Spatial Effects of Wind Generation and Its Implication for Wind Farm Investment Decisions in New Zealand

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ABSTRACT

Spill-over effects on electricity nodal prices associated with increased wind generation have not been examined in the literature. To examine these effects, we use spatial econometric models to estimate the direct and indirect effects of wind generation on nodal wholesale electricity prices. Spatial econometric models allow us to provide quantitative estimates of spill-over magnitudes and statistical tests for significance. Results show negative and significant effects are associated with increases in wind penetration, and the effect is stronger during peak hours and weaker during off-peak hours. Simulation results demonstrate net savings of NZ$8 million per MW of additional wind capacity installed at the CNI2 wind site. The findings provide valuable information on the evaluation of wind farm development in terms of site location, wholesale prices, and financial feasibility. Our approach also contributes to forecasting location specific wholesale electricity prices, and provides a better understanding of the implications of locating wind sites.

Keywords: Merit-order effect, Spatial econometrics, Wind penetration, Nodal price, Wind investment

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1. INTRODUCTION

To achieve a low-emission economy transition, the New Zealand Government aims to lift the share of electricity generated from renewable resources from 80% to 90% by 2025. Electricity generation in New Zealand is hydro-dominated, with around 57% of electricity generated by hydro during 2011–2014. Average electricity percentage generated from thermal sources was 21%, geothermal 15%, wind 5% and cogeneration 3% (ENZ, 2016). New Zealand has 34.5 MW of grid-connected solar power (EA-EMI, 2016). Expansion of hydro capacity is limited. On the other hand, New Zealand has a most favourable wind resource with plants operating at around 45% capacity. Given this potential, it is highly likely that wind power could contribute as much as 20% of electricity if the government's target of 90% is to be achieved.

New Zealand consists of two main islands: North Island and South Island. The transmission grid contains about 250 nodes. Electricity surplus of one island is transferred to the other island by a high-voltage direct current (HVDC) link. Total installed electricity capacity in New Zealand is approximately 10GW. Currently, both electricity generation and retail are open markets. Transmission and distribution are natural monopolies. Five major generators produce 95% of New Zealand's

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electricity. Each generator offers generation to Transpower, the Independent System Operator (ISO), in the form of offer stacks. Transpower is a state-owned enterprise and owns the National Grid. It ranks offers in order of price and selects the lowest-cost combination that satisfies demand. Using the SPD (Schedule, Pricing and Dispatch) method, nodal prices on the spot market are calculated every half hour. Notably, SPD can't be used to forecast the regional price effects by adding extra wind capacity.

Currently, there are 19 wind farms with 689 MW of installed capacity; the majority are located in Waikato, Manawatu, Wellington and Southland. Expansion of wind generated electricity has important implications for electricity supply in New Zealand. First, the total capacity of hydro storage is about 4.9 TWh (EA, 2013), which can only meet about 48 days of national demand (average hourly demand of 4263 MWh), making the electricity system vulnerable to periods of dry weather. Hydro reservoirs play a key role in the indirect storage of electricity, and we would expect increased inter-temporal substitution between generation sources, particularly wind, hydro, and thermal plants, compared to markets with a higher proportion of electricity generated from non-storable sources. Second, because international trade in electricity is not cost effective, the market response to sources of low cost wind generated electricity is conditional on the relative marginal cost of alternative sources, such as hydro, geothermal and gas. Third, given the intermittency of wind generated electricity, climatic conditions are significant in determining the merit-order of generation alternatives entering the market. When wind generation is low, base load capacity is typically hydro/coal/geothermal. When wind generation is high, wind displaces higher cost supply alternatives. When more low cost wind generation is added, this shifts the merit-order curve to the right and pushes out the most expensive generators. This results in the reduction of wholesale electricity price at a given level of demand. Wind generated electricity is likely to be quite variable and may require expensive natural gas backup since this ramps up faster than the alternatives. Consequently, the merit order effect (MOE) of wind generation is relatively larger during periods of peak demand. Fourth, increased wind generation at one grid injection node, contingent on hydro storage and demand, we expect to observe a reduction in the wholesale price at neighbouring connected nodes.

The impact of wind generation on electricity prices via the MOE has been examined in Ontario, Canada (Rivard and Yatchew, 2016), Germany (Sensfuß et al., 2008), Spain (de Miera et al., 2008) and Denmark (Munksgaard and Morthorst, 2008). However, policies in these countries directly support renewable energy sources (Haas et al., 2008). 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.[1]

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). In a spatial setting, the effect of an explanatory variable change at a particular site affects not only that site but also its neighbours (LeSage and Pace, 2009). In this context, the nodal price in one geographic location is affected by the nodal price in neighbouring locations. By establishing the geographic location of wind farms we estimate the spatial impact of wind-generated electricity at adjacent nodes, controlling for competing sources of electricity. Spatial econometric models can be used to forecast direct and indirect regional price reduction effects and explore the economics of developing wind farms at different locations.

This study attempts to answer a number of important questions: (1) How does an increase of wind penetration influence the nodal price? (2) Is the MOE larger during the peak demand, and

1. Wind penetration is defined as the ratio of wind generation to load.

smaller during the off-peak demand? (3) Can we use answers to question (1) to predict the regional price reduction for each node and to further explore where to build wind sites?

Our study contributes to the literature in several ways. First, the primary contribution is to extend the literature by employing spatial econometric methods to examine the MOE of increased wind penetration and its impact on wholesale price at the grid injection point and neighbouring nodes. We construct three spatial weight matrices, and evaluate different spatial models. Among them, we select a spatial fixed effects bias-corrected (Lee and Yu, 2010) Durbin model (SDM). Second, this is the first study to examine the MOE and the hourly MOE in New Zealand. Third, we apply estimation results to forecast regional wholesale price reduction effects and use these to estimate net financial savings at each node. None of the prior studies have examined regional price effects from wind expansion by considering the issue of local geographic spill-overs between nodal price and wind generation. The evidence affords insight into expanding and integrating wind generation into the electricity system. Transferability of the methodology is not limited. Although New Zealand does not import and export electricity, electricity is imported or exported across nodes. Therefore, in a market which does import or export electricity, we apply a spatial methodology to analyse spill-over effects. This analysis can be extended from a cross-region study to a cross-country study. This innovative approach can be applied within an electricity system that is influenced by generation or regulatory factors in neighbouring countries.

The paper is structured as follows. Section 2 provides a brief overview of the related literature. Section 3 describes data. Section 4 develops the econometric framework, and constructs spatial weight matrices. Section 5 presents the empirical results and simulation, and carries out a robustness check. Section 6 concludes this paper.

2. LITERATURE REVIEW

The impact of wind generation on electricity prices via the MOE has been examined widely. Empirical research consistently finds a negative impact of wind generation on electricity price. The extent of MOE varies across countries due to country-specific renewable energy sources (RES) policies, market design, trading opportunities across countries, rules governing the system operator, thermal profiles, transmission constraints, and models applied.

Rivard and Yatchew (2016) studied the Ontario electricity market when integrating renewables into the electricity system and found a 7 CAD/MWh decrease in the competitive hourly market price due to an increase of wind generation from 500 MW to 1500MW. In Germany, grid operators are required by law to buy electricity generated by specified RES at a guaranteed feed-in tariff (FIT). Electricity supply companies must purchase electricity generated by the RES in advance, which reduces purchases from other sources. Consumers pay for the additional cost of the FIT. This arrangement impacts the MOE. Using an agent-based model Sensfuß et al. (2008) found that raising the renewable capacity by 40% led to a 31% increase in the volume of the MOE. The price effect was similar to the impact of wind energy on market prices in Denmark, where reductions in the order of 12–15% were estimated (Morthorst, 2007). Ketterer (2014) examined the effect of wind generation on the level and volatility of electricity price in Germany based on a GARCH model and found that intermittent wind power reduces the price level but increases its volatility. In their study of Texas Zonal markets Woo et al. (2011) found that a 10% increase in the installed capacity of wind generation reduced price by 2% in the non-Western zones and around 9% in the Western zone, but increased price variance by less than 1% in the non-Western zones and 5% in the Western zone.

Introducing 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).

With the reduction of installation and capital cost of photovoltaic (PV), many countries have increased the deployment of PV. Recently, more attention is focussed on 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). Using time-series regression analysis on the effect of wind and PV on the German electricity spot price, Cludius et al. (2014) found that the MOE ranges from –0.94 to –2.27€/MWh for wind and from –0.84 to –1.37€/MWh for PV. In Italy, Clò et al. (2015) 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. Estimates of savings from solar production are not sufficient to offset the cost of related supporting schemes. Based on estimates of the MOE of solar power and other renewable sources (mainly water and wind), Luňáčková el al. (2017) found that promoting solar energy in the Czech Republic may be suboptimal. In New Zealand, small scale solar deployment has not yet impacted electricity prices and we do not include solar generation.

Two conclusions from the literature are relevant to our study. First, is that the impact on electricity prices is directly linked to wind conditions (Morthorst, 2007; Munksgaard and Morthorst, 2008), and time of day (Weigt, 2009). Morthorst (2007) conducted a structural analysis by decomposing the data on wind power from West Denmark into five separate categories according to wind speed and season. Spot prices were found to have fallen by approximately 4–6% in 2004 and 12–14% in 2005. Munksgaard and Morthorst (2008) investigated the impact of the re-designed FIT on power price in the Danish electricity market. They found a decreased spot price of 12–14% in West Denmark and 2–5% in East Denmark during extreme weather scenarios, in which wind power production exceeded 1,500 MW. Using a static optimisation model Weigt (2009) found that wind generation reduced price during peak hours, while there was only a small impact during off-peak hours. Second, the impact on electricity prices depends on the penetration of wind in the market (Jónsson et al., 2010). Using a non-parametric model, Jónsson et al. (2010) found that, on average, prices dropped by 17.5% when wind power penetration was more than 4%. They concluded that 40% of the electricity price variation could be allocated to wind power.

The New Zealand electricity market (NZEM) is an energy-only market with no capacity market or day-ahead market. Tipping et al. (2004) proposed a top-down NZEM spot prices model, incorporating an exponential function of the reservoir storage levels into a time series model. National storage level is very limited in New Zealand, making NZEM very sensitive to reservoir inflows. This results in the level and volatility of price fluctuation, being dependent on the amount of water in the reservoirs. They argued that this measure implicitly includes the expected annual average patterns of generation and inflows. Mason et al. (2010) explored a 100% renewable electricity generation system for New Zealand, in which wind accounts for 22–25% in the energy mix. They suggested load shifting could reduce wind energy spillage when incorporating variable generation into a stand-alone grid system. Using synthetic wind speed data provided by the National Institute of Water and Atmospheric Research, Suomalainen et al. (2015) studied the correlation between the seasonal patterns of wind, hydro, demand and prices. By considering the nature of wind and hydro storage levels, they found that sites located in the South Island are most favourable for balancing the hydro storage levels but face high transmission costs. A positive correlation was found between wind generation at CKS1, MWT3, CNIs and NTHs wind sites and electricity demand but with lower transmission costs. This study did not examine the price effect of wind penetration.

While there is empirical evidence regarding the MOE of wind, there is limited evidence on the impact of location on prices controlling for generation mix, season, and demand. Tsai and Eryilmaz (2018) used non-spatial econometric models and conducted regressions separately in four different load zones to assess the impact of wind generation on price in the ERCOT market. Annan-Phan and Roques (2018) applied an AR-GARCH model to examine the effects of domestic and foreign wind generation on cross-border power prices for the German and French market. However, the methods employed by Tsai and Eryilmaz (2018) and Annan-Phan and Roques (2018) do not examine the effect of wind generation at one node on the price at neighbouring nodes. Spatial econometric models estimate local geographic spill-overs using spatial weight matrices. A limited number of studies have applied spatial econometric models to electricity markets. Douglas and Popova (2011) provided a simple representation of the US transmission system and constraints. They concluded that forecasts of electricity prices should incorporate the effects of spatial correlation. Abate and Haldrup (2017) applied a space-time Durbin model to estimate Nord Pool daily electricity spot prices. Their results also confirm the importance of spatial dependence when forecasting over longer time horizons. Bowen and Lacombe (2017) examined the effects of spatial dependence on State renewable electricity policies. The spatial Durbin model (SDM) proved most useful in examining the impact of a renewable policy within a region on member States. Those studies do not examine the MOE and regional price reduction effects.

We apply a spatial econometric approach to estimate the MOE and provide estimates of the spatial and temporal effects of wind generation on regional wholesale prices. The results are used to estimate the economics of alternative wind farm locations.

3. DATA

The New Zealand Electricity Authority's Centralised Dataset (CDS) provides generation, realised nodal price and demand data every half hour. We use hourly data during the period of 1 January 2011 –31 December 2012. In 2011, there was a relatively large increase in installed wind capacity, reaching 623 MW. Installed capacity increased by 66 MW in 2014. The focus of this analysis is on estimation results obtained from the 2012 data. We use 2011 data to do a robustness check.

After excluding nodes that contribute less than 1% of annual demand, we use 11 of the 19 nodes, which is a 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. We further exclude the MAN node as it supplies the Tiwai aluminium smelter directly. A map of these nodes is depicted in Figure 1. Associated regions, generation plants, and spatial coordinates are reported in Table 1. At most there are two types of generation technology at each node.

We use generation share (the ratio of generation to load) instead of generation in the spatial regression analysis because we expect to use impact of generation share to explain the MOE. This also enables us to do further simulations with demand as given. For example, we can estimate the price impact of wind share at each node when demand is given, then with the estimation results, we can predict the regional price impact by increasing the wind share.

Table 2 provides descriptive statistics for nodal price, demand, generation share and generation,[2] at each node. Nodal prices vary by island and node. Average electricity demand is larger at nodes in North Island than South Island. Five nodes have electricity generated by wind. The largest wind generation is 133.89 MW at BPE node, the location of New Zealand's largest wind farm with a capacity of 300 MW. With this information, we calculate the average load factor for wind as 45%

2. Generation technology provides the average generation capacity at each node and isn't included in the models. Prior to the econometric estimation, the Harris and Tzavalis (1999) and Breitung (2000) unit-root test is applied to test the null hypothesis that price, wind/load, hydro/load, thermal/load and load contain unit roots. The test results reject the null hypothesis and are reported in Table A1.

Figure 1: Nodes in the study and the transmission line capacity in MW (only marked values for nodes in the study)

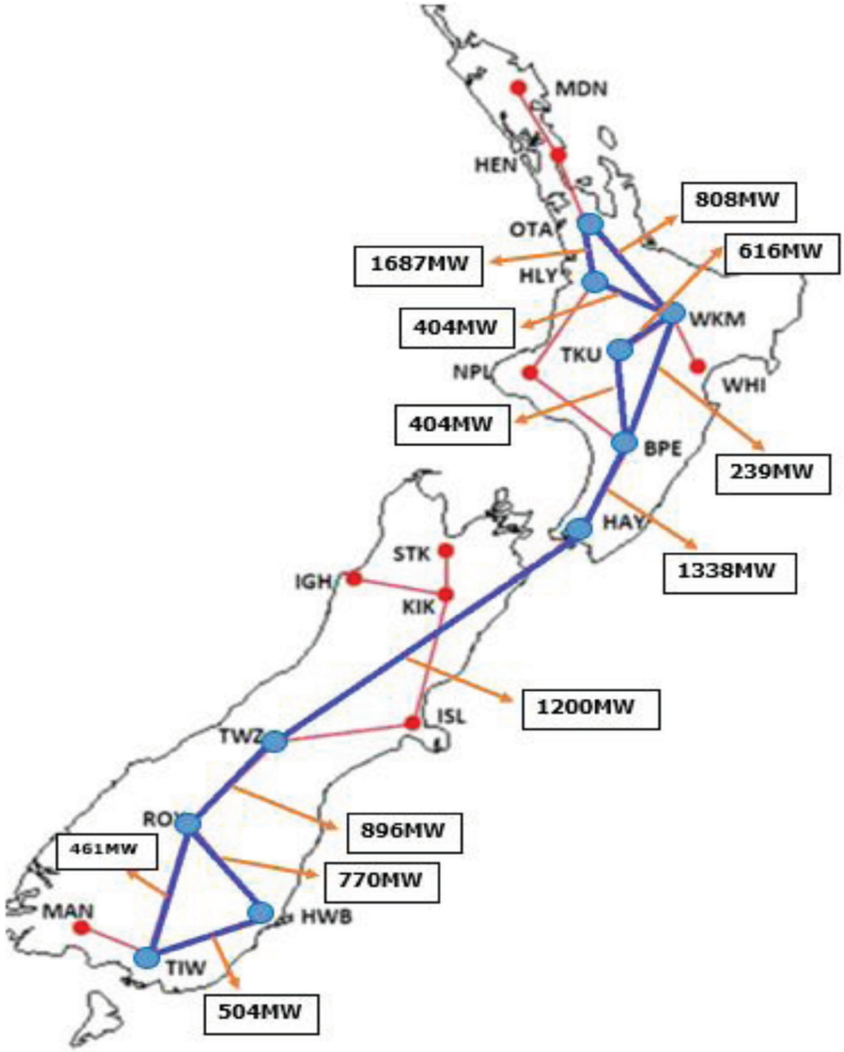


Table 1: Types of plant and X&Y coordinates

Node	Region	Plant types	Y-coordinate Latitude	X-coordinate Longitude
North Island				
BPE	Bunnythorpe	Wind	–40.2809	175.6396
HAY	Haywards	Wind	–41.150278	174.981389
HLY	Huntly	Thermal, Wind	–37.543889	175.152778
OTA	Otahuhu	Thermal	–36.9512	174.865383
TKU	Tokaanu	Hydro	–38.98113	175.768282
WKM	Whakamaru	Geothermal, Hydro	–38.419633	175.808217
South Island				
TWZ	Twizel	Hydro	–44.25	170.1
ROX	Roxburgh	Hydro	–45.475811	169.322555
HWB	Halfway Bush	Wind	–45.854722	170.475
TIW	Tiwai	Wind	–46.598034	168.364105

Table 2: Descriptive statistics of variables by node

	BPE (North Island)	HAY (North Island)	HLY (North Island)	HWB (South Island)	OTA (North Island)	ROX (South Island)	TIW (South Island))	TKU (North Island)	TWZ (South Island)	WKM (North Island)
Nodal Price	79.55 (41.62)	81.87 (44.43)	77.49 (37.88)	90.04 (72.88)	79.27 (39.15)	88.86 (72.09)	92.7 (75.85)	75.99 (37.85)	86.48 (69.41)	75.44 (37.04)
Load (MW)	189.48 (46.38)	349.98 (100.49)	21.25 (12.31)	107.67 (34.12)	808.48 (188.30)	36.32 (11.27)	667.39 (32.51)	4.29 (1.05)	50.58 (11.46)	601.54 (95.78)
Wind/load	0.71 (0.66)	0.18 (0.16)	1.75 (1.73)	0.18 (0.16)			0.03 (0.03)			
wind (MW)	133.89 (92.21)	56.03 (43.99)	24.86 (20.69)	16.46 (12.23)			20.97 (19.84)			
Hydro/load						10.49 (4.10)		20.46 (13.95)	14.56 (4.27)	0.77 (0.23)
hydro(MW)						358.49 (123.56)		90.31 (64.69)	732.46 (244.49)	472.76 (175.62)
Thermal/load			34.27 (17.05)		0.38 (0.20)					
thermal(MW)			620.89 (279.55)		308.01 (172.79)					
Geothermal/load										0.92 (0.18)
geothermal(MW)										538.10 (46.15)

Notes: Mean values. Standard deviation in parentheses.

at BPE. When generation share is larger than 1 electricity is exported from this node to other nodes. In contrast, when generation share is less than 1 electricity is imported from other nodes to meet demand at this node. For example, in the South Island, hydro shares range from 10.49 to 20.46, and these hydro plants are generation centers. In North Island, thermal shares are 0.38 at OTA, and 34.27 at HLY. This indicates that OTA is a load center, and HLY is a generation center. The volatile nature of wind generation is evidenced by the large standard error. With a load factor of 95%, geothermal generation is very stable and reliable. We use geothermal share as a reference category in regression models to avoid multicollinearity.

4. ECONOMETRIC FRAMEWORK

A spatial fixed effects bias-corrected (Lee and Yu, 2010) Durbin model (SDM) is used to examine the MOE of wind penetration.[3] The SDM outperforms both the pooled ordinary least squares (OLS) and panel fixed effects (FE) models because the OLS model does not correct for endogeneity, and both the OLS and FE models do not provide estimates of spill-over effects.[4] The SDM approach extends the previous literature (e.g. Munksgaard and Morthorst, 2008; Sensfuß et al., 2008) on the MOE of wind generation by addressing the potential spill-over effects to/from neighbouring regions.

3. Lee and Yu (2010) pointed out that estimation results obtained from fixed effects model with panel data need to be adjusted to compensate for spatial dependence in the unobserved effects.

4. The Difference in Difference (DID) approach is commonly used to evaluate the outcome of a policy change. It is not applicable to study the spill-over effect of wind on nodal prices.

The functional form is written as:[5]

$$y_{it} = \rho\sum_{j=1}^{N} w_{ij}\, y_{jt} + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\theta + load_{it}\,\psi + \sum_{j=1}^{N} w_{ij} load_{ijt}\phi + \mu_i + \varepsilon_{it} \tag{1}$$

Where

y_{it}—nodal price at node *i* at time *t;*
w_{ij}—the *i, j*-th element of a spatial nonnegative weights matrix *W;*
$w_{ij}\, y_{jt}$—the spatial lag of *y;* and it denotes that nodal price at node *i* , at time *t* depends on nodal price at neighbouring node *j;*
ρ—the dependence of y_{it} on nearby y_{jt}; the significance of ρ indicates the impact of a given nodal price on neighbouring nodes;
x_{it}—wind/load, hydro/load, thermal/load;
$w_{ij}\, x_{ijt}$—the spatial lag of *x;* and it denotes that y_{it} depends on generation technology share at neighbouring node *j;*
θ—the impact of *X* at neighbouring nodes on nodal price;
ψ—the impact of load on nodal price;
ϕ—the impact of load at neighbouring nodes on price;
μ_i *(i=1, ..., n)*—a spatial specific effect;
Error term ε_{it}—an idiosyncratic component which is assumed to be independent and identically distributed *(iid);* $\varepsilon_{it} \sim \mathrm{N}\left(0,\sigma_\varepsilon^2\right)$; and we also assume there are no spatial correlations in the error terms. We test these assumptions in Section 5.
We also use hourly dummy, weekday dummy, and seasonal dummy variables to control for the time deterministic factors.

Lee and Yu (2010) found biased estimates σ^2 in the spatial fixed effects model when N is large and T is fixed, and constructed a bias-correction approach to tackle this issue. Therefore, in this study, we adopt the bias correction procedure to estimate the MOE on nodal price.

We use load instead of residual load in the model because subtracting wind generation from load will affect estimation on wind/load by having load as the given amount.

Because both load and thermal/load are endogenous variables, we use seven days before, at the same hour, lagged variables as their instrumental variables. These variables satisfy two selection criteria: 'relevance' and 'validity'.[6]

The spatial weight matrix W in Eq. (1) is a fundamental component of a spatial model because it establishes which of the spatial units are neighbours and how their values are associated with each other. Diagonal elements of W are obviously set equal to zero. How to set up the values for the non-diagonal elements, and how to construct an empirically justifiable spatial weight matrix are crucial questions that need to be addressed in spatial econometrics.

5. The log-likelihood function of Eq. (1) is in Appendix. We tested a different speciation in which loads and wind in Eq. (1) are non-linear. Test results confirm the linear relationship as illustrated in Eq. (1).

6. For example, load at 9am yesterday, the day before yesterday and so on, must be relevant to load at 9am today because of similar electricity consumption patterns determined by repeated economic and social behaviour. But those past load variables do not directly affect the nodal price at 9am today. Regarding thermal generation, we use past days, at the same hour, thermal generation as alternative instrumental variables. We employ two steps in the regression analysis. Firstly, we use endogenous 'load' and 'thermal/load' variables as independent variables. Each is regressed on exogenous and instrumental variables. Then we use the predicted values to replace the original values of the endogenous variables in the spatial Durbin model.

We start with the traditional way to construct the distance and contiguity matrices based on geographical features. The distance weight matrix is built by using the coordinates of the 10 nodes in Table 1.[7] With the contiguity weight matrix, we treat nodes are neighbours if there is a transmission cable connecting them. To better capture power flow through the electricity network and examine the interaction between nodes, according to the approach proposed by Douglas and Popova (2011), and adopted by Abate and Haldrup (2017), we construct the transmission weight matrix where the non-diagonal elements are calculated based on the transmission line capacity, which is labelled in Figure 1 (Young et al., 2012).

Table 3 reports three spatial weight matrices that are row-standardized. The corresponding value of each non-zero element in the three matrices is different from one another. This implies that the extent of neighbourhood impact obtained varies based on the three matrices.

We test the following hypotheses: H1: increased wind generation is associated with lower nodal prices; H2: nodal prices increase during periods of low hydro storage and are associated with increased thermal generation; H3: the MOE is stronger during peak hours, and lower during off-peak hours.

5. ESTIMATION AND RESULTS

This section firstly justifies the need to consider spatial effects, and then selects the SDM to examine the MOE. Because the MOE is affected by the demand segment, we further explore the MOE in hours. The practical application of the SDM model is used to predict regional price, which could help to choose financially feasible wind sites. Lastly, a robustness check is carried out to verify estimation results.

5. 1 Test for spatial interaction effects

We use Moran's I test (Moran, 1950) for the existence of spatial autocorrelation in nodal prices. Moran's I test statistics reject the null hypothesis of no spatial dependence and reveal a significant positive spatial correlation, indicating that a spatial econometrics model should be applied to estimate the impact of wind generation on nodal prices.[8] However the Moran's I test cannot identify an alternative spatial model (Anselin and Rey, 1991). To further justify whether we should consider a spatially lagged term of nodal price or a spatial auto-correlated error term, we use the classic Lagrange Multiplier (LM)-tests proposed by Anselin (1988) and the robust LM-tests proposed by Anselin et al. (1996). Test results under the different weight matrices, i.e. the transmission, contiguity, and distance weight matrices are reported in Table 4.

Both LM and robust LM tests show that the hypotheses of no spatially lagged dependent variable and the hypotheses of no spatially auto-correlated error term must be rejected at 1% significance. These results show that the non-spatial model is rejected in favour of either the spatial lag or spatial error model when examining the MOE.

In Eq. (1), if unobserved effects, μ_i are correlated with explanatory variables, cross-section analysis from the OLS model will result in omitted unobservable biases. Because longitudinal

7. Different distances lead to different values for non-diagonal elements. Distance is used as a proxy for line-losses. The distance spatial weight matrix is constructed to be close to the transmission weight matrix. Therefore, we chose 300km as the threshold distance. Nodes within 300km receive a weight that is inversely proportional to the distance between the nodes and 0 if they are beyond 300km (Pisati, 2010).

8. The results of Moran's I test are reported in Appendix Table A2.

Table 3: Three row-standardized weight matrices

(1) Based on the distance (the threshold distance is 300 km)

Node	BPE	HAY	HLY	HWB	OTA	ROX	TIW	TKU	TWZ	WKM
BPE	0	0.355797	0.139561	0	0	0	0	0.297044	0	0.207598
HAY	0.53915	0	0	0	0	0	0	0.254787	0	0.206063
HLY	0.104822	0	0	0	0.442399	0	0	0.18638	0	0.266399
HWB	0	0	0	0	0	0.438938	0.237938	0	0.323124	0
OTA	0	0	0.597392	0	0	0	0	0.177117	0	0.225492
ROX	0	0	0	0.376256	0	0	0.309289	0	0.314455	0
TIW	0	0	0	0.304615	0	0.461925	0	0	0.23346	0
TKU	0.188337	0.106607	0.157335	0	0.110724	0	0	0	0	0.436997
TWZ	0	0	0	0.370418	0	0.420533	0.209049	0	0	0
WKM	0.128957	0.084472	0.220326	0	0.138108	0	0	0.428138	0	0

(2) Based on the contiguity (nodes are neighbours if there is a cable connected between them)

Node	BPE	HAY	HLY	HWB	OTA	ROX	TIW	TKU	TWZ	WKM
BPE	0	0.333333	0	0	0	0	0	0.333333	0	0.333333
HAY	0.5	0	0	0	0	0	0	0	0.5	0
HLY	0	0	0	0	0.5	0	0	0	0	0.5
HWB	0	0	0	0	0	0.5	0.5	0	0	0
OTA	0	0	0.5	0	0	0	0	0	0	0.5
ROX	0	0	0	0.333333	0	0	0.333333	0	0.333333	0
TIW	0	0	0	0.5	0	0.5	0	0	0	0
TKU	0.5	0	0	0	0	0	0	0	0	0.5
TWZ	0	0.5	0	0	0	0.5	0	0	0	0
WKM	0.25	0	0.25	0	0.25	0	0	0.25	0	0

(3) Based on the transmission line capacity (Young et al., 2012).

Node	BPE	HAY	HLY	HWB	OTA	ROX	TIW	TKU	TWZ	WKM
BPE	0	0.675416	0	0	0	0	0	0.203937	0	0.120646
HAY	0.527187	0	0	0	0	0	0	0	0.472813	0
HLY	0	0	0	0	0.806791	0	0	0	0	0.193209
HWB	0	0	0	0	0	0.604396	0.395604	0	0	0
OTA	0	0	0.676152	0	0	0	0	0	0	0.323848
ROX	0	0	0	0.362012	0	0	0.216737	0	0.421251	0
TIW	0	0	0	0.52228	0	0.47772	0	0	0	0
TKU	0.396078	0	0	0	0	0	0	0	0	0.603922
TWZ	0	0.572519	0	0	0	0.427481	0	0	0	0
WKM	0.115627	0	0.195452	0	0.390905	0	0	0.298016	0	0

data capture price at the same node over time, the time-invariant unobservable effects are eliminated by using a panel fixed effects model. Estimation results from the fixed effects (FE) models are consistent. In contrast, a random effects generalized least squares (GLS) model assumes that μ_i is uncorrelated with explanatory variables using the optimal combination of within-group and between-group variations. A Hausman test is used to identify whether the random effects GLS estimator is biased. Results for the models in columns 2 and 3 in Table 4 reject the null hypothesis that unobserved effects are uncorrelated with the explanatory variables of the equation. Therefore, fixed effects estimates are selected over the random effects.

Table 4: Non-spatial model with LM tests using *Transmission, Contiguity and Distance Weight Matrices*

VARIABLES	Pooled OLS	Panel fixed effects	Panel random effects
Wind/load	–5.9359***	–5.3451***	–5.3408***
	(0.287)	(0.298)	(0.298)
hydro/load	–0.3189***	–0.3416***	–0.3264***
	(0.023)	(0.034)	(0.034)
thermal/load	0.0468**	0.1170***	0.1262***
	(0.020)	(0.033)	(0.032)
load	–0.0042***	0.0810***	0.0711***
	(0.001)	(0.003)	(0.002)
Monday	11.8600***	9.7142***	9.9569***
	(0.611)	(0.607)	(0.608)
Tuesday	18.8381***	16.2609***	16.5672***
	(0.614)	(0.613)	(0.613)
Wednesday	20.1119***	17.4570***	17.7735***
	(0.614)	(0.613)	(0.613)
Thursday	18.6401***	15.9063***	16.2310***
	(0.614)	(0.614)	(0.613)
Friday	15.0525***	12.7115***	12.9924***
	(0.614)	(0.611)	(0.611)
Saturday	7.4662***	7.0770***	7.1324***
	(0.614)	(0.606)	(0.607)
spring	–44.3893***	–42.1742***	–42.4200***
	(0.467)	(0.468)	(0.468)
summer	–0.0822	3.2720***	2.8813***
	(0.466)	(0.471)	(0.470)
autumn	20.7973***	22.7382***	22.5007***
	(0.464)	(0.464)	(0.464)
Hourly dummies	Yes[a]	Yes	Yes
Constant	74.4055***	50.7108***	53.2797***
	(0.988)	(1.194)	(2.389)
R-squared	0.233	0.243	0.243
F-test	742.7	783	
		Hausman test-statistics—fixed versus random effects (Wald-test Chi2, probability) = (134.3, p=0.000)	

	Transmission W	*Contiguity W*	*Distance W*	*Transmission W*	*Contiguity W*	*Distance W*
LM test: no spatial lag	78608.20	90303.86	129221.30	78376.53	90095.60	129247.25
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Robust LM test: no spatial lag	1701.01	2252.78	1697.20	2677.67	2974.96	2510.59
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
LM test: no spatial error	77556.07	89065.02	127815.04	76296.80	87905.44	127004.42
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Robust LM test: no spatial error	648.87	1013.95	290.94	597.94	784.81	267.75
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.000]***

Notes: [a] denotes the hourly dummies are included as explanatory variables; Dependent Variable: Nodal Price ($/MWh) 2012; Authors' elaboration based on Matlab software; Observations=87,840, T=8784, 10 nodes; Geothermal generation is excluded in the model to avoid multicollinearity; The reference variables are 23:00, Sunday and winter; Standard errors of coefficient estimates and p-values of test results in parentheses; *** (**,*) indicates 1% (5%, 10%) level of significance.
Source: Electricity Authority (EA), Centralised Dataset.

5. 2 Coefficient estimation

If a non-spatial model is rejected based on the LM tests, the spatial Durbin model is recommended by Lesage and Pace (2009). The model extends the spatial lag model by including spatially lagged independent variables. As discussed previously, we adopt the spatial fixed effects bias-corrected Durbin model (SDM), as proposed by Lee and Yu (2010) to examine the MOE under three weight matrices. Following Eq. (1), the estimation results of the SDM are given in Table 5.

Table 5: Spatial Durbin Model (SDM) estimation results using *Transmission, Contiguity and Distance Weight Matrices and 2012 data*

	Coefficients (t-statistics)		
	Transmission W	Contiguity W	Distance W
wind/load	–0.5691***	–0.7531***	–0.1871***
	(–6.753)	(–9.440)	(–6.174)
hydro/load	–0.1262***	–0.1120***	–0.0712***
	(–13.317)	(–12.448)	(–20.757)
thermal/load	0.0773***	0.0757***	–0.0150***
	(8.636)	(8.929)	(–4.668)
load	0.0146***	0.0139***	0.0127***
	(22.488)	(22.044)	(53.171)
Spatially lagged dependent term(ρ)			
W*price	0.8926***	0.8996***	0.9648***
Spatially lagged independent terms	(1228.154)	(1320.019)	(4706.847)
W*wind/load	–1.4546***	–1.4825***	–0.3825***
	(–11.999)	(–11.020)	(–8.236)
W*hydro/load	–0.9205***	–0.7675***	–0.1360***
	(–43.0766)	(–40.833)	(–24.187)
W*thermal/load	0.1537***	0.1538***	0.0462***
	(12.086)	(10.233)	(9.536)
W*load	0.0105***	0.0140***	0.0023***
	(15.065)	(17.741)	(6.397)
R-squared	0.9423	0.9481	0.9925
Wald test spatial lag	2.2606e+03 (p=0.000)	2.1386e+03 (p=0.000)	821.4002 (p=0.000)
LR test spatial lag	2.3100e+03 (p=0.000)	2.1592e+03 (p=0.000)	824.6978 (p=0.000)
Wald test spatial error	3.2399e+03 (p=0.000)	3.2321e+03 (p=0.000)	2.7071e+03 (p=0.000)
LR test spatial error	3.2725e+03 (p=0.000)	3.2315e+03 (p=0.000)	3.0518e+03 (p=0.000)
Test for SAR (H_0:θ=0) chi2(4)	1511.19	1189.72	507.53
Prob > chi2	0.000	0.000	0.000
Test for SEM (H_0:θ+ρβ=0) chi2(4)	2012.46	1717.51	2106.47
Prob > chi2	0.000	0.000	0.000
Observations	87,840	87,840	87,840

Notes: Authors' elaboration based on Matlab software; Dependent Variable: Nodal Price ($/MWh) 2012; Observations=87,840, T=8784, 10 nodes; Geothermal generation is excluded in the model to avoid multicollinearity; T-statistics of coefficient estimates and p-values of test results in parentheses; *** (**,*) indicates 1% (5%, 10%) level of significance.
Source: Electricity Authority (EA), Centralised Dataset.

Depending on the value of parameters in Eq. (1), based on Elhorst (2014), we further test two hypotheses to examine whether the SDM model can be reduced to a Spatial Autoregressive Model (SAR) or a Spatial Error Model (SEM): (1) If $\theta = 0$, the SDM model becomes a SAR model by excluding exogenous interaction effects (WX); (2) If $\theta = -\beta\rho$, then the SDM model becomes a SEM model.[9] Both Wald and LR tests indicate that the hypothesis whether the SDM can be simplified to the SAR and SEM must be rejected. This confirms that the SDM should be selected.

Statistically significant coefficients on both spatially lagged dependent and independent variables at the 1 percent level strongly support the hypothesis that a nodal price observed at node i is determined by the price and other factors at neighbouring nodes.

We find the choice of weight matrix does affect the magnitude and significance of coefficients, which indicates that selecting an appropriate weight matrix is crucial in the spatial model. The signs of the coefficients are as expected, under both transmission W and contiguity W. The inconsistent coefficient between columns 1–2 and 3 indicates estimated bias from the model with

9. These models are used to test if there is spatial correlation in the error terms.

distance W. Without considering the transmission constraints under the contiguity W, the MOE of wind penetration is larger than those under the transmission W. Because the transmission W captures the characteristics of electricity network, we use it for spatial analysis.

The negative and significant coefficients on wind penetration show the price dampening effects of increased wind penetration. Enlarging hydro share also reduces nodal prices. In contrast, coefficients on the thermal share are significant and positive. This is plausible given that thermal energy is relatively more expensive.

The parameter estimates of the SDM in Table 5 do not give an explicit explanation of a change in wind penetration, and other technology shares, on nodal prices because of the feedback effects (or so-called global effects) from the $\left(I-\rho W\right)^{-1}$ term. We report marginal effects in Table 6. The total effect[10] of a 10% point increase in wind penetration on nodal prices is a reduction of \$1.8 per MWh, which is three times' larger than those obtained from the non-spatial model estimation in row 1 of Table 4. This shows that disregarding spatial spill-overs leads to an underestimation of the MOE of wind penetration on nodal prices.

Table 6: Total effects of nodal price (2012)

Dependent Variable: Nodal Price (\$/MWh) 2012

SDM Model	Transmission W	Contiguity W	Distance W
wind/load	–18.8461***	–22.2139***	–15.7113***
	(–13.465)	(–14.912)	(–10.446)
hydro/load	–9.7430***	–8.7682***	–5.7142***
	(–44.040)	(–42.472)	(–32.011)
thermal/load	2.1548***	2.2832***	0.8605***
	(15.457)	(13.827)	(5.503)
load	0.2340***	0.2779***	0.4143***
	(33.282)	(35.299)	(41.250)

Notes: Authors' elaboration based on Matlab software; Observations=87,840, T=8784, 10 nodes; Geothermal generation is excluded in the model to avoid multicollinearity; *** (**,*) indicates 1% (5%, 10%) level of significance; T-statistics of coefficient estimates and p-values of test results in parentheses.
Source: Electricity Authority (EA), Centralised Dataset.

Adding 10% point more hydro supply is estimated to reduce the nodal price by \$0.9 per MWh. In contrast, 10% point more thermal increases price by \$0.2 per MWh. Increased load also raises the nodal price. The impact of load on nodal price can't be explained in Table 6 because generation mix share contains load as its denominator.

5.3 Hourly estimation of MOE

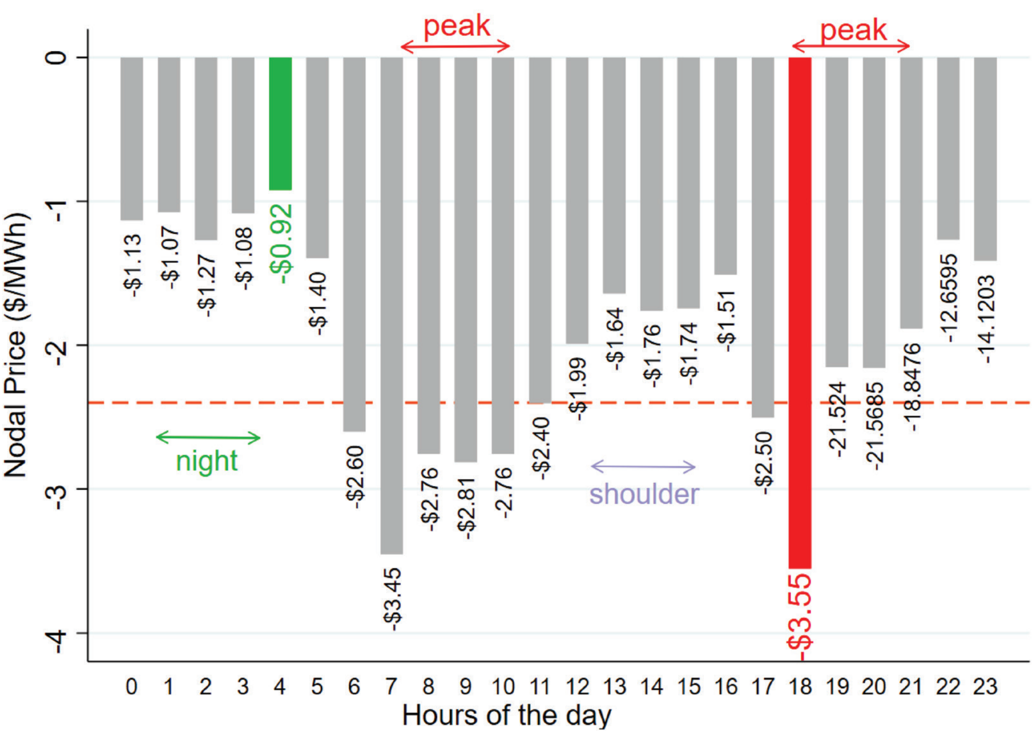
In New Zealand, price and demand follow morning and evening peaks. Approximately 5000 MW is required to meet morning and evening peaks. During the peak load period, the additional load is generated by the more expensive peaking plants which drive up the nodal price. The MOE is affected by the demand segment. Hourly effects are illustrated in Figure 2.[11] Negative and significant effects of wind penetration are found for each hour, but those effects vary from hour to hour. As expected, we find stronger impacts during the morning peak load from 6am to 11am and the evening peak from 5pm to 9pm, and lower during off-peak load from midnight to 5am. A 10%

10. The direct and indirect effects are available upon request. We find negative and significant direct and indirect effects of wind penetration on price.

11. Estimation results are reported in Table A3.

increase in the wind share has the highest price impact of $3.55 at 6pm, the lowest is $0.92 at 4am. These results are consistent with findings from Nicholson et al. (2010) and Pöyry (2010) but with more detailed information. The findings in Figure 2 provide insights into designing pricing plans for electricity market participants.

Figure 2: Average network hourly price effects of an increase of 10% in wind penetration



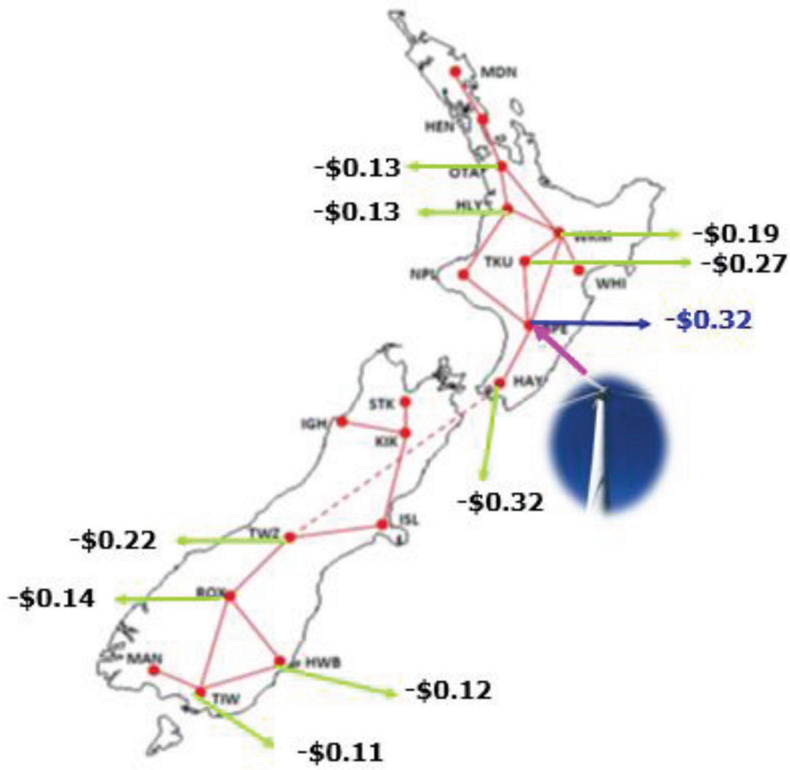
5.4 Price prediction and simulation

This section predicts the regional price effects of an increase in wind penetration at each node, and then evaluates the financial net savings derived from the price reduction due to increased wind penetration and the annual costs of adding wind capacity. Electricity generated from wind is currently injected into 5 out of 10 nodes: BPE with installed wind capacity 300.25 MW; HAY, 143MW; HLY, 64.4MW; HWB, 36MW; and TIW, 58MW. We simulate an increase in the same amount of wind penetration at each node using the model in Eq. (1). Table 7 presents the simulation results. In column 1, wind penetration at node BPE is increased by 10%. The price reduction is $0.32 at its own node, and ranges from $0.11 to $0.32 at its neighbouring nodes (See Figure 3). If we increase generation by the same amount at node HAY, we obtain negative and significant direct and spill-over effects, as reported in column 2. We apply the same method to the other eight nodes. The last row of Table 8 shows that the price reduction effects are different across nodes by increasing the same amount of wind penetration due to the regional network, line capacity, and other unobserved factors. This price reduction effect accrues to the wholesale market as financial savings, the extent to which this is passed on to consumers is beyond the scope of this research.

Table 7: Approximations for the impact on nodal price due to an increase in 10% wind penetration in 10 nodes using *transmission W.*

	The regional effect of a 10% point increase in wind penetration while keeping other controlled variables constant									
Node	BPE	HAY	HLY	HWB	OTA	ROX	TIW	TKU	TWZ	WKM
BPE	–0.3193	–0.4079	–0.1362	–0.0751	–0.1678	–0.1518	–0.0559	–0.1410	–0.2293	–0.1999
HAY	–0.3184	–0.4148	–0.0899	–0.1064	–0.1108	–0.2151	–0.0792	–0.0931	–0.3247	–0.1320
HLY	–0.1290	–0.1091	–0.4654	–0.0201	–0.5752	–0.0406	–0.0150	–0.1170	–0.0613	–0.3516
HWB	–0.1168	–0.2120	–0.0330	–0.3470	–0.0406	–0.4987	–0.2766	–0.0341	–0.2770	–0.0484
OTA	–0.1332	–0.1127	–0.4821	–0.0208	–0.5308	–0.0419	–0.0154	–0.1209	–0.0633	–0.3632
ROX	–0.1414	–0.2566	–0.0399	–0.2987	–0.0492	–0.4408	–0.2223	–0.0413	–0.3353	–0.0586
TIW	–0.1148	–0.2082	–0.0324	–0.3651	–0.0399	–0.4900	–0.2806	–0.0335	–0.2721	–0.0476
TKU	–0.2738	–0.2316	–0.2399	–0.0426	–0.2956	–0.0862	–0.0317	–0.2004	–0.1301	–0.3522
TWZ	–0.2167	–0.3932	–0.0612	–0.1684	–0.0754	–0.3403	–0.1253	–0.0633	–0.3508	–0.0898
WKM	–0.1916	–0.1621	–0.3557	–0.0298	–0.4384	–0.0603	–0.0222	–0.1738	–0.0911	–0.3593
Average Price effect	–0.1955	–0.2508	–0.1936	–0.1474	–0.2324	–0.2366	–0.1124	–0.1019	–0.2135	–0.2003

Figure 3: The regional price effect \$/MWh of a 10% point increase in wind penetration at BPE



Based on the total effects from Table 7, and annual electricity consumption 38,564 GWh in 2012 (MBIE, 2013), we calculate the annual wholesale market savings for each node and report those savings in column 2 of Table 8. The results show that increased wind generation would result in annual savings of between \$3.9 million and \$9.7 million in 2012 depending on the region.

The next step is to calculate the annual cost if we increase a certain amount of wind generation to reach the 10% wind/load share and to achieve the above price reduction at each node. This additional wind generation is calculated based on the average load reported in row 2 of Table 2.

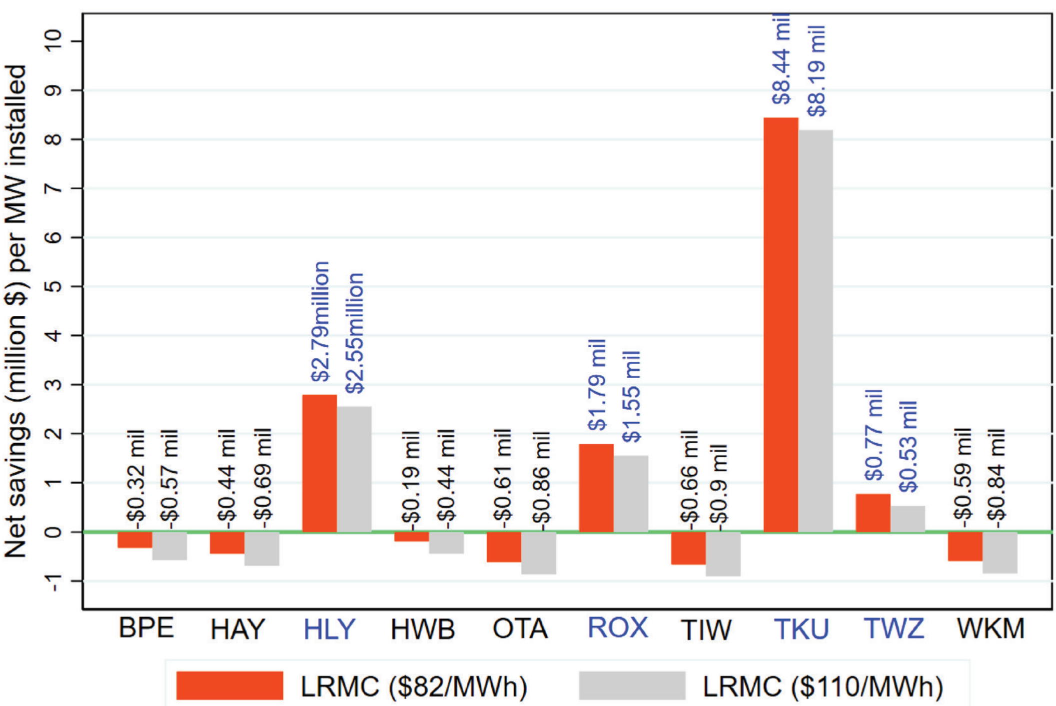
Table 8: Estimated costs of adding wind capacity to meet an increase of 10% wind/load and estimated annual savings using *transmission W* (policy implication for investing wind farms for different locations)

				LRMC ($82/MWh)			LRMC ($110/MWh)			
	1	2	3	4	5	6	7	8	9	10
Node	Price effect ($/MWh)	Annual savings (million $)	10%of load (MW)	Annual costs (million $)	Net Savings (million $)	Net Savings Per MW	Annual costs (million $)	Net Savings (million $)	Net Savings Per MW	Rank Per MW
BPE	–0.1955	7.5397	18.9480	13.6480	–6.1084	–0.3224	18.3083	–10.7687	–0.5683	6
HAY	–0.2508	9.6726	34.9980	25.2086	–15.5360	–0.4439	33.8165	–24.1438	–0.6899	7
HLY	–0.1936	7.4641	2.1250	1.5306	5.9335	2.7922	2.0533	5.4108	2.5463	2
HWB	–0.1474	5.6847	10.7670	7.7553	–2.0706	–0.1923	10.4035	–4.7188	–0.4383	5
OTA	–0.2324	8.9611	80.8480	58.2338	–49.2727	–0.6094	78.1186	–69.1575	–0.8554	9
ROX	–0.2366	9.1235	3.6320	2.6161	6.5074	1.7917	3.5094	5.6141	1.5457	3
TIW	–0.1124	4.3354	66.7390	48.0713	–43.7359	–0.6553	64.4859	–60.1505	–0.9013	10
TKU	–0.1019	3.9277	0.4290	0.3090	3.6187	8.4353	0.4145	3.5132	8.1893	1
TWZ	–0.2135	8.2334	5.5080	3.9673	4.2661	0.7745	5.3220	2.9114	0.5286	4
WKM	–0.2003	7.7228	60.1540	43.3282	–35.6054	–0.5919	58.1232	–50.4004	–0.8379	8

Long run marginal cost (LRMC), is commonly used in New Zealand as a significant consideration in future investment decisions (Sapere, 2018). Potential wind projects are filtered by wind farm investors according to the LRMC and development proceeds only when wholesale electricity prices are expected to be sufficient to make them economically viable (Deloitte, 2011).[12]

Net annual wholesale market savings are calculated under the two scenarios based on LRMC \$82/MWh and \$110/MWh, and are reported in columns 6 and 9 in Table 8. Correspondingly, we illustrate the estimated net annual savings per MW in Figure 4. We find positive net savings at 4 out of 10 nodes under both scenarios. According to 'net savings per MW', the most financially attractive wind site should be built close to TKU as it offers the largest net savings of \$8 million. In contrast, TIW is the least preferred option for wind development due to its net loss of \$0.7 million per MW installed. According to Browne et al. (2014), we match our nodes of interest with corresponding wind sites.[13] Our results show that wind generation at CNIs (i.e. CNI1 and CNI2) can meet electricity demand corresponding to Suomalainen et al. (2015). We conclude that CNI2 is the best wind site to develop because it offers the highest potential net annual savings.

Figure 4: Estimated net annual savings (million \$) per MW installed



12. A 2011 report, prepared for the NZ Wind Energy Association, written by Deloitte (Deloitte, 2011), based on a representative sample of projects, demonstrates that the LRMC was between \$78 and \$105/MWh in \$2010. Based on the consumer price index released from Stats NZ, we convert LRMC to \$82-\$110/MWh in \$2012 so as to be consistent with the 2012 data used in the study. LRMC, expressed in \$/MWh, is derived from using the net present value of sum of the capital and operating costs (\$) divided by net wind generation (MWh). It indicates an equivalent cost per unit of wind generation over the life of the plant.

13. See Table A4.

5.5 Robustness analysis

As a hydro-dominated electricity system, in a dry year (as was 2012), 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 now turn to an investigation of whether the effects of wind penetration on nodal prices are sensitive to weather conditions during dry or normal years. To verify our previous results based on the 2012 data, we carry out a robustness analysis on the impact of wind penetration on nodal prices using 2011 data (considered a "normal" year). Signs of the coefficients on variables of interest in Table 9 are consistent with those in Table 5. In terms of the marginal effects reported in Table 10, we find consistent results on wind penetration compared to those in Table 6. This shows that the impact of wind penetration in 2012 is quite similar to 2011. However, the marginal effects of hydro share and thermal share on nodal prices are determined by weather conditions and adjust accordingly during dry and normal years.

Table 9: Spatial Durbin Model (SDM) estimation results using *Transmission, Contiguity and Distance Weight Matrices and 2011 data*

	Coefficients (t-statistics)		
	Transmission W	Contiguity W	Distance W
wind/load	–0.8644***	–1.0359***	–0.6253***
	(–5.235)	(–5.620)	(–4.681)
hydro/load	–0.0530***	–0.0547***	–0.0699***
	(–3.312)	(–3.059)	(–5.379)
thermal/load	0.0444**	0.0067	–0.0376**
	(2.094)	(0.283)	(–2.190)
load	0.0097***	0.0098***	0.0080***
	(10.846)	(9.556)	(10.955)
W*price	0.8246***	0.8206***	0.8748***
	(740.280)	(720.050)	(1213.9492)
W*wind/load	–2.0086***	–2.7127***	–1.4011***
	(–8.551)	(–8.671)	(–7.007)
W*hydro/load	–0.5187***	–0.3956***	–0.0810***
	(–14.165)	(–10.512)	(–3.924)
W*thermal/load	0.1043***	0.1354***	0.0724***
	(3.463)	(3.228)	(2.824)
W*load	0.0105***	0.0122***	0.0104***
	(10.308)	(9.860)	(9.760)
R-squared	0.8636	0.8298	0.9107
Wald test spatial lag	371.3053 (p=0.000)	283.2499 (p=0.000)	161.3362 (p=0.000)
LR test spatial lag	366.5916 (p=0.000)	290.5234 (p=0.000)	170.2133 (p=0.000)
Wald test spatial error	644.1326 (p=0.000)	544.0206 (p=0.000)	423.6100 (p=0.000)
LR test spatial error	656.0936 (p=0.000)	588.3677 (p=0.000)	437.3261 (p=0.000)
Test for SAR (H_0:θ=0) chi2(4)	368.55	289.82	162.31
Prob > chi2	0.000	0.000	0.000
Test for SEM (H_0:θ+ρβ=0) chi2(4)	639.53	558.25	425.68
Prob > chi2	0.000	0.000	0.000
Observations	87,600	87,600	87,600

Notes: Authors' elaboration based on Matlab software; Dependent Variable: Nodal Price ($/MWh) 2011; Observations=87,600, T=8760, 10 nodes; Geothermal generation is excluded in the model to avoid multicollinearity; T-statistics of coefficient estimates and p-values of test results in parentheses; *** (**,*) indicates 1% (5%, 10%) level of significance.
Source: Electricity Authority (EA), Centralised Dataset.

Table 10: Total effect of nodal price (2011)

Dependent Variable: Nodal Price ($/MWh) 2011			
SDM Model	Transmission W	Contiguity W	Distance W
wind/load	–16.4090***	–20.9219***	–16.1337***
	(–10.495)	(–10.011)	(–8.434)
hydro/load	–3.2701***	–2.5150***	–1.2023***
	(–14.880)	(–10.641)	(–6.085)
thermal/load	0.8473***	0.7943***	0.2824
	(4.253)	(3.080)	(1.149)
load	0.1152***	0.1222***	0.1468***
	(18.888)	(18.037)	(17.503)

Notes: Authors' elaboration based on Matlab software; Observations=87,600, T=8760, 10 nodes; Geothermal generation is excluded in the model to avoid multicollinearity; *** (**,*) indicates 1% (5%, 10%) level of significance; T-statistics of coefficient estimates and p-values of test results in parentheses.
Source: Electricity Authority (EA), Centralised Dataset.

6. CONCLUSIONS AND POLICY IMPLICATIONS

The paper's main contribution follows from the application of the SDM model to estimate the spatial spill-over and temporal effects of wind penetration on nodal prices. We find a negative and significant relationship between nodal prices and wind penetration. Ignoring spatial spill-overs leads to an underestimation of the impact of wind generation on nodal prices. Increased wind-generated electricity injected into the grid lowers nodal price. Furthermore, surplus wind-generated electricity can be exported to neighbourhood nodes, which reduces their nodal price. The total effect of a 10% point increase in wind penetration on nodal prices is a reduction of $0.92 per MWh at 4am, and $3.55 per MWh at 6pm. These effects are statistically significant. Based on estimates from the SDM model, we further find that CNI2 is the best wind site for expanding wind capacity, offering a net savings of $8 million per MW of wind capacity installed. Development at TIW is the worst option because it results in a potential net loss of $0.7 million.

The ability of spatial econometric models to provide quantitative estimates of spill-over magnitudes, and to allow statistical testing for significance, represents a valuable contribution of spatial models to understanding and forecasting regional electricity prices, and locating financially feasible wind sites. This methodology will be applicable to analysing the cross-border effects in any electricity system that has opportunities to export or import electricity from neighbouring countries, such as Switzerland or Germany.

Having halted all off-shore oil and gas exploration and limited on-shore exploration in Taranaki, New Zealand's oil and gas province, Government policy is directed at transitioning to a low-emission economy. Achieving the target of 90% of electricity generated from renewable by 2025 will require investment in wind. In an energy-only market, the wholesale electricity price is a critical parameter when analysing the return on wind farm investment.

From the perspective of commercial investment in wind farm development significant negative spill-over effects indicate that scalability would be an advantage in a small electricity system like NZ where turbines can be added as demand increases. However, in an electricity market that receives no subsidies private investment must be financially viable. Investing in capacity at a given node can reduce the return to a generator's assets in the network and reduce the return to investment at neighbouring sites. Therefore, to incentivise wind farm investment, electricity demand needs to grow. This may come from growth in electrification of transport. 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. Reaching the goal of 20% of electricity from wind generation depends on growth in demand.

Our findings have policy implications for electricity system design and wind deployment. Adding more intermittent wind generation into the electricity system will create challenges for the system operator and market participants. Electricity generated by wind is independent and non-adjustable to electricity demand. Adding more intermittent wind generation will increase the volatility of nodal prices. Wind expansion requires a resilient power system that keeps frequency. In NZEM, geothermal provides base-load and hydro and thermal provide generation flexibility. Battery storage, hydro development, increased uptake of solar and demand response could contribute to balancing supply and demand. Although hydro can accommodate variations in demand it is vulnerable to drought weather. A key challenge is to ensure continuity of supply during dry-year events. Thermal generators provide a stable and flexible power supply. Closure of the Huntly thermal power station will increase the risk of supply disruption. The addition of more wind generation could lead to a need for more flexible peaking plants. Because peaking plants only generate for a short period, and maintaining those plants are expensive, this may lead to the debate on the need for a capacity market.

Wind farm development in New Zealand has faced community opposition. To illustrate, Meridian Energy proposed a NZ$2 billion 630 MW wind farm in Central Otago, making it the largest wind farm project in the Southern Hemisphere. The project met with strong opposition over the impact on amenity values. After a series of public hearings and litigation the project was abandoned in 2012, at a cost of approximately NZ$7 million. As noted earlier, Government does not provide financial subsidies to renewable sources of electricity generation. However, Government's National Policy Statement does provide guidance for planning and obtaining the necessary consents for development. [14] Guidance is limited to a requirement that decision makers recognise the benefits of renewable electricity generation at the time of applying for consents to proceed with development. Spatial mapping of potential wind sites that included wind speeds, environmental attributes and proximity to residential communities, combined with estimates of the economic benefits of additional wind generation could contribute to greater public acceptance and lower consenting costs.

The findings of this study have policy implications for wind farm development in New Zealand. An economic evaluation of expanding wind capacity for various wind sites derived from our spatial econometric models provides empirical evidence on where to build an economically viable wind farm. However, there is no national plan providing guidance as to the most desirable locations. Decisions to proceed with obtaining necessary planning consents are based on expected commercial returns within the context of network connection and any community resistance. The consent granting process does not assess the merits of a particular location against alternative sites. Investigating the most suitable sites for development, considering the wind resource, network connections, land ownership and proximity to potentially affected communities is a topic for future research that could provide guidance for a national policy on future development.

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14. https://www.mfe.govt.nz/more/energy/national-policy-statement-renewable-electricity-generation/about-nps.

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APPENDIX A: LIST OF ABBREVIATIONS

CDS	Centralised Dataset
EA	Electricity Authority
EMI	Electricity Market Information
ENZ	Electricity in New Zealand
FIT	Feed-in tariff
HVDC	High-voltage direct current
LM	Lagrange Multiplier
LR	Likelihood Ratio
LRMC	Long run marginal cost
ISO	Independent System Operator
MBIE	Ministry of Business, Innovation and Employment
MOE	Merit-order effect
NZ	New Zealand
NZEM	New Zealand electricity market
OLS	Ordinary Least Squares
RES	Renewable energy sources
SAR	Spatial Autoregressive Model
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SPD	Schedule, Pricing and Dispatch
SWEM	An agent-based modelling program designed specifically to model short-run firm behaviours in nodal pricing.
MW	Megawatt
GW	Gigawatt 1 Gigawatt = 1 000 megawatts
TW	Terawatt 1Terawatt = 1 000 000 megawatts

APPENDIX B: THE LOG-LIKELIHOOD FUNCTION

We assume the spatial specific effect μ_i is time-invariant. After substituting the solution for μ_i into the log-likelihood function of Eq. (1), the concentrated log-likelihood function with respect to β, ρ, σ^2, θ, φ, and ψ is written as:

$$LogL = -\frac{NT}{2}\log\left(2\pi\sigma^2\right) + Tlog\left|I_N - \rho W\right|$$
$$-\frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it}^{*} - \rho\left[\sum_{j=1}^{N} w_{ij} y_{jt}\right]^{*} - x_{it}^{*}\beta - \left[\sum_{j=1}^{N} w_{ij} x_{jt}\right]^{*}\theta - load_{it}^{*}\psi - \left[\sum_{j=1}^{N} w_{ij} load_{jt}\right]^{*}\phi\right)^{2} \quad \text{(A1)}$$

Where the asterisk denotes the demeaning procedure (Elhorst, 2010). The parameters β, ρ, σ^2, θ, φ, and ψ can be estimated by maximum likelihood. The endogeneity of $\sum_{j=1}^{N} w_{ij} y_{jt}$ is addressed by the second Jacobian term on the right-hand side of Eq. (A1) (Anselin, 1988).

Table A1: Results of panel unit root tests

Variables	Price	Wind/load	Hydro/load	Thermal/load	load
Harris-Tzavalis	0.9213***	0.9394***	0.8815***	0.8983***	0.9368***
Breitung	–56.9682***	–17.7995***	–27.4771***	–9.2645***	–32.0022***

Notes: Harris-Tzavalis and Breitung represent the panel unit root tests of Harris-Tzavalis (1999) and Breitung (2000), respectively. For both tests, Ho: Panels contain unit roots; Ha: Panels are stationary.
*** (**,*) indicates 1% (5%, 10%) level of significance.
The Test results reject the null hypothesis that the panels contain a unit root. Those panels have no unit root process and they are stationary.

Table A2: Results of Moran's I test for nodal prices using *Transmission, Contiguity and Distance Weight Matrices*

Weights	Moran's I	P-value
Transmission W	0.765	0.001
Contiguity W	0.813	0.000
Distance W	0.875	0.000

Source: authors' elaboration based on Centralised Dataset.

Table A3: Hourly effects of wind penetration on nodal price 2012 using *Transmission W*

hour	0	1	2	3	4	5
wind/load	–11.3182 **	–10.7481**	–12.7042**	–10.8320***	–9.2152**	–13.9567***
	(–2.475)	(–2.260)	(–2.706)	(–2.938)	(–2.361)	(–3.516)
hydro/load	–8.7180 ***	–7.7825***	–7.6491***	–6.9911***	–7.4383***	–7.2411***
	(–11.366)	(–8.649)	(–8.594)	(–9.917)	(–9.788)	(–10.412)
thermal/load	2.3655***	2.7592***	3.0026***	2.9363***	3.1668***	3.4209***
	(4.678)	(4.770)	(4.826)	(5.448)	(5.729)	(6.289)
load	0.4262***	0.5190***	0.5298***	0.6029***	0.5376***	0.3411***
	(4.609)	(4.691)	(4.658)	(6.462)	(5.742)	(4.907)
R-squared	0.9496	0.9354	0.9259	0.9429	0.9526	0.9593
hour	6	7	8	9	10	11
wind/load	–26.0118***	–34.5050***	–27.5595**	–28.1379**	–27.5647**	–24.0303**
	(–4.390)	(–4.014)	(–2.759)	(–2.905)	(–2.720)	(–2.689)
hydro/load	–8.5718***	–8.2590***	–10.2422***	–12.2274***	–12.7137***	–13.0494***
	(–10.276)	(–7.167)	(–7.318)	(–8.243)	(–8.801)	(–9.640)
thermal/load	4.1220***	3.7166***	1.6373*	1.4706	1.7185*	1.5472*
	(5.454)	(4.033)	(1.827)	(1.781)	(1.985)	(1.861)
load	0.2532***	0.3162***	0.3553***	0.2653***	0.3175***	0.3415***
	(5.460)	(8.243)	(7.440)	(4.397)	(4.665)	(4.968)
R-squared	0.9477	0.9505	0.9493	0.9284	0.9270	0.9274
hour	12	13	14	15	16	17
wind/load	–19.9022**	–16.4062**	–17.6092**	–17.44228**	–15.10202*	–25.0410**
	(–2.478)	(–2.291)	(–2.199)	(–2.446)	(–1.9145)	(–2.691)
hydro/load	–12.4421***	–11.9308***	–11.8058***	–10.6264***	–10.6608***	–12.9275***
	(–10.258)	(–10.670)	(–9.781254)	(–10.814)	(–10.250)	(–10.202)
thermal/load	1.5559*	1.8382**	1.787537**	1.7974**	1.6834**	2.6575**
	(2.071)	(2.802)	(2.380460)	(2.556)	(2.206)	(2.905)
load	0.3577***	0.3717***	0.366791**	0.3062***	0.2481***	0.1763***
	(5.320)	(6.038)	(5.324492)	(5.395)	(4.674)	(3.322)
R-squared	0.9381	0.9405	0.9423	0.9358	0.9430	0.9502
hour	18	19	20	21	22	23
wind/load	–35.5169***	–21.5240**	–21.5685**	–18.8476**	–12.6595*	–14.1203**
	(–3.916)	(–2.666)	(–2.534)	(–2.198)	(–2.078)	(–2.714)
hydro/load	–11.7827***	–12.1701***	–12.4226***	–14.0850***	–9.7318***	–10.2273***
	(–8.574)	(–9.687)	(–9.748)	(–10.716)	(–10.729)	(–11.477)
thermal/load	2.7282***	1.6733**	1.7608**	2.4001***	1.8894***	2.3075***
	(3.330)	(2.395)	(2.280)	(3.209)	(3.579)	(4.542)
load	0.2651***	0.2131***	0.2542***	0.2594***	0.2821***	0.2817***
	(5.827)	(4.874)	(4.919)	(4.214)	(3.969)	(3.408)
R-squared	0.9406	0.9454	0.9386	0.9496	0.9392	0.9333

Notes: Authors' elaboration based on Matlab software; Dependent Variable: Nodal Price ($/MWh) 2012; Observations=3660, T=366, 10nodes; Peak hours are highlighted in red text; T-statistics of coefficient estimates in parentheses; *** (**,*) indicates 1% (5%, 10%) level of significance.

Source: Electricity Authority (EA), Centralised Dataset.

Table A4: Matching SWEM Nodes to NIWA Wind Sites

North Island		South Island	
Node	Wind Site	Node	Wind Site
BPE	MWT1	TWZ	STH3
HAY	CKS1	ROX	STH3
HLY	NTH1	HWB	STH2
OTA	NTH1	TIW	STH2
TKU	CNI2		
WKM	NTH1		

Notes: Four wind sites in the North Island: MWT1, CKS1, NTH1 and CNI2; Two wind sites in the South Island: STH2 and STH3 (Browne et al., 2014)