fig.4. Nodal Prices by Season and Island

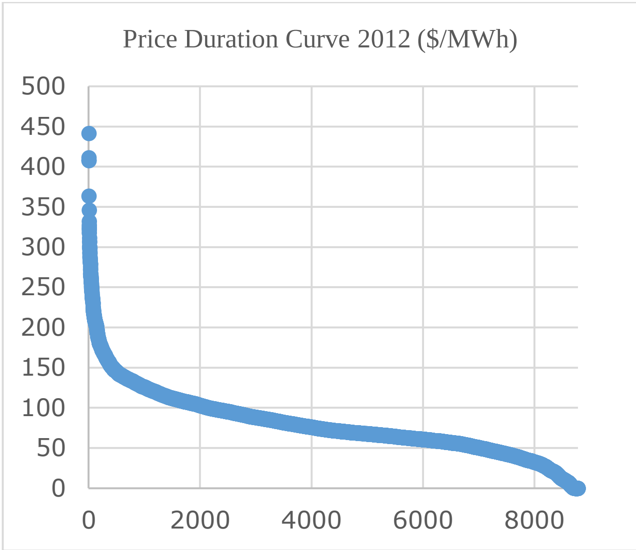
3.5. Load and price duration curves

Fig. 5 illustrates the hourly electricity demand and price duration curve throughout year 2012 in New Zealand. The area under the load duration curve represents the total electricity demand for year 2012. The minimum electricity demand was around 3000 MW, this was met by the base load plants. The average peak demand went over 5300 MW for about 580 hours. Correspondingly, the nodal price went over 150 $ per MWh during peak times. The graphs in Fig.5 reveal that nodal prices are significantly correlated with the demand segments. The highest nodal price occurs for peak load, and lowest for off peak load.

(a) Hourly Electricity Demand Duration Curve for 18 Nodes (Without node MAN)



(b) Price Duration Curve



Source: Electricity Authority (EA), Centralised Dataset.

Fig.5. Load and Price Duration Curves

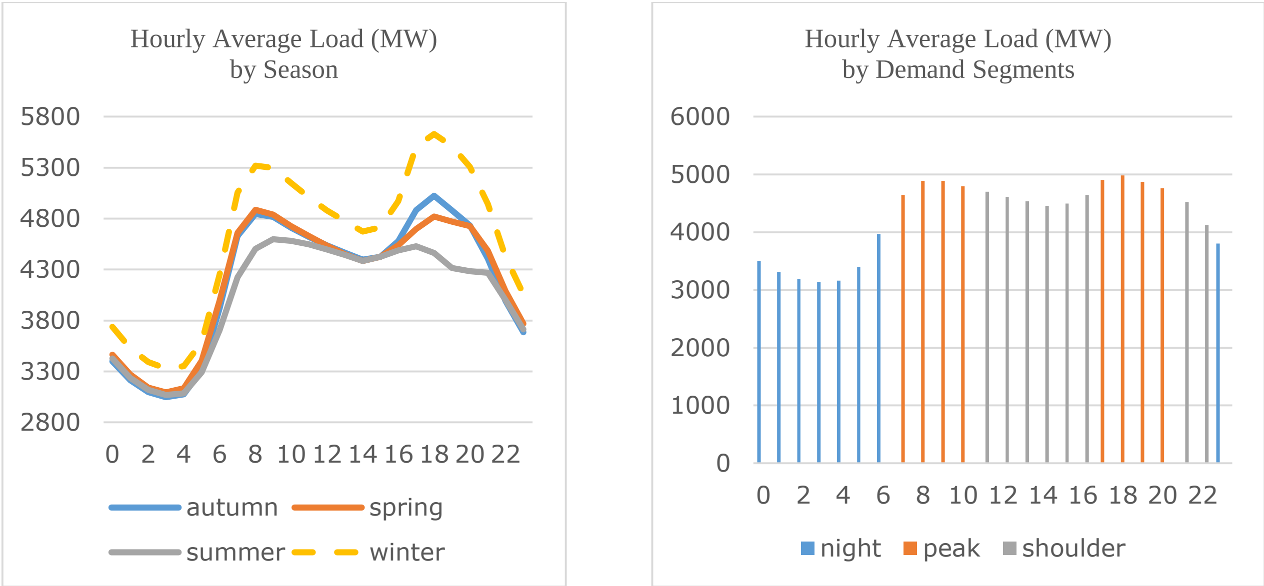
3.6. Hourly electricity demand

The electricity demand varies in time of day, week, and season due to the temperature condition, human, and commercial activities. Fig.6 illustrates average hourly demand by season and demand segments. In each season, we found similar hours for morning and evening peaks. As expected, the highest demand occurred in winter and the lowest demand occurred in summer. To investigate the demand impacts for the specified time, we further divided each day into three periods: peak, shoulder and night. Based on the Genesis Energy home pricing plans, we defined 7am -11am and 5pm-9pm as peak periods, 11am -5pm and 9 pm -11pm as shoulder periods, and 11pm -7am as night periods. As can be seen in Fig.6 (b), more than 5000 MW was required to meet morning and evening peaks.

3.7. Hourly Nodal prices

Fig.7 illustrates the hourly average nodal prices by season and demand segments. As is similar to ‘demand’ in Fig.6, the price follows morning and evening peaks. Even though the lowest demand was found in summer, the price during this time was not the lowest. The lowest price was found in spring. This reveals that the large amount of electricity generated by hydro is likely to reduce price in spring. Except for the fact that demand influences price, other factors, in particular, the availability of hydro, also determine the nodal price.

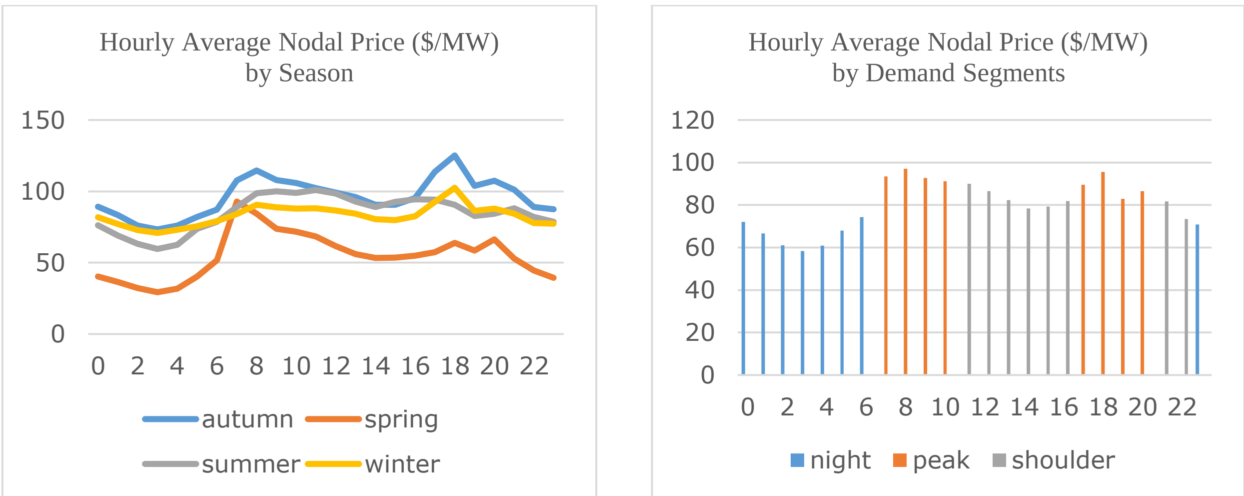
(a) Hourly Average Load by Season
(b) Hourly Average Load by Demand Segments



Source: Electricity Authority (EA), Centralised Dataset.

Fig.6. Hourly Average Load by Season and Demand Segments

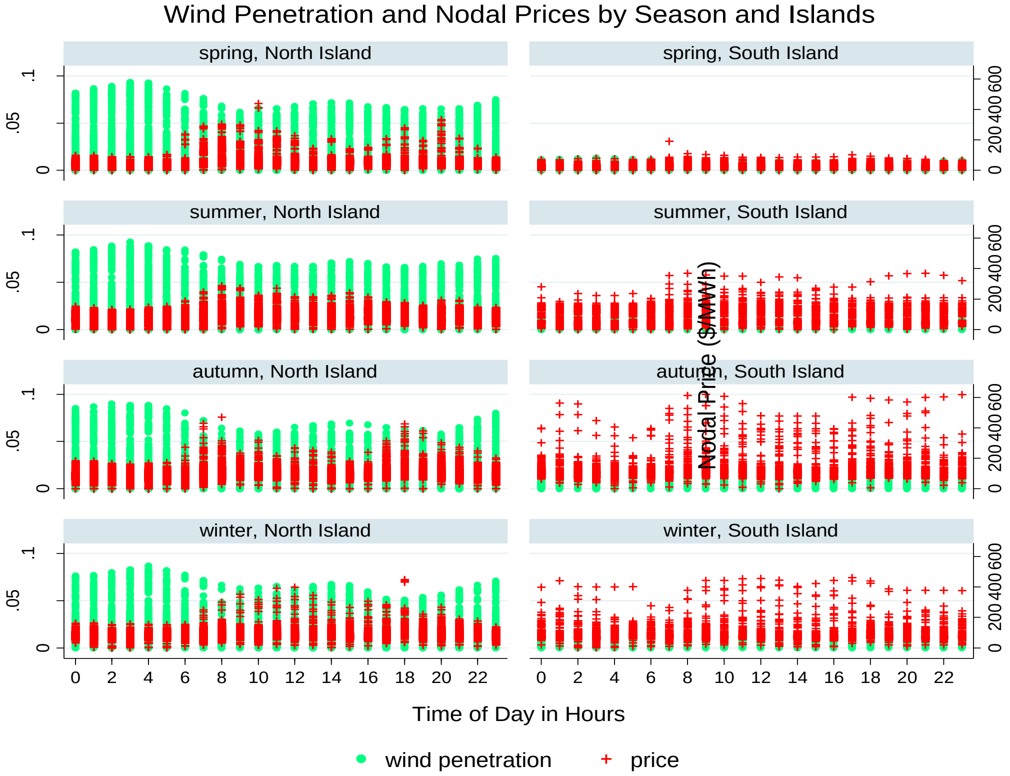
(a) Hourly Average Nodal Price by Season
(b) Hourly Average Nodal Price by Demand Segments



Source: Electricity Authority (EA), Centralised Dataset.

Fig.7. Hourly Average Nodal Price by Season and Demand Segments

3.8. Wind penetration and nodal prices

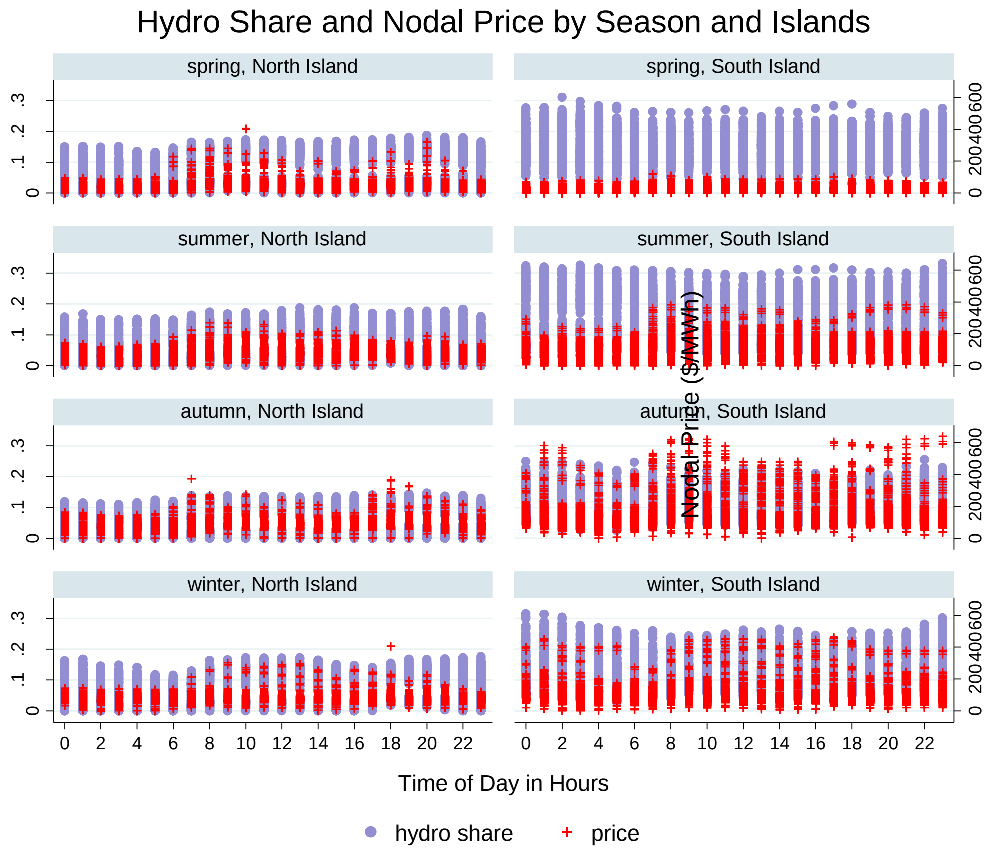


Source: Electricity Authority (EA), Centralised Dataset.

Fig.8. Hourly Wind Penetration and Nodal Prices by Season and Islands

To investigate the relationship between wind penetration and nodal price, we combined the hourly nodal prices and wind penetration into one graph, shown in Fig.8. Hourly and seasonal prices are very different between the two islands. Given that less than 5% of the electricity is generated by wind in the South Island, wind generation is unlikely to impact on nodal price. In contrast, wind plays a significant role in nodal price in the North Island. In general, there is a negative relationship between nodal price and wind penetration. This result is consistent with Jónsson, et al. (2010). The evidence in Fig.8 indicates that the impact of wind penetration on nodal price should be examined in the North Island to avoid aggregation errors.

3.9. Hydro share and nodal prices



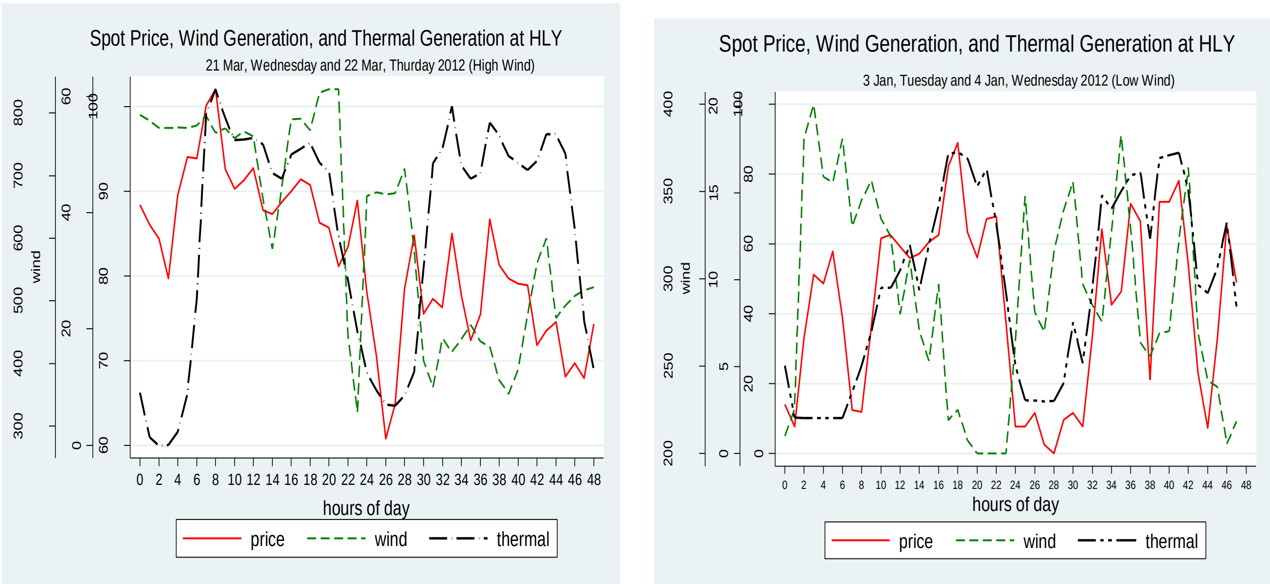
Source: Electricity Authority (EA), Centralised Dataset.

Fig.9. Hourly Hydro Share and Nodal Prices by Season and Islands

Because hydro generated approximately 60% of electricity, it is of interest to see the relationship between hydro share and nodal price. Hydro share is defined as the proportion of hydro generation to load. A large hydro share was found in spring in the South Island, correspondingly, the nodal price was low. During wet periods, surplus South Island generated electricity flows to the North Island resulting in higher nodal prices in the North Island. Autumn and winter were critically dry time periods in 2012 due to the low hydro power availability in the South Island and high electricity demand. The relatively small hydro storage (see Fig.3) drove high nodal price and large price spikes. Nodal prices rose during dry periods (prior to September 2012), and prices were higher in the South Island than in the North Island when HVDC transferred surplus North Island thermal power southwards to the South Island. With the addition of more thermal generation, further price spikes occurred. There is no clear relationship between hydro share and nodal price. This relationship needs to be examined in econometrics models.

3.10. Nodal prices, Wind generation and Thermal Generation at HLY

(a) High wind generation (b) Low wind generation



Source: Electricity Authority (EA), Centralised Dataset.

Fig.10. Nodal Prices, Wind and Thermal Generation at HLY

Apart from considering the relationships among wind, load and prices, we further explored the behaviour of thermal generators and their decisions in regard to generation and prices change. Because the HLY node has both wind and thermal generation, this allows the investigation of this interest. However, caution should be noted, small wind capacity (64.4 MW) compared to large thermal capacity (1453 MW) may weaken the role that wind plays on prices at the HLY node.

We selected four specific days; 21 March, 22 March, when wind generation was high, and 3 January, 4 January, when wind generation was low. 21 and 22 March were two days in autumn, which were drier than 3 and 4 January based on storage level in Fig.3. In this type of situation, water value was high and hydro generators kept water for the future, more profitable use. Nodal prices were high and thermal generators became profitable for the despatch of more thermal generation for meeting both base load and peak load. The graphs in Fig.10 illustrates the relationship among nodal pricing, thermal and wind generation under conditions of both high and low wind generation in two intra-days electricity market.

On 21 and 22 March 2012, on average, there was a high level of wind generation. In general, there was a positive relationship between spot price and thermal generation. Prices were high when thermal generation was high. Prices seemed to depend on thermal generation. Low prices were found at the night; high prices were found in the mornings and evenings; this corresponded to the periods of peak demand. The relationship between prices and wind generation was not clear on 21 March, it was negative on 22 March.

Similarly, on 3 and 4 January 2012, a positive relationship between thermal generation and prices was found except between 1am and 6am on 3 January. We have not found a good explanation for this anomaly. There was no clear relationship between nodal prices and wind generation.

In summary, when wind generation is small, this seems to have no impacts on nodal prices. Prices and thermal generation are positively correlated. Thermal generators would like to generate more to obtain high levels of profit from high nodal prices; by using more thermal generation to meet base and peak loads, which would push higher nodal prices. These statistical analyses are to be examined in our spatial models.

4. Econometric Framework

In this section, both non-spatial and spatial models are applied to examine the MOE of wind penetration. The spatial Durbin model addresses the potential spill over effects from neighbouring regions. This novel approach extends the previous literature (e.g. Munksgaard & Morthorst, 2008; de Miera et al., 2008; Sensfuss et al., 2008) on the MOE of wind generation.

Model 1: Non-Spatial Models

Model 1 examines the MOE of wind penetration in a non-spatial setting. We use ordinary least square (Pooled OLS) (without correction for endogeneity), and panel fixed effects (without considering spill-over effects) models as benchmarks for comparison purposes.

$$Price = F_{1\_OLS/FE}\,(wind/load,\ hydro/load,\ thermal/load,\ load,\ weekday,\ spring,\ summer,\ autumn)$$

Model 2: Spatial models

The generalized spatial Durbin model (SDM)[2]:

[2] There are a few tests to identify the spatial Durbin model as our best model. First, the augmented Dickey-Fuller unit-roots test is applied to test the null hypothesis that price, wind, geothermal, thermal and hydro follow unit root processes. The test results reject the null hypotheses. Those variables have no unit root process and they are stationary. Second, depending on the value of parameters in Eq. (1), based on Elhorst (2014), we have a number of model specifications: If $\theta = 0$, then this applies a Spatial Autoregressive Model (SAR) by excluding exogenous interaction effects (WX). If $\rho = 0$, then this excludes contemporaneous endogenous interaction effects (WY). If $\theta = -\beta\rho$, then this applies a Spatial Error Model (SEM). If none of above hypotheses is accepted, then this applies a Spatial Durbin Model (SDM). Third, among different models, we find results from the Spatial Durbin Model (SDM) perform best. Moran's I test

$$y_{it} = \alpha + \rho \sum_{j=1}^{n} w_{ij}\, y_{jt} + \sum_{k=1}^{K} X_{itk}\, \beta_k + \sum_{k=1}^{K} \sum_{j=1}^{n} w_{ij}\, X_{jtk}\, \theta_k + \psi load_{it} + \phi \sum_{j=1}^{n} w_{ij} load_{jt} + \sum_{i=1}^{3} M_i\, season_{it} + \pi weekday_{it} + \mu_i + \gamma_t + \nu_{it} \qquad (1)$$

Where: $y(it)$ denotes nodal price for node i at time t; each y_i depends on a weighted average of other observations in y, Wy is the spatial lag of y; w_{ij} is the element of spatial weight matrix; ψ measures the effect of load on nodal price; ϕ measures the impact of load at neighbouring nodes on price; μi (i=1, …, n) are unobserved effects and are drawn from an independent and identically distributed (iid) standard Gaussian random variable; γ_t measures time effects; ρ measures the dependence of *yi* on nearby *y*; the significance of ρ indicates the impact of a given nodal price on neighbouring nodes; and, λ measures the spatial correlation in the errors. We assume there are no spatial correlations in the error terms (ν_{it}). Generation technology share, such as wind/load, hydro/load and thermal/load, is represented by X. The matrix product WX denotes an average of the generation mix from neighbouring regions e.g., the nodal prices in node *j* depend on the generation which is generated by the types of technology in *j* as well as the generation in neighbouring nodes. WXθ is the vector of the average X_k over the neighbours of each node. θ measures the impact of X at neighbouring nodes on price; we also control for deterministic seasonal factors.

In Eq. (1), if unobserved effects, u_i, are correlated with explanatory variables, cross-section analysis will result in omitted unobservable biases. Longitudinal data captures the same node over time. Thus, unobservable effects are eliminated by using a panel fixed effects model, such that the estimation results from fixed effects models are consistent. However, this model cannot evaluate the time-invariant explanatory variables because they are removed by within-group transformation. In contrast, a random effects generalized least squares (GLS) model assumes that u_i is uncorrelated with explanatory variables in which GLS uses the optimal combination of within-group and between-group variations. If unobserved effects do not matter, then the GLS estimator is equal to the ordinary least squares (OLS) estimator.[3]

statistic reveals a significant positive spatial correlation (Moran's I = 0.155 with p-value of 0.016) shows that a spatial econometrics model should be applied to estimate the impact of wind generation on nodal prices. The estimations were executed in Stata using the command "xsmle" (Belotti et al. 2013).

[3] A Hausman test is used to identify whether the random effects GLS estimator is biased. The Hausman test results for the models in Tables A1 and 1 reject the null hypothesis that unobserved effects are uncorrelated with the explanatory variables of the equation. Therefore, fixed effects estimates were selected over the random effects to address unobserved heterogeneity.

Because the MOE is affected by demand segments and seasonal variation, we further decompose the North Island sample into two subsamples based on the demand segments and season. Thus, we use three spatial models to examine the MOE of wind penetration.

Model 2a: Spatial fixed effects Durbin Model

Price=F_{2a_SDM} ((price, wind/load, hydro/load, thermal/load, load) in neighbouring region, wind/load, hydro/load, thermal/load, load, weekday, spring, summer, autumn)

Model 2b: Spatial fixed effects Durbin Model by demand segments

Price=F_{2b_SDM} ((price, wind/load, hydro/load, thermal/load, load) in neighbouring region, wind/load, hydro/load, thermal/load, load, weekday, spring, summer, autumn)

Model 2c: Spatial fixed effects Durbin Model by season and demand segments

Price=F_{2c_SDM} ((price, wind/load, hydro/load, thermal/load, load) in neighbouring region, wind/load, hydro/load, thermal/load, load, weekday)

As discussed previously, half-hour nodal prices in the North Island are very different from prices in the South Island due to line constraints and line losses. The results would be biased if we estimated New Zealand as a whole; this is due to the aggregation error of nodal prices. Moreover, the results from spatial lag estimation would be biased due to the weaker dependence between the dispersed nodes across each island. To examine these hypotheses, we apply spatial fixed effects Durbin models on the New Zealand sample and the North Island sample, respectively. The residual in the models for the North Island sample captures the effects from nodes in the South Island. Evidence from the regression results indicates that a spatial model performs better in the North Island rather than in New Zealand as a whole. The plausible reason for this is that the larger distance between the nodes located on the two islands weakens the spatial impact on nodal prices. Therefore, in this spatial analysis, we focus on six nodes in the North Island as highlighted in blue in Fig.2.

Generation plants supplying the nodes referred to in the previous paragraph are reported in Table 2. The location for those particular nodes are quantified and are represented by X and Y coordinates. The spatial weight matrix W in Eq. (1) reveals the spatial relationship among observations. It gives information about which of the observations are neighbours and how their values are associated with each other. In our analysis, the 6 nodes are not contiguous; therefore, distance is used to construct the spatial weight matrix. Nodes with distance d_{ij} receive a weight that is inversely proportional to the distance between the nodes and 0 if they are beyond a certain distance band D (Pisati, 2010).

The diagonal elements of the spatial matrix W are set equal to zero and the non-diagonal elements are non-zero for observations that are spatially close to one another and zero for those that are distant from each other. There are no spatial effects if the distance band goes to zero. In this case, the spatial regression results approximate those of ordinary least squares (OLS) estimation for cross-sectional data. We set the distance band to the maximum distance to guarantee that all nodes have at least one neighbour.

In a spatial setting, the effect of an explanatory variable change in a particular unit affects not only that unit but also its neighbours (LeSage and Pace, 2009). Two main approaches to the implementation of spatial econometrics for controlling spatial heterogeneity are currently in use. In this context, either the nodal price in one region is affected by the nodal price in neighbouring regions, or, the nodal price in one region is affected by the unknown characteristics of the neighbouring regions.

Direct effects are applied to test the hypothesis as to whether a particular variable has a significant effect on the dependent variable in its own location, and indirect effects to test the hypothesis whether or not spatial spill-overs exist (LeSage and Pace, 2009). Exogenous interaction effects capture the impact that generation at a particular location in some way depends on independent explanatory variables at other locations. Estimates of the total effects reflect the sum of the direct plus indirect effects.

5. Estimations and Results

We report on four sets of estimations based on the whole of New Zealand including the North and South Islands (see Table A1 in Appendix A.), the North Island (see Table 3), the demand segments (see Table 4), and the four seasons and demand segments in the North Island (see Table 5). Non-spatial models, such as OLS, fixed effects and random effects are applied to examine the effect of wind penetration on price in New Zealand and in the North Island. The potential problem of "omitted unobservable bias" from OLS is addressed in the fixed or random effects models. The Hausman test results reject the null hypothesis that individual node specific error is uncorrelated with the explanatory variables of the nodal prices equation. Therefore, fixed effects estimates were selected over the random effects to address heterogeneity. In addition, the results from spatial models and non-spatial models were significantly different, and auxiliary tests confirmed the choice of spatial Durbin model as the relevant estimation method to account for geographic spillovers.[4]

Following Models 1 and 2a, in Section 3, estimation results are given in Table 3. There are five columns for the three specific estimation methods. Columns 1 and 2 report results from pooled OLS, fixed effects estimation using non-spatial models. Columns 3 to 5 present the direct, indirect and total effects using a spatial Durbin model.

[Table 3 here]

The results in row 1 show the MOE of wind penetration when the electricity demand is given. A comparison of spatial model results that control for geographic spill-overs, with the pooled OLS and fixed effects results in Table 3 give the following findings:

[4] Among models (SAC, SAR, SEM and SDM), results from the Spatial Durbin Model (SDM) perform best.

Firstly, the coefficients on wind penetration are negative and significant in all models, but are larger in the spatial model than those in the non-spatial model. The result indicates the prices dampening effects of raising wind penetration and an underestimated basis from non-spatial models.

Secondly, coefficients on hydro share change dramatically, from being positive in non-spatial models to being negative in spatial models. On average, enlarging hydro share reduces nodal prices.

In contrast, the coefficients on thermal share are significant and positive in both non-spatial and spatial models. This reflects that thermal energy, as an expensive resource, would increase nodal prices by using more thermal power to generate electricity. Moreover, the indirect effects of thermal generation on nodal prices are greater than the direct effects.

These results are consistent with the hypothesis that adding wind reduces nodal prices and that adding thermal generation increases nodal prices.

The extent of MOE depends on the steepness of both the demand and the supply curves. Given the demand, we examine the MOE in different demand segments, those are peak, shoulder, and night. Following Model 2b, the results are reported in Table 4.

[Table 4 here]

For each demand segment, we find negative and significant direct and indirect effects associated with changes in both types of neighbourhood wind penetration, suggesting that the higher levels of wind generation in node *i* lead, not only to a reduction in the nodal prices in node *i*, but also to a reduction in the nodal prices in neighbourhood node *j*.

Estimates of the direct effects (the main diagonal elements) indicate that a 10% increase of wind penetration in node *i* is associated with a reduction of 0.3$ to 0.5$ per MWh in nodal price at node *i*.

Estimates of the indirect effects (spatial spill-overs, the off-diagonal elements) show that spatial spill-over effects from changes in wind generation in neighbourhood node *i* led to a cumulative decrease in nodal prices. The estimate for scalar indirect effect accumulates into spill-overs affecting the immediately neighbouring regions, and in addition, the neighbours of these regions and the neighbours of the neighbours of the regions, and so on. In other words, a change in the wind generation of one node impacts upon the price at neighbouring nodes, as well as the neighbours to those neighbouring nodes, and so on. The magnitude of the spill-over effects on immediate neighbours would be greater than those on more distant neighbourhoods. The indirect effects for wind generation are that a 10% increase in wind penetration at neighbouring node is associated with a price drop of 1.4 $ to 2.6 $ per MWh. The magnitude of the average indirect effects coming from neighbouring nodes are larger than those of the direct effects from its own node due to, at most, two types of generation technology being present at each node.

The total effects of a 10% increase in wind penetration on nodal prices are a reduction of 1.7 $ per MWh at night, 2.3 $ per MWh at shoulder, and 3.1 $ per MWh at peak. These effects are statistically significant. The strongest impacts of wind penetration on nodal prices are found during peak times, and weakest impacts occur during the night. These results are consistent with findings from Nicholson et al. (2010) and Pöyry (2010).

Due to the heterogeneity across different seasons, we further decompose the North Island sample. Following Model 2c, after excluding season dummy variables, the results of the estimation are given in Table 5.

[Table 5 here]

For each season and each demand segment, we find negative and significant direct and indirect effects associated with changes in both types of neighbourhood wind penetration, suggesting the existence of spill-overs and scalability of wind farms.

In spring, summer, and autumn, we find the strongest MOE of wind penetration on nodal prices during peak times, and the weakest MOE occurs during the night. In winter, the strongest MOE is found during the shoulder period, the medium MOE occurs during the peak period and the weakest MOE during the night. This can be explained by Fig.11. This indicates that the magnitude of MOE depends on the extent of the difference in marginal cost of generation technology.

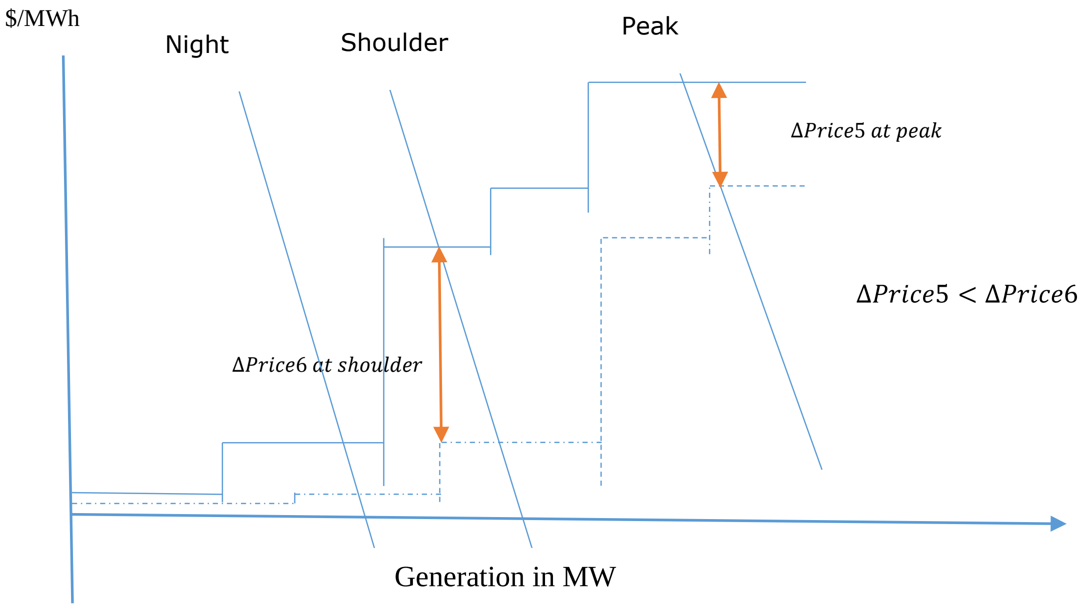


Fig.11. Merit-order Effects of Wind in Different Demand

The coefficients for thermal power change significantly from spring to winter. In summer, autumn and winter, thermal generation has the opposite effect on nodal prices to that of wind generation. Because the cost of electricity generation is relatively high from thermal plants, the more electricity generated by thermal plants, the higher the price will be. This is explained by shifting the merit-order supply curve to the left after substituting hydro generation with thermal generation. Consequently, there is a positive impact from thermal generation on nodal prices. The surplus of electricity generated by thermal plants exported to neighbourhood nodes is estimated to increase a neighbourhood nodal price due to the high cost of generation. The total effect is that a 10% increase in thermal share is estimated to increase the price by 0.1 $ per MWh at night in autumn and 0.54 $ per MWh at peak periods in summer.

Adding 10% more hydro supply is estimated to reduce the nodal price by 0.13$ per MWh at night, 0.29 $ per MWh at shoulder, and 0.46 $ per MWh at peak in spring. There was no significant effect of hydro generation on price in autumn when the storage level was low and hit a historical hydro risk curve. This reveals hydro is different from wind, and it depends closely to rainfall. During wet seasons, hydro, behaving the same as wind, has the MOE. But during dry seasons, hydro generator will consider the opportunity cost of hydro, and provide hydro offers based on the marginal cost plus opportunity cost of hydro.

With regard to the statistically significant coefficients for load support, our hypothesis is that rising loads raise nodal prices. The magnitude effects of load on prices is uneven over the four seasons. A relatively small effect in winter may indicate that there are small variations in load, or low elasticity of demand, in winter.

Our results show that ignoring spatial spill-overs leads to an underestimation of the MOE of wind penetration on nodal prices. The ability of spatial regression models to provide quantitative estimates of spill-over magnitudes and to allow statistical testing for the significance of these represents a valuable contribution of spatial regression models to understanding electricity prices.

Generally, we find raising wind into electricity system tends to reduce nodal prices via the MOE. The extent of MOE is greater during peak times. These results are consistent with literature (e.g. Jónsson, et al., 2010; de Miera et al., 2008; Weigt, 2009). But, we evaluate the MOE of wind penetration in a spatial econometric model, which is the principle contribution of our paper. In addition, estimation results are done by season and demand segments. The evidence would reveal how hydro inflow impacts nodal prices during dry and wet seasons, during different demand segments when increasing wind penetration into the system. For example, in our model, in spring 2012, electricity was imported from the South Island to the North Island via the HVDC link. The amount of electricity, mainly generated by hydro in the South Island, balanced the shortage of electricity in the North Island. In this situation, the price variation from wind would have been reduced by hydro generation.

6. Conclusion

The study examined the MOE of wind penetration on nodal prices in the NZEM based on the centralised dataset. The study addresses the heterogeneity that is important for electricity price analysis, and it extends the literature as follows. First, a spatial econometric model estimates the direct and indirect MOE of wind penetration on nodal prices. Second, we provide estimates of the impact of other types of generation technology on nodal prices. Third, we evaluate nodal price effects during dry periods and wet periods because the NZEM is hydro-dominated and hydro storage affects the MOE. Fourth, the MOE is further examined in different demand segments using a spatial econometric model.

After estimations, we find the negative and significant relationship between nodal prices and wind penetration, both directly and indirectly. Importantly, the results are based on an electricity supply system that receives no subsidies and no grid access priorities.

The paper's main contribution follows from the application of the spatial Durbin (SDM) model to estimate the spatial spill-over effects of wind penetration on nodal prices. Estimates of the direct effects (the main diagonal elements) indicate that a 10% increase of wind penetration in node *i* is associated with a reduction of 0.3$ to 0.5$ per MWh in nodal price in node *i*. The indirect effects for wind generation are that a 10% increase in wind penetration at neighbouring node is associated with a price drop of 1.4 $ to 2.6 $ per MWh. The total effects of a 10% increase in wind penetration on nodal prices are a reduction of 1.7 $ per MWh at night, 2.3 $ per MWh at shoulder, and 3.1 $ per MWh at peak. These effects are statistically significant.

Our results show that ignoring spatial spill-overs leads to an underestimation of the impact of wind generation on nodal prices. Increased amount of wind being injected into the grid lowers nodal price; this result is not sensitive to the electricity demand[5]. Wind speed in one wind site is complementary to the wind speed in another wind site. Surplus wind generated electricity can be exported to neighbourhood nodes, which reduces nodal price (See Wen and Sharp, 2017). The significantly negative spill-over effects indicate that scalability would be a big advantage in a small electricity system like NZ in which it can add turbines as demand increases. We also find that price variation from wind would have been reduced by hydro generation. These have been validated from the industrial perspective. The ability of spatial regression models to provide quantitative estimates of spill-over magnitudes and to allow statistical testing for the significance of these represents a valuable contribution of spatial regression models to the understanding electricity prices.

With an average load factor of around 45% it is highly likely that wind generation will expand in the near future, particularly if demand grows. Adding more intermittent wind generation into the electricity system will create challenges for the system operator and market participants. On the one hand, electricity generated by wind is independent and non-adjustable with respect to electricity demand. Our results show that high levels of variable renewable electricity production can been balanced by adjusting the output from hydro and thermal power plants. Unlike Norway, for example, New Zealand cannot achieve balance by adjusting imports/exports. The entry of load balancing investments into the market will depend on the cost of alternative technologies relative to existing sources of supply. The magnitude of MOE depends on the extent of the difference in marginal cost of generation technology. The finding in this study provides system operator and investors with valuable information when enlarging wind penetration in need of considering flexibility, and cost of fuel switching in time of day and dry or wet seasons. This methodology will be applicable to analysing the cross-border effects in any electricity system that has export or import electricity from neighbouring countries such as Switzerland or Germany.

[5] We have examined models with and without load, and found the similar effects of wind penetration on nodal prices. This indicates that wind generation is not sensitive to demand.

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TABLE 1

Summary of Estimated Reduction in Electricity Price

Authors	Country	Model	MOE Price Effect	
			(% Δ Price)	(EUR/MWh)
Morthorst (2007)	West Denmark	No model	At >150 MW (5 – 14) At > 500 MW (12-14)	-
Munksgaard & Morthorst (2008)	West Denmark East Denmark	No model	12 – 14 2-5	4
Jónsson, et al. (2010)	West Denmark	Non-parametric	17.5 (Penetration > 4%)	17
Sensfuss et al. (2008)	Germany	PowerACE	-	8
Weigt (2009)	Germany	Optimisation	-	11
de Miera et al. (2008)	Spain	Simulation	11.7-25.1	8

TABEL 2
Types of plant and X&Y coordinates of the 11 nodes
(6 nodes in the North Island and 5 nodes in the South Island)

Index	Node in the North Island	Plant types	Y-coordinate Latitude	X-coordinate Longitude
1	BPE – Bunnythorpe	Wind	-40.2809	175.6396
2	HAY – Haywards	Wind	-41.150278	174.981389
3	HLY – Huntly	Thermal, Wind	-37.543889	175.152778
4	OTA – Otahuhu	Thermal	-36.9512	174.865383
5	TKU – Tokaanu	Hydro	-38.98113	175.768282
6	WKM - Whakamaru	Geothermal, Hydro	-38.419633	175.808217
7	TWZ	Hydro	-44.25	170.1
8	ROX	Hydro	-45.475811	169.322555
9	HWB	Wind	-45.854722	170.475
10	TIW	Wind	-46.598034	168.364105
11	MAN	Hydro	-45.521389	167.277778

TABLE 3
Effects of Wind Penetration on Nodal Price 2012 (North Island)
Non-Spatial (Model 1) and Spatial Models (Model 2a)

	Dependent variable: The nodal prices in 2012 dollars ($/MWh)				
	Sample: North Island				
	Model 1 Non-spatial Models		Model 2a A Spatial Durbin Model (SDM)		
	(1)	(2)	(3)	(4)	(5)
Explanatory Variables	OLS	Panel fixed effects	Direct	Indirect	Total
Wind/load	-6.7228***	-7.8588***	-3.6373***	-17.7377***	-21.3749***
	[0.258]	[0.258]	(0.229)	(1.089)	(1.317)
hydro/load	0.0612***	0.1259***	-0.2080***	-0.9258***	-1.1338***
	[0.023]	[0.031]	(0.029)	(0.142)	(0.171)
Thermal/load	0.4085***	0.4761***	0.0300	0.2865**	0.3165**
	[0.018]	[0.028]	(0.027)	(0.127)	(0.154)
load	0.0125***	0.1173***	0.0541***	0.2285***	0.2827***
	[0.001]	[0.002]	(0.001)	(0.007)	(0.008)
weekday	14.5410***	10.1575***	1.5053***	5.9491***	7.4544***
	[0.411]	[0.404]	(0.206)	(0.814)	(1.020)
spring	-23.5514***	-18.9217***	-4.1572***	-16.4298***	-20.5871***
	[0.527]	[0.516]	(0.277)	(1.093)	(1.369)
summer	4.6822***	12.2171***	4.0560***	16.0302***	20.0862***
	[0.525]	[0.522]	(0.283)	(1.121)	(1.404)
autumn	10.9243***	15.5028***	5.7142***	22.5836***	28.2978***
	[0.523]	[0.512]	(0.274)	(1.087)	(1.361)
sigma2_e					24.5848***
					(0.167)
Constant	66.3761***	30.5652***			/
	[0.590]	[0.820]			/
R-squared					
F-test	993.2	1541			/
R2	0.131	0.0493			0.247
rho		0.454			0.9525***
					(0.000)
Number of nodes	6	6			6
Observations	52704	52704			52,704

Notes: rho in column (2) is the fraction of variance due to individual effects.
Positive significant spatial parameter rho (ρ) in column (5) indicates that spatial lagged models rather than spatial error models are employed into the spatial analysis. Geothermal generation is excluded in the model to avoid multicollinearity.
The reference variables are weekend and winter.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Source: Electricity Authority (EA), Centralised Dataset.

TABEL 4

The Spatial Fixed Effects of Wind Penetration on Nodal Price 2012 (North Island)

A Spatial Durbin Model (SDM) (Model 2b)

Dependent variable: The nodal prices in 2012 dollars ($/MWh)

Sample: North Island by Demand Segments

	peak			shoulder			Night		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
wind/load	-5.111***	-26.10***	**-31.21*** **	-3.897***	-19.69***	**-23.59*** **	-2.946***	-14.13***	**-17.08*** **
	(0.671)	(3.242)	**(3.908)**	(0.327)	(1.524)	**(1.845)**	(0.195)	(0.945)	**(1.139)**
hydro/load	0.0549	0.270	0.325	-0.161***	-0.671***	-0.831***	-0.0694**	-0.253*	-0.322*
	(0.0732)	(0.357)	(0.430)	(0.0353)	(0.168)	(0.203)	(0.0306)	(0.151)	(0.181)
thermal/load	-0.00339	0.165	0.161	0.306***	1.607***	1.913***	0.0484	0.369**	0.417**
	(0.0742)	(0.361)	(0.435)	(0.0384)	(0.183)	(0.221)	(0.0334)	(0.163)	(0.196)
load	0.118***	0.530***	0.648***	0.100***	0.428***	0.529***	0.0739***	0.339***	0.413***
	(0.00573)	(0.0278)	(0.0335)	(0.00380)	(0.0179)	(0.0216)	(0.00330)	(0.0160)	(0.0193)
weekdays	YES	YES	YES	YES	YES	YES	YES	YES	YES
seasons	YES	YES	YES	YES	YES	YES	YES	YES	YES
rho			0.960***			0.923***			0.965***
			(0.000610)			(0.00115)			(0.000541)
sigma2_e			33.28***			33.29***			5.965***
			(0.391)			(0.389)			(0.0705)
Observations	17,568	17,568	17,568	17,568	17,568	17,568	17,568	17,568	17,568
R-squared	0.173	0.173	0.173	0.391	0.391	0.391	0.378	0.378	0.378
Number of id	6	6	6	6	6	6	6	6	6

Notes: Based on Genesis Energy home pricing plans (https://www.genesisenergy.co.nz/understand-our-pricing-plans), we define 7am-11am and 5pm-9pm as peak periods, 11am-5pm, 9pm-11pm as shoulder periods, and 11pm-7am as night periods.

Positive significant spatial parameter rho (ρ) indicates that spatial lagged models rather than spatial error models are employed into the spatial analysis.

The models include weekdays and seasonal variables. Full results are available upon request.

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Source: Electricity Authority (EA), Centralised Dataset.

TABLE 5

The Spatial Fixed Effects of Wind Penetration on Nodal Price 2012 (North Island)

A Spatial Durbin Model (SDM) (Model 2c)

Dependent variable: The nodal prices in 2012 dollars ($/MWh)

Sample: North Island by Season and Demand Segments

	spring			summer			autumn			winter		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	peak	shoulder	night	peak	shoulder	night	peak	shoulder	night	peak	shoulder	night
Wind/load	-26.51*	-15.91***	-14.01***	-36.41***	-33.68***	-21.43***	-43.03***	-38.68***	-12.74***	-14.05*	-19.94***	-11.69***
	(15.85)	(3.693)	(1.833)	(3.897)	(3.536)	(2.548)	(5.434)	(3.293)	(2.448)	(7.884)	(5.973)	(2.706)
Hydro/load	-4.582**	-2.837***	-1.340***	-1.782***	-2.301***	1.405***	1.952***	2.125***	0.409	-0.393	-0.484	-1.202***
	(1.797)	(0.418)	(0.249)	(0.537)	(0.456)	(0.411)	(0.677)	(0.441)	(0.419)	(0.635)	(0.472)	(0.314)
Thermal/load	-5.857**	-1.519**	2.323***	5.449***	5.025***	3.979***	3.328***	3.156***	0.995***	0.0616	3.045***	1.222***
	(2.347)	(0.602)	(0.435)	(0.314)	(0.271)	(0.285)	(0.435)	(0.274)	(0.325)	(0.582)	(0.472)	(0.319)
load	0.997***	0.573***	0.376***	0.741***	0.685***	0.538***	0.852***	0.547***	0.642***	0.355***	0.590***	0.295***
	(0.141)	(0.0498)	(0.0276)	(0.0449)	(0.0419)	(0.0497)	(0.0408)	(0.0349)	(0.0400)	(0.0307)	(0.0348)	(0.0269)
weekday	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
rho	0.985***	0.973***	0.984***	0.954***	0.951***	0.972***	0.930***	0.932***	0.966***	0.931***	0.879***	0.963***
	(0.000466)	(0.000807)	(0.000465)	(0.00140)	(0.00149)	(0.000881)	(0.00208)	(0.00203)	(0.00106)	(0.00210)	(0.00357)	(0.00116)
sigma2_e	13.88***	3.650***	0.619***	13.95***	14.38***	4.657***	44.17***	21.23***	6.909***	37.97***	75.76***	4.702***
	(0.330)	(0.0856)	(0.0146)	(0.329)	(0.339)	(0.111)	(1.030)	(0.495)	(0.163)	(0.888)	(1.755)	(0.111)
Observations	4,368	4,368	4,368	4,368	4,368	4,368	4,416	4,416	4,416	4,416	4,416	4,416
R-squared	0.027	0.140	0.269	0.514	0.512	0.466	0.391	0.321	0.227	0.210	0.258	0.180
Number of id	6	6	6	6	6	6	6	6	6	6	6	6

Notes: Based on Genesis Energy home pricing plans (https://www.genesisenergy.co.nz/understand-our-pricing-plans), we define 7am-11am and 5pm-9pm as peak periods, 11am-5pm, 9 pm-11pm as shoulder periods, and 11pm-7am as night periods.
Positive significant spatial parameter rho (ρ) indicates that spatial lagged models rather than spatial error models are employed into the spatial analysis.
The models include weekday's variables. Full results are available upon request.
Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Electricity Authority (EA), Centralised Dataset.

Appendix A. Other Estimation Results

New Zealand as a whole (Table A1)

a. Non-spatial model

Price= $F_{A1\_OLS/FE}$ (wind/load, hydro/load, thermal/load, weekday, load, spring, summer, autumn)

b. Spatial model

Price=F_{A1_SDM} ((price, wind/load, hydro/load, thermal/load, load) in neighbour region, wind/load, hydro/load, thermal/load, weekday, load, spring, summer, autumn)

Table A1 Nodal price 2012 (New Zealand)

	Dependent variable: The nodal prices in 2012 dollars ($/MWh)		
	Sample: New Zealand		
	Non-spatial model		**Spatial model**
VARIABLES	(1) Pooled OLS	(2) Panel fixed effects	(3) A Spatial Durbin Model(SDM)
wind/load	-7.1328***	-5.8817***	23.06***
	[0.318]	[0.330]	(3.519)
hydro/load	-0.2313***	-0.2096***	-4.571***
	[0.025]	[0.037]	(0.415)
thermal/load	0.0975***	0.0503	-13.62***
	[0.022]	[0.036]	(0.465)
load	0.0006	0.1151***	0.308***
	[0.001]	[0.002]	(0.0211)
Weekday	12.9077***	9.9838***	0.213
	[0.383]	[0.381]	(2.362)
Spring	-46.1579***	-43.2000***	-79.27***
	[0.490]	[0.488]	(2.590)
Summer	-0.0056	4.4955***	7.833***
	[0.489]	[0.489]	(2.729)
Autumn	22.9278***	25.8553***	59.20***
	[0.487]	[0.483]	(2.368)
Constant	82.4220***	49.7062***	/
	[0.530]	[0.817]	/
F-test	2932	3322	
R2	0.195	0.0867	0.170
R2_W	/	0.216	0.170
Sample size	96624	96624	96624
Number of groups	11	11	11

Notes: Positive significant spatial parameter rho (ρ) in column (3) indicates that spatial lagged models rather than spatial error models are employed into the spatial analysis. Geothermal generation is excluded in the model to avoid multicollinearity. The reference variables are weekend and winter.
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Source: Electricity Authority (EA), Centralised Dataset.