Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
The impact of COVID-19 containment measures on changes in electricity demand

Le Wen a, Basil Sharp a, Kiti Suomalainen a, Mingyue Selena Sheng a,∗, Fengtao Guang b

a Energy Centre, Department of Economics, University of Auckland, Auckland, New Zealand
b Research Center of Resource and Environmental Economics, School of Economics and Management, China University of Geosciences, 430074, Wuhan, China

A R T I C L E   I N F O
Article history:
Received 18 July 2021
Received in revised form 12 October 2021
Accepted 17 November 2021
Available online 11 December 2021

JEL classification:
C22
Q41
Q48

Keywords:
COVID-19
Electricity demand
Containment measures
Alert level
Structural breaks

A B S T R A C T
Emergency measures imposed by governments around the world have had massive impacts on the energy sector, resulting in dramatic reductions in total energy demand. The New Zealand government introduced strict containment measures in response to the Covid-19 virus. We use an augmented auto-regressive-moving-average model to assess the impact of containment measures on wholesale electricity demand. The study spans the period 27 February 2020 to 23 February 2021. Results show that the Alert Level-4 lockdown had the largest, significant, and negative effect on electricity demand compared to other containment level measures. Specifically, Alert Level 4 resulted in a 12% reduction in wholesale electricity demand. Structural breaks in the data are evident as containment progressed to Alert Level 1. This unprecedented experiment provides insights into underlying patterns of electricity demand, therefore, projection of economic activity. Furthermore, the analysis offers insights into the performance of the electricity market when both aggregate demand and the pattern of demand change in response to exogenous constraints. Finally, the outcomes of this analysis also provide a robust reference for other countries on how the New Zealand market performed.

© 2021 Elsevier Ltd. All rights reserved.

1. Introduction

COVID-19, an infectious disease that spread quickly and simultaneously in multiple countries, was declared a pandemic by the World Health Organization on 11 March 2020 [1]. To effectively control COVID-19 and avoid community transmission, governments worldwide implemented social isolation and restrictions. Studies found that strict contingency measures that limit COVID-19 spread have a positive effect on the environment [2], improve air quality [3,4], and change in patterns of water demand [5]. More prominently, emergency measures imposed by governments have had massive impacts on the energy sector, resulting in dramatic drops in total energy demand. Following a New York statewide stay-at-home order in March 2020, the electricity load averaged 22% less than during the month of January [6]. Load reductions in the 20%–30% range have also been reported in Italy [7] and India [8]. In response to emergency measures implemented by governments, changes in the daily electricity demand is also evident. For example, confinement measures in Australia resulted in an overall reduction in total daily load and a dramatic increase in residential demand [9]. Electricity consumption has been shown to mirror economic activity and provide policy-relevant information prior to the release of national aggregate data such as gross domestic product (GDP) [10]. Although studies have explored the association between emergency measures and electricity consumption, few studies have comprehensively applied econometric models to examine the impact of government restrictions on electricity consumption.

In New Zealand, sector-level electricity consumption is: industrial 37%, residential 32%, commercial 24%, and agriculture 6%, respectively.1 With more restrictive containment measures in place, we expect residential electricity consumption to increase, and industrial and commercial consumption to decline due to work-from-home (WFH) arrangements and business closures. We also expect the electricity price to fall since the electricity generated by low marginal cost technology can meet the low electricity demand based on the merit-order effect. That is, the cheapest form is dispatched first, and the most expensive conventional generation is dispatched last [11]. New Zealand responded to COVID-19 with a strong “go hard, go early” approach. Hence, in this study, we seek to answer the following research questions:

1 Retired from https://www.mbie.govt.nz/building-and-energy/energy-and-natural-resources/energy-statistics-and-modelling/energy-statistics/electricity-statistics/.

https://doi.org/10.1016/j.segan.2021.100571
2352-4677/© 2021 Elsevier Ltd. All rights reserved.
what is the impact of containment measures on electricity demand? How do containment measures shape electricity demand? Is the impact structural? Do containment measures reduce electricity price and carbon emissions? Can the reduced electricity price discourage renewable energy investment and therefore, delay achieving the New Zealand government’s environmental targets of 100% renewable electricity by 2030 and its sustainable net-zero carbon goal by 2050? Answers to the above questions will provide insights into the performance of New Zealand’s electricity market during government imposed emergency measures in 2020/2021. Fig. 1 shows a detailed analytical scheme of this study.

The remainder of the study is structured as follows. Section 2 describes the data and the timeline of three rounds’ of alert levels changes, beginning with Alert Level 4 on 26 March 2020 through to the return to Alert Level 1 on February 23rd 2021. Results are presented in Section 3, followed by conclusions in Section 4.

2. Data and methodology

2.1. Data

Data on the wholesale electricity market, provided by the New Zealand Electricity Authority, include price, grid-connected generation, grid-connected demand, and HVDC transfers.\(^2\) We use daily and half-hourly trading period data. Temperature data were obtained from the National Institute of Water and Atmospheric Research (NIWA)’s CliFO web access service.\(^3\) Electricity

\(^2\) Retrieved from https://www.emi.ea.govt.nz/Wholesale/Dashboards/NMVSIC?si=db|NMVSIC,s|dmt,v|0.

\(^3\) Retrieved from https://niwa.co.nz/climate/our-services/obtaining-climate-data-from-niwa.
end user data and emissions data were obtained from MBIE. To align with the alert system introduced in March 2020, the study spans the period 27 February 2020 to 23 February 2021. There were three periods of restrictive measures: pre-lockdown (27 February 2020–25 March 2020), COVID-19 Alert Level 4 (26 March 2020–27 April 2020), COVID-19 Alert Level 3 (28 April 2020–13 May 2020), COVID-19 Alert Level 2 (14 May 2020–8 June 2020); COVID-19 Alert Level 1 (9 June 2020–8 November 2020), and so on until the late February 2021 (see the timeline of alert level changes in Fig. 2). Electricity demand in the corresponding weekdays and weekends in 2019 and 2020 is used as the baseline incorporating seasonal patterns such as increases in electricity consumption in winter to derive percentage change in electricity consumption as the dependent variable. We compare electricity demand on 27/2/2019 Thursday with electricity demand on 28/2/2019 Thursday to obtain the difference, and then divide the difference by electricity demand on 28/2/2019 to derive the percentage change on 27/2/2020. Likewise, we compare electricity demand on 1/3/2020 Sunday with that on 3/3/2019 Sunday, and similarly for all days in our period of study to obtain the percentage change in electricity demand.

Fig. 2 illustrates the percentage change in electricity demand over the sub-periods. The horizontal line indicates the average change. Compared to electricity demand in the corresponding weekdays and weekends in 2019 and 2020, electricity demand experienced a minimal, about 2%, increase on average before the lockdown. A substantial decrease, on average approximately 12%, was observed during the Alert Level-4 lockdown due to the reduced commercial and industrial activity. From Alert Level 2 onwards, electricity demand increased due to the less restrictive containment measures, increased economic activity, and increased demand for heating demand due to colder weather.

Fig. 3 illustrates the weekly and daily electricity demand comparison between 2020 and 2019. In Fig. 3(a), the blue line shows the trend in total national electricity demand for the third week entering Alert Level 4 (6/4/2020–12/4/2020) and the red line shows demand for a reference week (8/4/2019–14/4/2019) in 2019. The electricity demand pattern in 2020 weekdays is similar to 2020 weekends (see blue line). The gap between these lines shows the reduction in electricity demand due to the strictest government containment measure, Alert Level 4. During Alert Level 4, most businesses closed except for essential services and lifeline utilities. Reduced activities in commercial and industrial businesses decreased electricity demand during both weekdays and weekends. Based on electricity statistics provided by MBIE, we find that compared to the same quarter ended in June 2019, commercial and industrial reduced consumption by 16% and 11%, respectively. During Alert Level 4, people were instructed to stay at home, work remotely if possible and maintain social distancing if outside. These government announcements led to an 8% increase in residential demand. In April 2020, monthly business electricity demand reduced by 24% compared to 2019; in contrast, monthly residential electricity demand increased by 9% compared to 2019.⁵

Fig. 3(b) shows the daily comparison for a weekday (10/4/2020) and a weekend (11/4/2020) of April during Alert Level 4 and a reference weekday (12/4/2019) and a weekend (13/4/2019) in 2019. The blue line illustrates the trend in electricity demand on 10/4/2020, a weekday, the cyan line is the trend on 11/4/2020, a weekend, the red line for a similar weekday in 2019, and the orange line for a similar weekend in 2019. Interestingly, the weekday electricity demand pattern coincided with the weekend pattern during the lockdown. The electricity demand pattern with morning and evening peaks of weekdays during the lockdown was similar to those for a weekend in 2019 because most people stayed and worked at home over the weekdays in 2020. Changes in community mobility also reflect economic activity and electricity demand. For example, Wen et al. [13] tracked mobility to three destination types (workplaces, retail/recreation, and public transport hubs) via three transport modes (walking, driving, public transport) across four regions from 15 February to 9 July 2020 in New Zealand. They found that the impact of Alert Level 4 reduced mobility by 68%–88% against January baselines. The morning peak demand in 2020 was delayed by a few hours compared to 2019 weekdays, possibly reflecting less concentrated household activity that was common prior to leaving for work and school. There was a significant reduction in energy demand in 2020 weekday demand compared to 2019 weekends and weekdays. This was probably due to the reduced commercial and industrial loads over the lockdown. The gap between the orange line (Saturday, 13/4/2019) and the cyan line (Saturday, 11/4/2020) in Fig. 3(b) is the electricity demand used for businesses opening in 2019 but closing in 2020, indicating that a large portion of businesses were active during the weekends in 2019. The weekly and daily electricity demand pattern changes between the lockdown in 2020 and the corresponding time in 2019 in New Zealand show similarities to those in Spain [14].

2.2. Empirical model

We use an augmented autoregressive-moving-average (ARMA) model to examine the impact of alert levels on electricity demand [15,16].

\[
\Delta \text{Elec}_t = \sum_{i=1}^{p} \rho_i \Delta \text{Elec}_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \eta_t \beta + \mu + \epsilon_t
\]  

(1)

In Eq. (1), the modified ARMA model combining both p autoregressive terms and q moving average terms is represented by ARMA (p, q); \( \mu \) denotes a constant term and \( \epsilon_t \) is the residual term at \( t \), which is assumed independent and identically normally distributed as \( N (0, \sigma^2) \); \( \Delta \text{Elec}_t \) is the change in electricity demand at \( t \); which is related to changes in electricity demand in previous periods – the first term in the right-hand side of Eq. (1), and also related to the current residual and the residuals from previous periods – the second term \( \eta_t \) is a 1 x k vector, representing alert levels and the temperature variable; k is the number of alert levels plus one; and \( \beta \) is a k x 1 coefficient vector, estimating the impact of alert levels on electricity demand.

2.3. Cumulative sum test

The cumulative sum test proposed by Brown et al. [17] and later developed by Ploberger and Krämer [18] is used to check for the presence of structural breaks in the time series of the annual growth rate of electricity consumption over the period 27/2/2020–23/2/2021. The objective of this test is to determine whether the cumulative sum of the partial sequences occurring in the tested sequence is too large or too small relative to the expected behaviour of that cumulative sum for random sequences.
Fig. 2. Electricity demand pattern changes relative to baseline (controlled for seasonal effect).
Notes: Authors’ elaboration based on wholesale trends data (Time scale: day), Electricity Authority. The baseline is the actual value, for the corresponding weekdays in 2019 and 2020 (e.g. 27/2/2020 Thursday vs 28/2/2019 Thursday; 1/3/2020 Sunday vs 3/3/2019 Sunday; and so on.). Timeline of alert level changes: ① The pre-lockdown period: 27/02/2020–25/03/2020; ② Alert Level 4: 26/03/2020–27/04/2020; ③ Alert Level 3: 28/04/2020–13/05/2020; ④ Alert Level 2: 14/05/2020–8/06/2020; ⑤ Alert Level 1: 9/06/2020–11/08/2020; # Mixed Alert Levels Auckland 3/ elsewhere 2: 12/08/2020–30/08/2020; π Alert Level 2: 31/08/2020–21/09/2020; # Mixed Alert Levels Auckland 2/ elsewhere 1: 22/09/2020–07/10/2020; # Alert Level 1: 8/10/2020–14/02/2021; # Mixed Alert Levels Auckland 3/ elsewhere 2: 15/02/2021–17/02/2021; Mixed Alert Levels Auckland 2/ elsewhere 1: 18/02/2021–22/02/2021; Alert Level 1: 23/02/2021–26/02/2021.

Fig. 3. Electricity demand profile comparison.
Notes: Authors’ elaboration based on wholesale trends data (Time scale: trading period), Electricity Authority.
(a) Weekly comparison for the third week entering Alert Level 4 (6/4/2020–12/4/2020) and a reference week in 2019 (8/4/2019–14/4/2019).
(b) Daily electricity demand profile comparison for a weekday of April (10/4/2020) and a weekend (11/4/2020) during Alert Level 4 in 2020 and a reference weekday (12/4/2019) and a weekend (13/4/2019) in 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
The change rate of electricity demand is estimated as a function of its first-order lag with a constant term. Under the null hypothesis, the cumulative sum of residuals will have mean zero. If the null hypothesis is rejected, it implies the existence of a structural break in the data.

3. Results and discussion

3.1. ARMA models results

The Dickey–Fuller test [19] and the Phillips–Perron test [20] are used to examine if changes in electricity demand follow a unit-root process. The null hypothesis was rejected at 1% level.\(^7\) We use an autocorrelation function (ACF) to find \(q\) (cuts off after lag \(q = MA(q)\)) and partial autocorrelation function (PACF) to find \(p\) (cuts off after lag \(p = AR(P)\)). We find \(p = 1\) or 5 and \(q = 1, 2\) or 3. Therefore, there are six possible ARMA\((p,q)\) models: ARMA\((1,1)\); ARMA\((1,2)\); ARMA\((1,3)\); ARMA\((5,1)\); ARMA\((5,2)\); ARMA\((5,3)\).

Table 1 presents estimation results for each alternative ARMA model. As expected, the strictest containment measure — Alert Level 4 had the largest negative impact on the percentage change in electricity demand than other containment measures and is statistically significant at the 95% level in all models. Alert Level 4 reduced the percentage change in electricity demand by 12% compared to that in the pre-lockdown period. The result is in line with Santiago et al. [21], who found a 13.4% decrease in electricity consumption over 14/03/2020–30/04/2020 in comparison with the mean value of the previous five years in Spain. Santiago et al. [21] did not use an econometric model in their analysis. The magnitude of containment measures effects drops from 12% to 3% at Alert Level 3 in the first round, but the effect is negative

\(^7\) Results of unit root tests are reported in Appendix Table A.1.

| VARIABLES | ARMA (1,1) | ARMA (1,2) | ARMA (1,3) | ARMA (5,1) | ARMA (5,2) | ARMA (5,3) |
|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| First round |           |           |           |           |           |           |
| \(\alpha\)Level_4 | -11.85*** | -11.46*** | -12.08*** | -11.63*** | -11.71*** | -11.73*** |
| \(\alpha\)Level_3 | -2.779 | -2.620 | -2.999 | -2.804 | -2.764 | -2.806 |
| \(\alpha\)Level_2 | 1.259 | 1.297 | 1.115 | 0.814 | 0.748 | 0.778 |
| \(\alpha\)Level_1 | 1.046 | 1.111 | 0.894 | 0.942 | 1.155 | 1.156 |
| Second round |           |           |           |           |           |           |
| \(\alpha\)Level_32 | -0.875 | -0.830 | -1.157 | -1.002 | -0.961 | -1.015 |
| \(\alpha\)Level_2 | 0.364 | 0.391 | 0.134 | -0.0232 | 0.140 | 0.137 |
| \(\alpha\)Level_1 | (3.368) | (3.504) | (3.242) | (3.551) | (3.479) | (3.436) |
| \(\alpha\)Level_21 | -2.474 | -2.529 | -2.490 | -2.615 | -2.308 | -2.324 |
| \(\alpha\)Level_1 | -2.477 | -2.362 | -2.632 | -2.545 | -2.543 | -2.538 |
| Third round |           |           |           |           |           |           |
| \(\alpha\)Level_32 | -3.590 | -3.465 | -3.474 | -3.745 | -3.935 | -3.989 |
| \(\alpha\)Level_21 | -2.409 | -2.277 | -2.868 | -2.847 | -2.877 | -2.889 |
| \(\alpha\)Level_1 | (5.297) | (5.476) | (5.564) | (5.594) | (5.730) | (5.808) |
| Temperature | -0.00755*** | -0.00765*** | -0.00740*** | -0.00770*** | -0.00813*** | -0.00826*** |
| Lagged AR terms | Yes* | Yes* | Yes* | Yes* | Yes* | Yes* |
| Lagged MA terms | Yes* | Yes* | Yes* | Yes* | Yes* | Yes* |
| AIC | 1840.851 | 1840.809 | 1835.237 | 1836.111 | 1835.932 | 1837.809 |
| BIC | 1903.161 | 1907.014 | 1905.336 | 1913.999 | 1917.714 | 1923.485 |
| Observations | 363 | 363 | 363 | 363 | 363 | 363 |

Notes: *Yes denotes variables are included in the model. Standard error in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Reference category: the pre-lockdown period 27 February 2020–25 March 2020;

The first period of restrictive measures:
- Alert Level 4 (lockdown): 26/03/2020–27/04/2020;
- Alert Level 3 (Restrict): 28/04/2020–13/05/2020;
- Alert Level 2 (Reduce): 14/05/2020–8/06/2020;
- Alert Level 1 (Prepared): 9/06/2020–11/08/2020;

The second period of restrictive measures:
- Mixed Alert Levels Auckland 3/ elsewhere 2: 12/08/2020–30/08/2020;
- Alert Level 2: 31/08/2020–21/09/2020;
- Mixed Alert Levels Auckland 2/ elsewhere 1: 22/09/2020–07/10/2020;
- Alert Level 1: 8/10/2020–14/02/2021;

The third period of restrictive measures:
- Mixed Alert Levels Auckland 3/ elsewhere 2: 15/02/2021–17/02/2021;
- Mixed Alert Levels Auckland 2/ elsewhere 1: 18/02/2021–22/02/2021;
- Mixed Alert Levels Auckland 2/ elsewhere 1: 23/02/2021–26/02/2021.

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) measure the goodness of fit. A lower AIC or BIC value indicates a better fit. We also check the significance of the coefficients when selecting the best model. For the brevity, we report the significant level. The full results that include 95% confidence interval are available upon request.
but not significant. In the second and third rounds of alert level changes, we find no significant effect of more restrictive mixed alert levels (i.e., Auckland at Alert Level 3 and elsewhere at Alert Level 2) on change in electricity demand. The evidence reflects that business managers and residents gradually learned from experience and handled the situation more smoothly under the restricted containment measures. Under Alert Level 2, businesses opened, and people could go back to work only if following public health guidance and keeping physical distancing, likely boosting electricity demand. After transiting to Alert Level 1, there is no restriction on most activities. Business activities could continue uninterrupted, resulting in no significant changes in electricity demand. We find no significant effects of Alert Level 2 and Alert Level 1 on the change in electricity demand in comparison to the pre-lockdown period. Temperature has a small and significant effect on electricity demand. A 1% increase in temperature reduces electricity demand by 0.008%.

3.2. Cumulative sum test result

The percentage change in electricity demand declined over Alert Level 4 and Alert Level 3. We use the cumulative sum test to determine whether the decrease in the percentage change in electricity demand during the study period is attributed to structural change. Structural breaks are evident if the plot of a recursive cumulative sum process breaks its corresponding confidence intervals. Fig. 4 is the recursive cumulative sum plot of changes in electricity demand. The cumulative sum test statistic shows a 5 percent level of significance, indicating that changes over the period from 2/04/2020 to 27/05/2020 are structurally significant. The occurrence of structural change happened after 26 March 2020, beginning with Alert Level 4, indicating that the strictest containment measure resulted in reduced economic activity. The decrease in electricity demand was related to the reduction in community mobility, such as travelling to retail and recreation venues and workplaces [22]. Dramatic structural breaks caused by the Alert Level-4 lockdown were also evident in community mobility in New Zealand [13].

### Table A.1

| Variable           | Changes in electricity demand |
|--------------------|-------------------------------|
| Dickey–Fuller test | −5.571***                     |
| Phillips–Perron test | −5.334***                   |

Note: *** denotes statistical significance at the 1% level.

4. Concluding remarks

Covid-19 containment measures in New Zealand reshaped electricity demand. Results show that the Alert Level-4 lockdown had the largest, significant, negative effect on electricity demand compared to other containment measures. The lockdown led to a 12% reduction in electricity demand. Structural breaks associated with the progressive return to Alert Level 1 are evidenced in the data.

This study provides empirical evidence on changes in the level and pattern of electricity demand due to COVID-19 containment measures. Electricity demand and economic activity are obviously correlated and in the absence of evidential data we would expect changes in GDP to correlate with changes in electricity demand.

---

8 The cumulative sum test result of changes in electricity demand is reported in Appendix Table A.2.

9 GDP data are not generated with temporal granularity, i.e., reported yearly, whereas alert impacts are intra-annual.
Associated with the reduced electricity demand, there was a 62.5% drop in electricity price compared to 2019 during the Alert Level-4 lockdown. We conjecture that changes in the merit-order stack could explain this price drop. With the drop in demand higher-cost sources of electricity will not be dispatched by the system operator, leaving base load sources such as geothermal and low-cost sources such as hydro and wind being offered to the market. The disruptive reduction in electricity demand due to the COVID-19 outbreak could provide the opportunity to preserve some hydro generation in autumn for later use in winter [23–25]. However, based on historical hydro risk curves, the weather was dry from May to November (i.e., dry in winter and spring) and demand was high in winter in 2020. Thus, compared to 2019, an 11% increase in coal generation and 8% in gas generation was associated with decreased hydro generation in 2020. Accordingly, electricity generation emissions increased by 11% from 4923 kilotonnes of carbon dioxide equivalent (kt CO₂-e) in 2019 to 5,445 kt CO₂-e in 2020, mainly from increased coal and gas generation. Price was high based on the merit-order effect. For example, in June 2020, average electricity price was 64% higher than in 2019.

Lower electricity prices due to lower demand during the lockdown may temporarily discourage renewable energy investment and delay the transition to net-zero carbon emissions by 2050. But other important factors, namely seasonal rainfall patterns and demand, affect the generation mix and carbon emissions in a hydro-dominated electricity system. Therefore, the dry year problem needs to be resolved in order to achieve the government’s net-zero carbon goal and ensure the electricity sector meets New Zealand’s future economic growth in a sustainable manner. Another disruptive change in electricity demand due to the COVID-19 outbreak is the transformation in work patterns in the future with people working from home. Different alert levels, spatially and temporally, were applied across regions throughout New Zealand, and the electricity market was able to cope with regional heterogeneity in electricity demand as it unfolded. Both the transformation in work patterns and regional heterogeneity are expected to change the shape of electricity demand, which raises the interest to be considered in future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was jointly supported by the Energy Education Trust of New Zealand and the Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund 2017 (Research project 3714101).

Appendix

See Tables A1 and A2.

References

[1] W.H.O. World Health Organization, Coronavirus disease 2019 (COVID-19) situation report-51, 2020, http://www.who.int/docs/default-source/coronaviruse/situation-reports/20200311-sitrep-51-covid-19.pdf?sfvrsn=1ba2aef7_10 (Accessed 30 September 2021).

[2] Q. Wang, M. Su, A preliminary assessment of the impact of COVID-19 on electricity demand in China, Science. Total Environ. 728 (2020) 138915.

[3] S. Mahato, S. Pal, K.G. Ghosh, Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Sci. Total Environ. 730 (2020) 130806.

[4] M.A. Zambrano-Monserrate, M.A. Ruano, L. Sanchez-Alcalde, Indirect effects of COVID-19 on the environment, Sci. Total Environ. 728 (2020) 138813.

[5] J. Kazak, S. Szewrański, T. Piławka, K. Tokarczyk-Dorociak, K. Janiak, M. Świąder, Changes in water demand patterns in a European city due to restrictions caused by the COVID-19 pandemic, in: Desalination and Water Treatment, Vol. 222, 2021.

[6] S.A. Van Vactor, The Impact of Covid-19 on Energy Markets, Special Covid-19 Edition 2020, IAEE Energy Forum, 2020, pp. 12–16.

[7] E. Ghiani, M. Galici, F. Pilo, Impact on electricity consumption and market pricing of energy and ancillary services during pandemic of COVID-19 in Italy, Energies 13 (2020) http://dx.doi.org/10.3390/en13113357.

[8] Beyer, R.C.M., S. Franco-Bedoya, V. Galdo, Examining the economic impact of COVID-19 in india through daily electricity consumption and nighttime light intensity, in: Policy Research Working paper 9291, World Bank, 2020.

[9] P. Mastropietro, P. Rodilla, C. Battle, Emergency measures to protect energy consumers during the Covid-19 pandemic: A global review and critical analysis, Energy Res. Soc. Sci. (2020) 101678.

[10] D. Benatia, Electricity Markets under Lockdown: Insights from New York, Special Covid-19 Edition 2020, IAEE Energy Forum, 2020, pp. 55–58.

[11] L. Wen, B. Sharp, E. Shai, Spatial effects of wind penetration and its implication for wind farm investment decisions in New Zealand, Energy J. 41 (2) (2020) 47–72, http://dx.doi.org/10.5547/01959574.41.2wen.

[12] MBIE, COVID-19 impact evident in new energy data, 2020, https://www.mbie.govt.nz/about/news/covid-19-impact-evident-in-new-energy-data/.

[13] L. Wen, M. Sheng, B. Sharp, The impact of COVID-19 on changes in community mobility and variation in transport modes, N. Z. Econ. Pap. (2021) http://dx.doi.org/10.1080/00779954.2020.1870536.

[14] A. Bahmanyar, A. Estebanez, D. Ernst, The impact of different COVID-19 containment measures on electricity consumption in Europe, Energy Res. Soc. Sci. (2020) 101683.

[15] P. Whittle, Hypothesis Testing in Time Series Analysis, Almqvist and Wiksell, 1951.

[16] G. Box, G. Jenkins, Time Series Analysis: Forecasting and Control, Holden-Day, San Francisco, 1970.

[17] R.L. Brown, J. Durbin, J.M. Evans, Techniques for testing the constancy of regression relationships over time, J. R. Statist. Soc. 37 (1975) 149–192.

CRediT authorship contribution statement

Le Wen: Conceptualization, Methodology, Formal analysis, Writing – original draft, Drafting: Review & Editing. Basil Sharp: Conceptualization, Writing - Review & Editing. Kiti Suomalainen: Resources, Writing - Review & Editing. Mingyue Selena Sheng: Methodology, Writing - Review & Editing. Fengtao Guang: Methodology, Investigation, Project administration.

Table A.2

| Period          | Statistic | Test statistic | 1% critical value | 5% critical value | 10% critical value |
|-----------------|-----------|---------------|------------------|-------------------|-------------------|
| 27/2/2020–23/2/2021 | Recursive | 2.246***       | 1.143            | 0.948             | 0.850             |

Note: *** denotes statistical significance at the 1% level.

Acknowledgments

This work was jointly supported by the Energy Education Trust of New Zealand and the Ministry of Business, Innovation and Employment (MBIE) Endeavour Fund 2017 (Research project 3714101).

Appendix

See Tables A1 and A2.

References
[18] W. Ploberger, W. Krämer, The cusum test with Ols Residuals, Econometrica 60 (1992) 271–285.
[19] D.A. Dickey, W.A. Fuller, Distribution of the estimators for autoregressive time series with a unit root, J. Am. Stat. Assoc. 74 (366) (1979) 427–431, http://dx.doi.org/10.1080/01621459.1979.10482531.JSTOR2286348.
[20] P.C.B. Phillips, P. Perron, Testing for a unit root in time series regression, Biometrika 75 (2) (1988) 335–346, http://dx.doi.org/10.1093/2Fbiomet/2F75.2.335.
[21] I. Santiago, A. Moreno-Munoz, P. Quintero-Jiménez, F. García-Torres, M.J. Gonzalez-Redondo, Electricity demand during pandemic times: The case of the COVID-19 in Spain, Energy Policy 148 (2021) 111964.
[22] S. Percy, B. Mountain, Covid–19 and Social Distancing: Does It Show Up in the Demand for Electricity?, Special Covid–19 Edition 2020, IAEE Energy Forum, 2020, pp. 38–39.
[23] I.G. Mason, S.C. Page, A.G. Williamson, A 100% renewable electricity generation system for New Zealand utilising hydro, wind, geothermal and biomass resources, Energy Policy 38 (8) (2010) 3973–3984.
[24] I. Khan, M.W. Jack, J. Stephenson, Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity, J. Cleaner Prod. 184 (2018) 1091–1101, http://dx.doi.org/10.1016/j.jclepro.2018.02.309.
[25] Interim Climate Change Commission, Accelerated electrification – evidence, analysis and recommendations, 2019, Wellington, New Zealand.