Smart Meters and Distributed Generation: Panel Causality Evidence

Fatih Cemil Özbuğday[1] and Önder Özgür[2]

Abstract

Both the relevant literature and the regulatory authorities' policy reports suggest that there is a relationship between smart meters and distributed generation and that an essential tool for the integration of distributed generation into electric systems is the smart meter technology. However, to date, there has been no formal or scientific test of this proposition. This article examines the relationship between advanced metering infrastructure (AMI) and distributed generation (DG), which are expected to be among the critical components of future electricity markets. For this purpose, long monthly time series data were used for four different consumer groups (commercial, industrial, residential and small- and medium-sized enterprises) for the network reporting regions in New Zealand and a panel Granger causality analysis was conducted. The econometric results establish a two-way causality relationship between AMI penetration and DG uptake rate. These findings are in line with the propositions in the literature and policy papers, and they comprise policy implications.

Keywords: Smart meters; distributed generation; panel causality analysis; New Zealand

JEL Codes : Q40, Q48, O13

[1]**Corresponding Author** Department of Economics, Ankara Yıldırım Beyazıt University, Ankara, Turkey. fcozbugday@ybu.edu.tr

[2]Department of Economics, Ankara Yıldırım Beyazıt University, Ankara, Turkey. onderozgr@gmail.com

1. Introduction

The industrial organization of electricity markets has been experiencing a radical transformation. Once organized around a single vertically-integrated company, energy markets have gone through a restructuring process in which competitive segments such as generation and retail are vertically separated from natural monopoly networks and liberalized. The liberalization of generation and retail segments brought many opportunities that did not exist before. One of these opportunities is "distributed generation."

Distributed generation (DG) can be briefly defined as small-scale electricity generation at the point of consumption using mostly renewable resources such as solar or wind power3. With the rise of DG, instead of just consuming electricity, consumers can also generate electricity (Pepermans et al., 2005). On-site generation reduces the load on the grid and becomes a substitute for distribution and transmission lines investment and massive generating plants construction (El-Khattam and Salama, 2004). It is a cost-effective way of improving reliability and power quality (Lopes et al., 2007). By increasing voltage in the network, DG can also offer ancillary services and improve quality of supply (Bayod-Rujula et al., 2009). Furthermore, DG technologies alleviate environmental problems (see Akorede et al., 2010) and enhance energy security via diversification of energy sources (Lopes et al., 2007). However, all these benefits require the integration of DG into electric power system, which requires exhaustive technical (Viral and Khatod, 2013; Paliwal et al., 2014; Tan et al., 2014; Prakash and Khatod, 2016), regulatory (Cossent et al., 2009; De Joode et al., 2009; Frías et al., 2009), and economic planning (Vogel, 2009; Ropenus et al., 2011; El-Khattam et al., 2004). All these thorough planning requires detailed and timely information.

One source of required increased and detailed information is advanced metering infrastructure (AMI) or smart meters. By generating more accurate consumption data on a shorter time interval basis, enabling remote reading and automatic meter data processing, and two-way communication for consumer involvement, smart meters allow the integration of DG into the electric power system. Consumers have more information and control over the amount and timing of their electricity consumption owing to AMI, and thus can calculate the benefits from the on-site generation more precisely.

On the electricity distribution side, AMI enables electricity distributors to operate, control and manage their networks more effectively since they have better information about the current

[3] For a more detailed definition, see Ackermann et al. (2005).

situation about power demand and supply in the grid (Bae et al., 2014). When DG capacity is increased in the grid, optimizing the usage of the network requires more timely and accurate metering information which can only be provided by smart meters. Furthermore, network operators can better manage the variability brought about by the integration of DG with intermittent generation structure (e.g., solar panels) owing to the metering information. Thus, accommodating more on-site generation, especially for sources with intermittent nature, would be much more comfortable with AMI.

In brief, the literature on smart grids puts forward that these will facilitate DG, especially from renewable sources (Wolsink, 2012; Farhangi, 2010). AMI maximizes the value of distributed generation to both their owners and the distribution network. Therefore, adding more DG necessitates a smarter network with advanced metering infrastructure. This idea is also voiced in the European Commission’s Communication on a Roadmap for Moving to a Competitive Low-Carbon Economy in 2050 (EU COM, 2011), which identifies investment in smart grids as a critical enabler for a future low-carbon electricity system, facilitating, inter alia, increased shares of renewables and distributed generation.

However, despite the abundance of arguments suggesting that smart meters facilitate the integration and penetration of DG, no formal study relates the presence of smart meters to distributed generation uptake. The primary objective of this paper is to investigate the role of advanced metering infrastructure on distributed generation uptake rate in New Zealand context.[4] To this end, we use monthly data from retail reports published in the website of New Zealand Electricity Authority (https://www.emi.ea.govt.nz/Retail/Reports) and perform panel time series analyses to identify the causality relationship between AMI penetration and DG uptake rate for four consumer groups (commercial, industrial, residential, and small- and medium-sized enterprise (SME)). The results of the analyses indicate a bidirectional causality between AMI penetration and DG uptake rate for all consumer segments.

The originality of the paper stems from that it is the first study in the relevant literature that examines the relationship between AMI and DG empirically. In doing so, the study provides a

[4] New Zealand is comparable to the United Kingdom in terms of land size. It has a population of approximately 4.8 million. Since the country consists of two islands located in a remote region of the southern hemisphere, the electricity sector is closed and self-sufficient. There are no means for export or import of electricity. The unique and radical approach to the restructuring and deregulation of the electricity industry makes the New Zealand case even more interesting (Bertram and Twaddle, 2005; Nillesen and Pollitt, 2011; Ozbugday and Nillesen, 2013). It has been the first country to have ever implemented the ownership unbundling of electricity retailing from distribution.

disaggregated analysis where detailed time series data for different consumer segments are used.

The structure of the paper is as follows: Section 2 describes the data used in the study and explains the methodology. Empirical results are displayed in Section 3. Finally, Section 4 discusses the findings and concludes.

2. Data and Methodology

2.1.Data Source and Variables

The data for the study are compiled from retail reports published on the website of New Zealand Electricity Authority (https://www.emi.ea.govt.nz/Retail/Reports). The retail reports include monthly data on a wide range of indicators at network reporting region level. Network reporting regions are mainly formed by traditional Electricity Power Board networks and harmonize with pricing regions conventionally used in the retail market.[5] Our data cover 30 network reporting regions, which represent the whole New Zealand territory. These regions are displayed in Table 1. In each region, four different customer segments are defined: residential, commercial, small- and medium-sized enterprise (SME) and industrial. These market segments, however, are not necessarily mutually exclusive. The market segment breakdowns start from September 2013.

Table 1: List of Network Reporting Regions

	Region Name
1	Ashburton (Electricity Ashburton)
2	Auckland (Vector)
3	Bay of Islands (Top Energy)
4	Buller (Buller Electricity)
5	Central Canterbury (Orion New Zealand)
6	Central Otago (Aurora Energy)
7	Counties (Counties Power)
8	Eastern Bay of Plenty (Horizon Energy)
9	Eastland (Eastland Network)
10	Hawke's Bay (Unison Networks)
11	Kapiti and Horowhenua (Electra)
12	King Country (The Lines Company)

[5] https://www.emi.ea.govt.nz/Glossary#N

13	Manawatu (Powerco)
14	Marlborough (Marlborough Lines)
15	Queenstown (Aurora Energy)
16	South Canterbury (Alpine Energy)
17	Southland (The Power Company)
18	Taranaki (Powerco)
19	Tasman (Network Tasman)
20	Taupo (Unison Networks)
21	Tauranga (Powerco)
22	Thames Valley (Powerco)
23	Waikato (WEL Networks)
24	Waipa (Waipa Networks)
25	Wairarapa (Powerco)
26	Waitaki (Network Waitaki)
27	Waitemata (Vector)
28	Wanganui (Powerco)
29	Wellington (Wellington Electricity)
30	Whangarei and Kaipara (Northpower)

Notes: Names in parentheses are the names of the network operator in the region.

To construct the variables to be used in the analysis, we use installation control points (ICP), and AMI counts in a region. ICP count is the total number of installation control points (ICPs) in a network reporting region. An ICP is a physical connection point on a network, and it is the point at which a retailer supplies electricity to a consumer. AMI count in a network reporting region is given as the total number of ICPs with advanced metering infrastructure (AMI). AMI, in this context, is an integrated system of smart meters, data management systems, and communications networks that allows two-way communication between customers and suppliers.[6] We calculate *AMI PENETRATION* in a region by dividing AMI count by ICP count. The second variable of interest, *DG UPTAKE RATE*, is the percentage of ICPs that have installed DG in a network reporting region. These two variables are constructed for four different consumer groups including residential, commercial, small and medium-size enterprise (SME) and industrial. The definitions and details of these variables are presented in **Error! Reference source not found.**.

[6] https://www.smartgrid.gov/recovery_act/deployment_status/sdgp_ami_systems.html

Table 2: Definitions of the Variables

Variable	Definition	Market Segment	Period
ICP COUNT	The total number of installation control points (ICPs) in a network reporting region. An ICP is a physical connection point on a network and it is the point at which a retailer supplies electricity to a consumer.	Residential	2013 September-2017 July (47 months)
		Commercial	2013 September-2017 July (47 months)
		SME	2013 September-2017 July (47 months)
		Industrial	2013 September-2017 July (47 months)
AMI COUNT	The total number of ICPs with advanced metering infrastructure (AMI) in a network reporting region. AMI is an integrated system of smart meters, data management systems, and communications networks that allows two-way communication between customers and suppliers.	Residential	2013 September-2017 July (47 months)
		Commercial	2013 September-2017 July (47 months)
		SME	2013 September-2017 July (47 months)
		Industrial	2013 September-2017 July (47 months)
AMI PENETRATION	AMI Count / ICP Count	Residential	2013 September-2017 July (47 months)
		Commercial	2013 September-2017 July (47 months)
		SME	2013 September-2017 July (47 months)
		Industrial	2013 September-2017 July (47 months)
DG UPTAKE RATE	The percentage of ICPs that have installed distributed generation (DG) in a network reporting region.	Residential	2013 September-2017 July (47 months)
		Commercial	2013 September-2017 July (47 months)
		SME	2013 September-2017 July (47 months)
		Industrial	2013 September-2017 July (47 months)

Descriptive statistics for these variables are provided in **Error! Reference source not found.**.

Table 3: Descriptive Statistics

	Mean	Median	Max.	Min.	Std. Dev.	Observations
AMI PENETRATION COMMERCIAL	31.646	30.605	71.781	0.257	21.213	1410
AMI PENETRATION INDUSTRIAL	34.329	33.276	81.348	0.174	23.901	1410

AMI PENETRATION RESIDENTIAL	49.064	50.893	97.382	0.015	29.611	1410
AMI PENETRATION SME	36.500	35.779	84.734	0.252	24.461	1410
DG UPTAKE RATE COMMERCIAL	0.218	0.166	0.949	0.029	0.174	1410
DG UPTAKE RATE INDUSTRIAL	0.449	0.340	1.750	0.030	0.358	1410
DG UPTAKE RATE RESIDENTIAL	0.497	0.396	2.166	0.033	0.385	1410
DG UPTAKE RATE SME	0.203	0.152	0.933	0.010	0.168	1410

2.2.Methodology

This study performs panel data analyses to identify the causality relationship between *AMI PENETRATION* and *DG UPTAKE RATE* in four consumer groups including commercial, industrial, residential, and SME. Before proceeding with the implementation of the causality analysis between variables of interest, there are two primary tasks needed to be executed. First proposition to be tested is whether there is a cross-sectional dependence across the panel units. If the large cross-sectional dependence is not dealt with proper estimation methods, one may not get the efficiency improvement arising from panel data estimation (Bahattacharya et al. 2016). Cross-sectional dependence, on the other hand, will guide us to select the appropriate unit root testing procedure. Performing first generation unit root tests ignoring the cross-sectional dependence provides biased results (Menyah et al. 2014). The analysis, therefore, goes on with the estimation of panel unit root and stationary tests to derive time series properties of the variables before proceeding to test for causality analysis.

In the presence of common regulatory or economic shocks, cross-sectional dependence across network reporting regions should exist. Therefore, in the current analysis, we first investigate whether there exists cross-sectional dependence among our observational units.

2.2.1. Testing for Cross-Sectional Dependence

To test the cross-sectional dependence on panel data, the current paper first employs the well-known Breusch-Pagan LM test procedure proposed by Breusch and Pagan (1980). This testing procedure in the context of fixed N and as $T \to \infty$ is based on an LM statistics which is estimated by the pair-wise correlation of the fitted-model residuals. Fitted model computed by Ordinary Least Squares (OLS) allows intercept and slope coefficients to vary across units.

The Breusch-Pagan LM test considers the following panel data specification (Menyah et al. 2014):

$$y_{it} = \alpha_i + \beta_i' x_{it} + \varepsilon_{it} \quad (1)$$

for i=*1, 2, ..., N* and t=*1, 2, ..., T,* where *i* represents panel units, *t* is the time dimension, x_{it} is a kx1 vector for regressors, α_i, and β_i are the individual intercepts and slope coefficients, respectively. The LM test statistic is calculated as follows (Breusch and Pagan (1980):

$$Breusch-Pagan\ LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \quad (2)$$

where $\hat{\rho}_{ij}$ is the pair-wise correlation of the residuals from Equation (1). Breusch-Pagan LM statistics has a χ^2 distribution with $\frac{N(N-1)}{2}$ degrees of freedom under the null of zero correlation.

This paper then performs the bias-adjusted LM test of error cross-section independence proposed by Pesaran et al. (2008) for large panel data sets when N→∞ and T→∞. The modified version of the LM test uses the exact mean and variance of the LM statistics. CDLM adjusted test modifies the Breusch-Pagan LM test by using exact mean and variance of the LM statistics. CDLM adjusted test statistics can be calculated as follows (Pesaran et al. 2008):

$$CDLM_{adj} = \sqrt{\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{v_{Tij}} \quad (3)$$

where μ_{Tij} shows mean and v_{Tij} represents variance. CDLM adjusted test statistic has asymptotically standard normal distribution. The null hypothesis of this test assumes cross-sectional independence against the alternative of cross-sectional dependence.

2.2.2. Unit Root and Stationarity Tests

Since first-generation unit root tests for panel data are not robust and provide a minor improvement in the case of cross-sectional dependence, this paper performs second-generation panel unit root tests and identify the order of integration for each variable. The first one performed is the well-known Cross-Sectionally Augmented Dickey-Fuller (CADF) Test which is proposed by Pesaran (2006) and considers both heterogeneity and cross-sectional dependence across panels. This test modifies the standard Augmented Dickey-Fuller (ADF) regression with lagged values and first differences of individual series. CADF test procedure provides t-statistics for individual cross-section units. The simple average of the individual CADF statistics, referred as Cross-Sectionally Augmented IPS statistics, allows to infer the order of each series in the panel context.

A simple dynamic linear heterogeneous panel data model is represented as follows (Pesaran, 2007):

$$x_{it} = (1 - \emptyset_i)\mu_i + \emptyset_i x_{i,t-1} + u_{it} \tag{4}$$

for i = 1…., N; t = 1…, T, where x_{it} is the observation on i th cross-section unit at time t. CADF test procedure then estimates the following model by OLS.

$$\Delta x_{it} = \alpha_i + \beta_i x_{i,t-1} + \Sigma_{j=1}^{p_i} c_{ij} \Delta x_{i,t-j} + d_i t + h_i \bar{x}_{t-1} + \Sigma_{j=0}^{p_i} \eta_{ij} \bar{x}_{i,t-j} + \varepsilon_{i,t} \tag{5}$$

The model incorporates the cross section means of the current value of x_{it}, lagged values of x_{it} and lagged values of the differenced cross-section mean for an approximation of common factor. This procedure solves the potential autocorrelation problem.

CIPS statistic is the average of the individual *t* values obtained by CADF regression (Pesaran, 2007):

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i \tag{6}$$

CIPS test performs the null hypothesis that all individual units are not stationary against the alternative that at least one unit is stationary.

On the other hand, the study also performs another test developed by Carrion-i Silvestre et al. (2005), which allows structural breaks in the series and is labeled as panel KPSS (PANKPSS). Since structural breaks can affect the limiting distribution of individual statistics, controlling structural shifts is crucial to coping with the size distortion problem (Nazlıoğlu and Karul, 2017). PANKPSS test also considers both heterogeneity and cross-sectional dependence across panels under the null of the stationary.

The model proposed by Carrion-i Silvestre et al. (2005) to test the null hypothesis of stationarity is as follows:

$$y_{it} = \delta_{it} + \beta_i t + u_{it} \tag{7}$$

for *i = 1…., N*; *t = 1…, T*; where, $\delta_{it} = \sum_{k=1}^{m_i} \varphi_{i,k} \, D\left(T_{b,k}^i\right)_t + \sum_{k=1}^{m_i} \theta_{i,k} DU_{i,k,t} + \delta_{i,t-1} + \vartheta_{i,t}$.

In this equation, $\vartheta_{i,t}$ is i.i.d with mean 0, and $\sigma^2_{\vartheta i}$ variance, $\alpha_{i,0} = \alpha_i$, for *i = 1…., N* individuals; *t = 1…, T* time periods. $D\left(T^i_{b,k}\right)_t$ and $DU_{i,k,t}$ are dummy variables and defined as follows:

$$D\left(T^i_{b,k}\right)_t = \begin{cases} 1, & t = T^i_{b,k} + 1 \\ 0, & elsewhere \end{cases}$$

$$DU_{i,k,t} = \begin{cases} 1, & t > T^i_{b,k} \\ 0, & elsewhere \end{cases}$$

where $T^i_{b,k}$ represents *k*th the date of break for *i*th individual. This model allows for multiple structural breaks up to *k = 1…., m* with an assumption that u_{it} and $\vartheta_{i,t}$ are independently distributed. Under the null hypothesis that $\sigma^2_{\varepsilon,i} = 0$, equation (7) can be written in the following form (Carrion-i Silvestre et al. (2005)):

$$y_{it} = \delta + \sum_{k=1}^{m_i} \varphi_{i,k} DU_{i,k,t} + \sum_{k=1}^{m_i} \theta_{i,k} DT^*_{i,k,t}\, \beta_i t + u_{i,t} \tag{8}$$

where

$$DT^*_{i,k,t} = \begin{cases} t - T^i_{b,k,t}, & t > T^i_{b,k} \\ 0, & elsewhere \end{cases}$$

Thus, this model allows that the structural shifts have different effects over cross-sectional units, they exist at various points in time for each unit, and the number of breaks differs among these cross-sections. Under the heterogeneity assumption, the formula for the test statistic can be represented by the following equation:

$$LM(\lambda) = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{\gamma}_i^{-2} T^{-2} \sum_{t=1}^{T} \hat{S}^2_{i,t} \right) \tag{9}$$

where $\hat{\gamma}^2 = \frac{1}{N}\sum_{i=1}^{N} \hat{\gamma}_i^2$, $S^2_{i,t} = \sum_{j=1}^{t} u^2_{i,j}$ and λ_i is a vector that represents the relative position of the break dates during the period T for each cross-sectional unit.

2.2.3. Panel Causality Test

Identifying the causal relationships between variables of interest are essential for policymakers to implement appropriate policies. This paper, therefore, performs the causality analysis proposed by Dumitrescu and Hurlin (2012). This test extends the standard Granger causality analysis to panel data context by testing cross-sectional linear restrictions on the coefficients of the model. The testing procedure considers both the heterogeneity in the model and the heterogeneity of the causal relationship. The advantages of this test are as follows (Dogan and Seker, 2016): (i) the test is flexible in cases of both T>N and N>T, (ii) it provides robust results for unbalanced and heterogenous panels, (iii) this test can be employed in the presence of cross-sectional dependence and, (iv) the current test solves the problems posed by homogeneity assumption of the standard Granger causality test.

The linear heterogenous panel regression model of Dumitrescu and Hurlin (2012) test is as follows:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{10}$$

where $y_{i,t}$ and $x_{i,t}$ stand for two stationary variables, $\varepsilon_{i,t}$ is error term. $\beta_i = \left(\beta_i^{(1)}, \dots, \beta_i^{(K)}\right)'$ and the individual effects α_i are assumed to be fixed in the time dimension.

This non-causality test proposes an average Wald statistic that tests the null hypothesis of no causal relationship between any of the individual panel units against the alternative of the causal relationship that occurs at least one cross-section unit of the panel.

$$H_0 = \beta_i = 0 \; for \; \forall_i = 1, \dots, N$$

$$H_1 = \begin{Bmatrix} \beta_i = 0 \; for \; \forall_i = 1, \dots, N_1 \\ \beta_i \neq 0 \; for \; \forall_i = N_1 + 1, \dots, N \end{Bmatrix}$$

Having described the methodology, we present the results of the analyses in the next section.

3. Empirical Results

3.1.Cross-Sectional Dependence Tests

Before investigating the stationarity of *AMI PENETRATION* and *DG UPTAKE RATE* variables for each group, we first perform the Breusch-Pagan LM and Bias-Corrected Scaled LM tests. The results of cross-sectional dependence tests are presented in Table 4, which displays the test statistics and their probability values.

Table 4: Results of the Cross-Sectional Dependence Tests

Variables	Breusch-Pagan LM		Bias-Corrected Scaled LM	
	Statistic	Prob.	Statistic	Prob.
AMI PENETRATION COMMERCIAL	18,014.900	0.000	595.688	0.000
DG UPTAKE RATE COMMERCIAL	11,491.430	0.000	374.521	0.000
AMI PENETRATION INDUSTRIAL	16,560.720	0.000	546.387	0.000
DG UPTAKE RATE INDUSTRIAL	8,238.859	0.000	264.249	0.000
AMI PENETRATION RESIDENTIAL	17,287.870	0.000	571.039	0.000
DG UPTAKE RATE RESIDENTIAL	18,975.450	0.000	628.254	0.000
AMI PENETRATION SME	17,677.860	0.000	584.261	0.000
DG UPTAKE RATE SME	141,87.220	0.000	465.918	0.000

Since the relevant probability values are smaller than 0.05, they provide supportive evidence to reject the null hypothesis of cross-sectional independence for *AMI PENETRATION* and *DG UPTAKE RATE* in all consumer segments. Since these groups operate under the same regulatory environment and there are regional linkages among the panel units, a shock affecting one individual unit also creates spillover effects to other panel units.

3.2.Unit Root Tests

In the presence of cross-sectional dependence across the panel units, employing first-generation panel unit root tests may provide misleading results. Since employed variables are in favor of cross-sectional dependence, this study performs second-generation unit root tests, namely CADF test and PANKPSS tests considering correlations among panel units.

Table 5 shows CADF test results, which consists of constant and trend terms. CIPS statistics derived from CADF test displays mixed results. On the one hand, results with constant do not reject the null of a unit root for the variables *AMI PENETRATION COMMERCIAL*, *DG UPTAKE RATE COMMERCIAL*, *AMI PENETRATION INDUSTRIAL*, *AMI PENETRATION RESIDENTIAL*, and *DG UPTAKE RATE RESIDENTIAL* whereas the test statistics for other variables reject the null hypothesis at 5% percent level. On the other hand, the results with constant and trend imply that variables *AMI PENETRATION COMMERCIAL*, *DG UPTAKE RATE COMMERCIAL*, *AMI PENETRATION INDUSTRIAL*, *DG UPTAKE RATE INDUSTRIAL*, *AMI PENETRATION RESIDENTIAL*, and *AMI PENETRATION SME* are not stationary in their levels (I(1)) whereas the other variables seem to be stationary (I(0)).

Table 5: CADF Test Results

Variables	CADF Test (CIPS Statistics) Constant	Constant & Trend
AMI PENETRATION COMMERCIAL	-1.570	-2.115
Δ (AMI PENETRATION COMMERCIAL)	-3.190*	-3.657*
DG UPTAKE RATE COMMERCIAL	-2.098***	-2.239
Δ (DG UPTAKE RATE COMMERCIAL)	-4.148*	-4.463*
AMI PENETRATION INDUSTRIAL	-1.659	-2.218
Δ (AMI PENETRATION INDUSTRIAL)	-3.142*	-3.435*
DG UPTAKE RATE INDUSTRIAL	-2.162**	-2.565
Δ (DG UPTAKE RATE INDUSTRIAL)	-4.290*	-4.353*
AMI PENETRATION RESIDENTIAL	-2.141***	-2.108
Δ (AMI PENETRATION RESIDENTIAL)	-2.081***	-2.808*
DG UPTAKE RATE RESIDENTIAL	-1.598	-2.426*
Δ (DG UPTAKE RATE RESIDENTIAL)	-3.696*	-3.932*
AMI PENETRATION SME	-1.610	-2.045
Δ (AMI PENETRATION SME)	-3.156*	-3.473*
DG UPTAKE RATE SME	-2.235**	-2.343*
Δ (DG UPTAKE RATE SME)	-4.266*	-4.310*

Notes: Critical values of stationarity test for constant model is -2.30, -2.16, and -2.08 for 1%, 5% and 10%; and the critical values for constant and trend model is -2.78, -2.65, -2.58 for 1%, 5% and 10% respectively. *, ** and *** represent the stationarity with these significance levels. Δ denotes the first difference. A maximum lag is chosen as 9, and optimum lag is determined by SIC.

Since CADF test provides mixed results and it does not consider the structural changes, this paper additionally utilizes the PANKPSS test. This test allows for structural changes up to five breaks. The test also allows examining the stationarity of the series under the heterogeneity of the long-run variances across observational units. The results of the PANKPSS test is presented in Table 6.

Table 6: Carrion-i Silvestre (PANKPSS) Test Results

	Breaks in Constant	Breaks in Constant &Trend

	Test Statistics (Heterogenous)	Critical Values	Test Statistics (Heterogenous)	Critical Values
AMI PENETRATION COMMERCIAL	25.012*	27.477 40.663 68.739	20.590*	85.300 114.858 173.502
DG UPTAKE RATE COMMERCIAL	30.327	20.847 30.139 34.378	37.155*	66.795 89.433 142.802
AMI PENETRATION INDUSTRIAL	3.905*	17.920 25.601 50.642	13.961*	147.505 184.086 258.773
DG UPTAKE RATE INDUSTRIAL	-2.581*	15.260 20.841 34.784	9.386*	44.813 61.623 104.031
AMI PENETRATION RESIDENTIAL	8.061*	21.559 30.424 54.478	40.120*	75.39 102.872 153.076
DG UPTAKE RATE RESIDENTIAL	17.842*	23.457 34.545 64.847	8.459*	31.306 43.885 72.867
AMI PENETRATION SME	15.289*	24.118 35.600 40.848	11.164*	99.367 134.807 198.770
DG UPTAKE RATE SME	2.672*	13.098 17.716 30.449	69.838*	62.152 85.263 133.642

Notes: Critical values are 0.10, 0.05 and 0.01 respectively and obtained by 5000 bootstraps. Optimum lags are determined by Bayesian Information Criterion (BIC). Test statistics allow for heterogeneity in long-run variances. *Series are stationary at their levels.

Bootstrap critical values are also presented in the table, and the order of the variables are identified by comparing the tests statistics and bootstrap critical values. PANKPSS test results are evident that all the variables are stationary in their levels. All the variables, therefore, appear to be $I(0)$. Thus, we can proceed to panel causality test with the level values of the variables.

3.3.Dimitrescu-Hurlin Panel Causality Test Results

The results of the Dumitrescu-Hurlin panel causality test for the first lag of the variables are illustrated in Table 7[7]. The rejection of the null hypothesis in Dumitrescu-Hurlin panel causality test indicates that y is the Granger cause of x for all units in an analysis.

Table 7: Dumitrescu-Hurlin Panel Causality Test Results (Lag = 1)

Direction (y→x)	W-stat	Zbar-stat	Prob. Value	Conclusion
AMI PENETRATION COMMERCIAL → DG UPTAKE RATE COMMERCIAL	4.517	12.344	0.000	Reject H_0
DG UPTAKE RATE COMMERCIAL → AMI PENETRATION COMMERCIAL	4.496	12.267	0.000	Reject H_0
AMI PENETRATION INDUSTRIAL → DG UPTAKE RATE INDUSTRIAL	3.002	6.953	0.000	Reject H_0
DG UPTAKE RATE INDUSTRIAL → AMI PENETRATION INDUSTRIAL	7.138	21.669	0.000	Reject H_0
AMI PENETRATION RESIDENTIAL → DG UPTAKE RATE RESIDENTIAL	6.577	19.674	0.000	Reject H_0
DG UPTAKE RATE RESIDENTIAL → AMI PENETRATION RESIDENTIAL	9.395	29.703	0.000	Reject H_0
AMI PENETRATION SME → DG UPTAKE RATE SME	4.060	10.719	0.000	Reject H_0
DG UPTAKE RATE SME → AMI PENETRATION SME	6.780	20.396	0.000	Reject H_0

Note: → denotes unidirectional causality relationship.

Since the relevant probability values are smaller than 0.05, they favor rejecting the null of non-causality for *AMI PENETRATION* and *DG UPTAKE RATE* variables. The results of this analysis, therefore, indicates that there is bidirectional causality between *AMI PENETRATION* and *DG UPTAKE RATE* for all consumer segments. More precisely, *AMI PENETRATION* can be used to forecast the future values of *DG UPTAKE RATE*, as well as *DG UPTAKE RATE* can

[7] Analyses with two or three lags are also provide comparable results. They are illustrated in the Appendix.

be a tool for estimating the future values of *AMI PENETRATION*. Thus, policies aiming to improve *AMI PENETRATION* and *DG UPTAKE RATE* significantly affect each other interchangeably.

4. Discussion and Conclusion

The liberalization of electricity markets and the development of information technology have transformed the industrial organization of electricity markets. Particularly, along with growing environmental concerns, the future characteristics of electricity markets will be the networks' getting smarter and generation's becoming more distributed rather than being central. Examining the relationship between these two components can provide important clues for policymakers.

Both the relevant literature and the regulatory authorities' policy reports suggest that there is a relationship between smart meters and distributed generation and that an essential tool for the integration of distributed generation into electric systems is the smart meter technology. However, to date, there has been no formal or scientific test of this proposition.

This article examines the relationship between advanced metering infrastructure (AMI) and distributed generation (DG), which are expected to be among the key components of future electricity markets. For this purpose, long monthly time series data were used for four different consumer groups (commercial, industrial, residential and small- and medium-sized enterprises) for the network reporting regions in New Zealand. First, the possible cross-sectional dependency among observational units because of common regulatory and economic shocks was tested, then unit root tests that allow cross-sectional dependency and structural breaks were implemented. These tests concluded that the data were stationary, and, therefore panel Granger causality tests were applied to analyze the relationship between AMI and DG variables.

The findings are in line with the propositions in the literature and policy papers, and they comprise policy implications for prospects. According to the results of the panel Granger causality tests, a two-way causality relationship between AMI and DG was established for all consumer groups analyzed. Thus, AMI penetration can be used to forecast the future values of DG uptake rate, as well as DG uptake rate can be a tool for estimating the future values of AMI penetration. Therefore, policies to promote AMI or DG will result in the promotion of both variables.

Examining the relationship between AMI and DG empirically, this study is first in the literature. Since it used detailed time series analysis for different consumer segments, it is a more disaggregated analysis and, therefore, the findings are more convincing.

References

Ackermann, T., Andersson, G. and Söder, L. (2001). Distributed generation: a definition. *Electric Power Systems Research, 57*(3), 195-204.

Akorede, M.F., Hizam, H. and Pouresmaeil, E. (2010). Distributed energy resources and benefits to the environment. *Renewable and Sustainable Energy Reviews, 14*(2), 724-734.

Bae, M., Kim, H., Kim, E., Chung, A.Y., Kim, H. and Roh, J.H. (2014). Toward electricity retail competition: Survey and case study on technical infrastructure for advanced electricity market system. *Applied Energy, 133*, 252-273.

Bayod-Rújula, A.A. (2009). Future development of the electricity systems with distributed generation. *Energy, 34*(3), 377-383.

Bhattacharya, M., Paramati, S. R., Ozturk, I., & Bhattacharya, S. (2016). The effect of renewable energy consumption on economic growth: Evidence from top 38 countries. *Applied Energy, (162)*, 733-741.

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies, 47*(1), 239-253.

Cossent, R., Gómez, T. and Frías, P. (2009). Towards a future with large penetration of distributed generation: Is the current regulation of electricity distribution ready? Regulatory recommendations under a European perspective. *Energy Policy, 37*(3), 1145-1155.

De Joode, J., Jansen, J.C., Van der Welle, A.J. and Scheepers, M.J.J. (2009). Increasing penetration of renewable and distributed electricity generation and the need for different network regulation. *Energy Policy, 37*(8), 2907-2915.

Depuru, S.S.S.R., Wang, L. and Devabhaktuni, V. (2011). Smart meters for power grid: Challenges, issues, advantages and status. *Renewable and Sustainable Energy Reviews, 15*(6), 736-2742.

Dogan, E., & Seker, F. (2016). Determinants of CO 2 emissions in the European Union: The role of renewable and non-renewable energy. *Renewable Energy, (94)*, 429-439.

El-Khattam, W. and Salama, M.M. (2004). Distributed generation technologies, definitions and benefits. *Electric Power Systems Research, 71*(2), 119-128.

El-Khattam, W., Bhattacharya, K., Hegazy, Y. and Salama, M.M.A. (2004). Optimal investment planning for distributed generation in a competitive electricity market. *IEEE Transactions on Power Systems, 19*(3), 1674-1684.

EU COM. (2011). A Roadmap for moving to a competitive low carbon economy in 2050. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions no:112, Brussels.

Farhangi, H. (2010). The path of the smart grid. *IEEE Power and Energy Magazine, 8*(1), 18-28.

Frías, P., Gómez, T., Cossent, R. and Rivier, J. (2009). Improvements in current European network regulation to facilitate the integration of distributed generation. *International Journal of Electrical Power & Energy Systems, 31*(9), 445-451.

Lluís Carrion-i-Silvestre, J., Barrio-Castro, D., & López-Bazo, E. (2005). Breaking the panels: An application to the GDP per capita. *The Econometrics Journal, 8*(2), 159-175.

Lopes, J.P., Hatziargyriou, N., Mutale, J., Djapic, P. and Jenkins, N. (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electric Power Systems Research, 77*(9), 1189-1203.

Menyah, K., Nazlioglu, S., & Wolde-Rufael, Y. (2014). Financial development, trade openness and economic growth in African countries: New insights from a panel causality approach. *Economic Modelling, (37)*, 386-394.

Nazlioglu, S., & Karul, C. (2017). A panel stationarity test with gradual structural shifts: Re-investigate the international commodity price shocks. *Economic Modelling, (61)*, 181-192.

Ozbugday, F.C. and Nillesen, P.H., 2013. Efficiency and Prices of Regulation-Exempt Consumer-Owned Natural Monopolies: A First Look at Electricity Distributors in New Zealand. *Annals of Public and Cooperative Economics, 84*(4), 361-381.

Paliwal, P., Patidar, N.P. and Nema, R.K. (2014). Planning of grid integrated distributed generators: a review of technology, objectives and techniques. *Renewable and Sustainable Energy Reviews, (40)*, 557-570.

Pepermans, G., Driesen, J., Haeseldonckx, D., Belmans, R. and D'haeseleer, W. (2005). Distributed generation: definition, benefits and issues. *Energy Policy, 33*(6), 787-798.

Perasan, H. (2006) A simple panel unit root test in the presence of cross section dependence. Cambridge University, Working Paper, No: 0346.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2), 265-312.

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal, 11*(1), 105-127.

Prakash, P. and Khatod, D.K., 2016. Optimal sizing and siting techniques for distributed generation in distribution systems: A review. *Renewable and Sustainable Energy Reviews, (57)*, 111-130.

Ropenus, S., Jacobsen, H.K. and Schröder, S.T. (2011). Network regulation and support schemes–How policy interactions affect the integration of distributed generation. *Renewable Energy, 36*(7), 1949-1956.

Tan, W.S., Hassan, M.Y., Majid, M.S. and Rahman, H.A. (2013). Optimal distributed renewable generation planning: A review of different approaches. *Renewable and Sustainable Energy Reviews, (18)*, 626-645.

Viral, R. and Khatod, D.K. (2012). Optimal planning of distributed generation systems in distribution system: A review. *Renewable and Sustainable Energy Reviews, 16*(7), pp.5146-5165.

Vogel, P. (2009). Efficient investment signals for distributed generation. *Energy Policy, 37*(9), 3665-3672.

Wolsink, M. (2012). The research agenda on social acceptance of distributed generation in smart grids: Renewable as common pool resources. *Renewable and Sustainable Energy Reviews, 16*(1), 822-835.