Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 141 (2017) 86–90

Energy Procedia

www.elsevier.com/locate/procedia

4th International Conference on Power and Energy Systems Engineering, CPESE 2017, 25-29 September 2017, Berlin, Germany

Solar Photovoltaic Energy and Its Spatial Dependence

Sergio Copiello[a]*, Carlo Grillenzoni[a]

[a] IUAV University of Venice, Dorsoduro 2206, 30123 Venice, Italy

Abstract

In the last decade, solar photovoltaic has started to play a significant role in the energy mix consumption. Although this growth has involved almost all the western countries, marked differences in the regional distribution of photovoltaic generation capacity have been observed. These differences appear to be weakly related to climate conditions in general, and to solar radiation specifically. The literature has started to investigate the other underlying determinants, suggesting to consider the occurrence of spatial proximity effects. Accordingly, this study aims to analyze whether and to what extent the photovoltaic energy production depends on local factors, such as climate, demand, income, innovative and responsible behavior, and so forth. Through a spatial autoregressive model, we find that the regional distribution of photovoltaic production capacity is affected by strong spatial dependence. We show that the availability of photovoltaic energy may be explained by peer effects, such as diffusion of habits and emulation of neighbors.

Keywords: solar photovoltaic; spatial energy; spatial data; peer effects; neighborhood effects

1. Introduction and background literature

The energy production and consumption models have experienced significant changes during the last decades [1]. On the supply side, although fossil fuels are still the most prominent sources, the transition to renewables is underway. Many countries have massively developed photovoltaic (PV) power generation systems. As a case in point, the share of electricity consumption met by solar energy is now more than 5% in Germany and up to 7% in Italy [2].

* Corresponding author. Tel.: +39 41 257 1387.
E-mail address: copiello@iuav.it

10.1016/j.egypro.2017.11.017

Nomenclature

Ci	creativity index [%]	Pp	per capita photovoltaic production [kWh]
Ec	per capita electricity consumption [kWh]	Ps	consumption met by photovoltaic [%]
Ef	exogenous factors	Sr	solar radiation [MJ/m2]
Gdp	per capita gross domestic product [Euros]	α	constant
Hd	housing density [Building/km2]	$\beta,\gamma,\delta,\omega$	regression coefficients
Hm	average size of households	s	spatial indicator
Ir	innovative and responsible behaviour	s-1	indicator for spatially lagged variables

Worldwide, the installed capacity has grown to over ten times the level in 2007 [2]. According to IEA's Outlook, solar energy is expected to play an increasing role in the years to come [3]. The above framework suggests investigating the PV deployment at regional and local scale and its determinants, the knowledge of which is rather limited. Balcombe et al. [4] have reviewed the motivations and barriers to the adoption of microgeneration technologies. Besides the local climate characteristics - especially the level of solar radiation [5] - several socioeconomic factors - such as age, income, investment cost, expected and actual return on investment - have been found to explain the consumers' propensity to use renewable energy systems [6-11]. Balta-Ozkan et al. [12] show that also electricity demand, population density, pollution, and education are significant drivers.

Spatial dependence characterizes many ecological and social phenomena. It means that the behavior of a unit is affected by what happens in the surrounding areas, due to the so-called peer interaction effects, such as the diffusion of habits and the emulation of neighbors. A devoted research branch has stressed that proximity, neighborhood effects, and peer effects are important in shaping the spatial deployment of PV installations [11-17]. These effects turn out to play a prominent role, more than climate conditions [18]. A comprehensive review of the literature mentioned above can be found in Balta-Ozkan et al. [12].

2. Models, data, and method

We are interested in analyzing the dynamic relationship between the per capita PV production (Pp), the share of electricity consumption met by PV energy (Ps), and other explanatory covariates, in order to understand the behavior of the solar energy market. Our data are not simple cross-sectional because a spatial order characterizes the observations in the sample, which thus are not interchangeable. The spatial contiguity of the units raises a problem of serial correlation that seriously affects the statistical properties of the estimates. Analogous to the time series analysis, the issue can be solved by using spatial autoregressive (SAR) systems that include lagged terms [19,20,21]. SAR systems are useful to express the bivariate relationship between energy production and consumption.

Let us define the spatial index s=[latitude, longitude]. The first-order lagged dependent variables Pp_{s-1} and Ps_{s-1} are represented by the average values of Pp_s and Ps_s in the surrounding areas. Besides these lagged dependent variables, the other explanatory variables we consider are as follows: Ec_s represents the per capita electricity consumption; Ir_s is the vector of variables assumed as proxy of innovative and responsible behavior; Ef_s is the vector of exogenous factors. The three following variables approximate innovative and responsible behavior: creativity index (Ci_s); technology index; waste recycling rate. The vector of exogenous factors include several variables: latitude; solar radiation (Sr_s); surface area; residential buildings; housing density (Hd_s); population density; households; average number of members per household (Hm_s); per capita gross domestic product (Gdp_s), manufacturing firms, share of Plc and Ltd companies.

If the errors ε_s are mutually independent, then the estimation of the SAR system can be performed by separate equations. Accordingly, the two regression models, with parameters α, β, γ, δ, and ω are as follows:

$$Pp_s = \alpha + \beta\, Pp_{s-1} + \gamma\, Ec_s + \boldsymbol{\delta}'\mathbf{Ir}_s + \boldsymbol{\omega}'\mathbf{Ef}_s + \varepsilon_s \quad (1)$$

$$Ps_s = \alpha + \beta\, Ps_{s-1} + \gamma\, Ec_s + \boldsymbol{\delta}'\mathbf{Ir}_s + \boldsymbol{\omega}'\mathbf{Ef}_s + \varepsilon_s \quad (2)$$

$$\ln(Pp_s) = \alpha + \beta \ln(Pp_{s-1}) + \gamma \ln(Ec_s) + \boldsymbol{\delta}' \ln(\mathbf{Ir}_s) + \boldsymbol{\omega}' \ln(\mathbf{Ef}_s) + \varepsilon_s \tag{3}$$

$$\ln(Ps_s) = \alpha + \beta \ln(Ps_{s-1}) + \gamma \ln(Ec_s) + \boldsymbol{\delta}' \ln(\mathbf{Ir}_s) + \boldsymbol{\omega}' \ln(\mathbf{Ef}_s) + \varepsilon_s \tag{4}$$

The use of the logarithmic transformation is motivated by possible non-linear relationships between the variables. Eqs (1)-(4) are estimated using the Ordinary Least Squares method (with robust standard errors according to the White's dispersion matrix), by performing a forward stepwise regression. The packages we use are R and Gretl. The data cover 110 provinces in Italy (according to the NUTS3 classification). The spatially lagged dependent variables are defined according to the proximity structure of the units (Fig. 1).

3. 3. Results and discussion

Tables 1 and 2 show the results. As expected, the share of electricity consumption met by solar photovoltaic energy depends on climate factors; however, their statistical significance is rather limited. The solar radiation Sr_s hardly explains more than 5% of Pp_s variance, this raises questions about plant efficiency, network distribution and location policies of solar facilities. Instead, latitude and surface area are excluded from the models due to collinearity issues.

Table 1. Results of the linear models according to Eqs. (1) and (2).

Dependent	Pp_s				Dependent	Ps_s			
	β	*t-stat*	*p-value*	*V.i.f.*		*β*	*t-stat*	*p-value*	*V.i.f.*
const	970.2840	2.397	0.0183		const	57.6107	5.678	0.0000	
Pp_{s-1}	0.5111	4.136	0.0001	1.133	Ps_{s-1}	0.4393	2.573	0.0115	1.453
Ec_s					Ec_s	-0.0013	3.025	0.0031	1.392
Ci_s	-92.5855	5.489	0.0000	1.033	Ci_s	-1.9563	4.716	0.0000	1.181
Sr_s	0.2099	3.200	0.0018	1.164	Sr_s				
Gdp_s					Gdp_s	-0.0002	1.903	0.0598	1.771
Adj. R^2	0.3486				Adj. R^2	0.3739			
F-stat	18.1196		0.0000		F-stat	14.1993		0.0000	
White's test	15.2935		0.0832		White's test	13.2599		0.5062	

Table 2. Results of the logarithmic models according to Eqs. (3) and (4).

Dependent	$\ln(Pp_s)$				Dependent	$\ln(Ps_s)$			
	β	*t-stat*	*p-value*	*V.i.f.*		*β*	*t-stat*	*p-value*	*V.i.f.*
const	5.3553	1.710	0.0903		const	13.6455	4.483	0.0000	
$\ln(Pp_{s-1})$	0.6068	4.865	0.0000		$\ln(Ps_{s-1})$	0.5258	4.802	0.0000	1.534
$\ln(Ec_s)$	0.4209	2.846	0.0053		$\ln(Ec_s)$	-0.4753	3.119	0.0024	1.397
$\ln(Ci_s)$	-2.9160	4.325	0.0000		$\ln(Ci_s)$	-3.3504	4.760	0.0000	1.283
$\ln(Hd_s)$	-0.3945	4.017	0.0001		$\ln(Hd_s)$	-0.3515	3.295	0.0013	1.385
$\ln(Hm_s)$	4.1082	4.189	0.0001		$\ln(Hm_s)$	3.0297	3.047	0.0029	1.476
Adj. R^2	0.5265				Adj. R^2	0.5854			
F-stat	25.3647		0.0000		F-stat	39.9121		0.0000	
White's test	27.5117		0.1215		White's test	26.2341		0.1582	

Id	City	Neighbors	Id	City	Neighbors
1	Torino	2 4 5 6 7 9	56	Grosseto	52 53 55 65
2	Vercelli	1 3 6 7 8 9 20	57	Prato	43 50 51
3	Novara	2 8 14 17 20	58	Perugia	54 55 59 60 61 62 63 66
4	Cuneo	1 5 10 11	59	Terni	55 58 65 66
5	Asti	1 4 6 11	60	Pesaro	47 54 58 61
6	Alessandria	1 2 5 11 12 20 39	61	Ancona	58 60 62
7	Biella	1 2 9	62	Macerata	58 61 63 64
8	Verbania	2 3 14	63	Ascoli Piceno	58 62 64 66 71
9	Aosta	1 2 7	64	Fermo	62 63
10	Imperia	4 11	65	Viterbo	55 56 59 66 67
11	Savona	4 5 6 10 12	66	Rieti	58 59 63 65 67 70 71
12	Genova	6 11 13 39 40	67	Roma	65 66 68 69 70
13	La Spezia	12 40 48	68	Latina	67 69 76
14	Varese	3 8 15 17 25	69	Frosinone	67 68 70 75 76
15	Como	14 16 23 25	70	L'Aquila	66 67 69 71 72 74 75
16	Sondrio	15 18 19 23 26 27	71	Teramo	63 66 70 72
17	Milano	3 14 18 20 21 24 25	72	Pescara	70 71 73
18	Bergamo	16 17 19 21 23 25	73	Chieti	70 72 74 75
19	Brescia	16 18 21 22 27 28	74	Campobasso	73 75 76 77 81
20	Pavia	2 3 6 17 24 39	75	Isernia	69 70 73 74 76
21	Cremona	17 18 19 22 24 39 40	76	Caserta	68 69 74 75 77 78
22	Mantova	19 21 28 34 41 42 44	77	Benevento	74 76 78 79 81
23	Lecco	15 16 18 25	78	Napoli	76 77 79 80
24	Lodi	17 20 21 39	79	Avellino	77 78 80 81 87
25	Monza	14 15 17 18 23	80	Salerno	78 79 87
26	Bolzano	16 27 30	81	Foggia	74 77 79 86 87
27	Trento	16 19 26 28 29 30	82	Bari	83 84 86 87 88
28	Verona	19 22 27 29 33 34	83	Taranto	82 84 85 88
29	Vicenza	27 28 30 31 33	84	Brindisi	82 83 85
30	Belluno	26 27 29 31 35 38	85	Lecce	83 84
31	Treviso	29 30 32 33 38	86	Barletta-A-T	81 82 87
32	Venezia	31 33 34 35 38	87	Potenza	79 80 81 82 86 88 89
33	Padova	28 29 31 32 34	88	Matera	82 83 87 89
34	Rovigo	22 28 32 33 44	89	Cosenza	87 88 90 92
35	Udine	30 32 36 38	90	Catanzaro	89 91 92 93
36	Gorizia	35 37	91	Reggio di C.	90 93 96
37	Trieste	36	92	Crotone	89 90
38	Pordenone	30 31 32 35	93	Vibo Val.	90 91
39	Piacenza	6 12 20 21 24 40	94	Trapani	95 97
40	Parma	12 13 21 39 41 48	95	Palermo	94 96 97 98 99
41	Reggio E.	22 40 42 48 49	96	Messina	91 95 99 100
42	Modena	22 41 43 44 49 50	97	Agrigento	94 95 98
43	Bologna	42 44 45 50 51 57	98	Caltanissetta	95 97 99 100 101
44	Ferrara	22 34 42 43 45	99	Enna	95 96 98 100
45	Ravenna	43 44 46 51	100	Catania	96 98 99 101 102
46	Forlì	45 47 51 54	101	Ragusa	98 100 102
47	Rimini	46 54 60	102	Siracusa	100 101
48	Massa	13 40 41 49	103	Sassari	104 106 107
49	Lucca	41 42 48 50 51 53	104	Nuoro	103 105 106 107 108
50	Pistoia	42 43 49 51 57	105	Cagliari	104 106 108 109 110
51	Firenze	43 45 46 49 50 53 54 55 57	106	Oristano	103 104 105 109
52	Livorno	53 56	107	Olbia-Temp.	103 104
53	Pisa	49 51 52 55 56	108	Ogliastra	104 105
54	Arezzo	46 47 51 55 58 60	109	Medio C.	105 106 110
55	Siena	51 53 54 56 58 59 65	110	Carbonia-I.	105 109

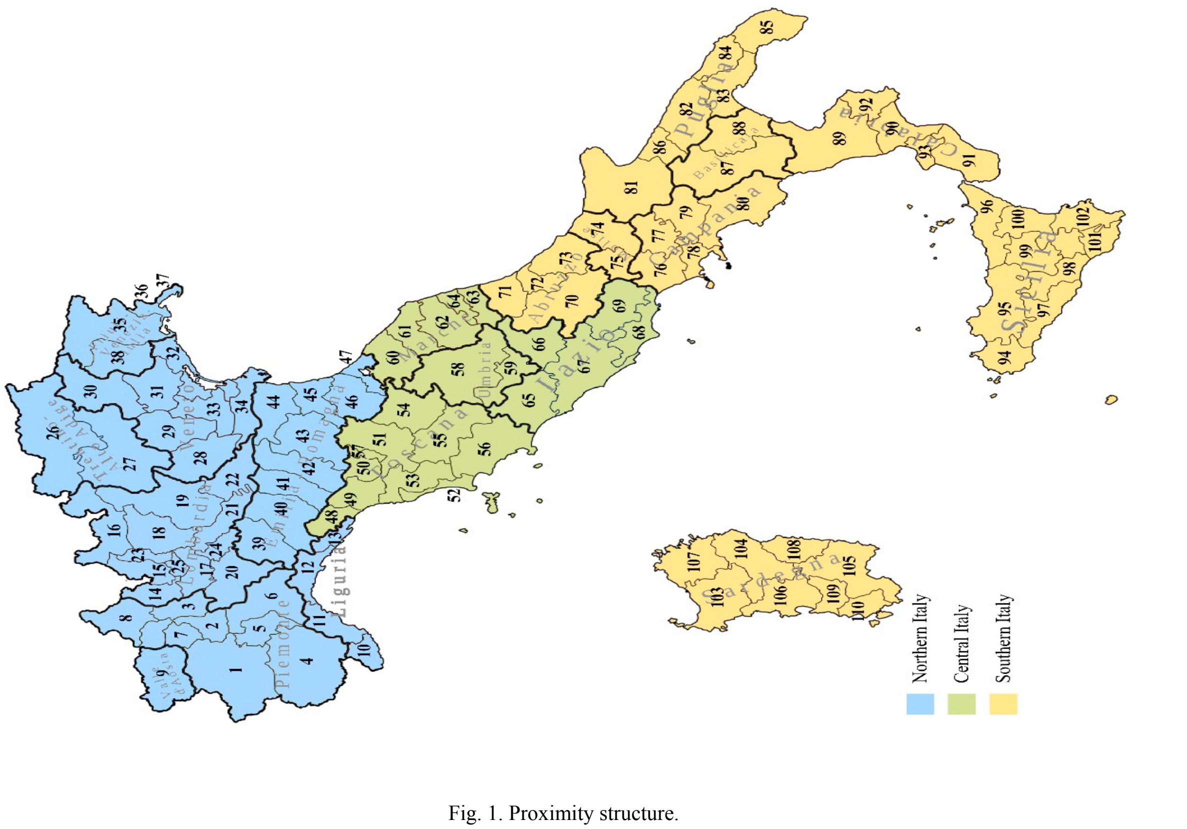

Fig. 1. Proximity structure.

Other significant variables are Ci_s, Gdp_s, Hd_s, and Hm_s. The unexpected result is that they all have a negative sign. The adoption of innovative and responsible behavior does not emerge as a driver of photovoltaic production. The fact that Pp_s and Ps_s are high where income and housing density are lower, as well as where the number of household's members is higher, confirms that photovoltaic production is strong in the less developed areas of the country. The role played by electricity consumption is controversial: Ec_s positively affects Pp_s but negatively Ps_s.

The most notable outcome is that solar photovoltaic energy shows a strong spatial dependence, both at production and consumption levels. The logarithmic model enables to explain nearly the 53% of Pp_s variance, but more than 18% of the same variance is explained by the photovoltaic production in the surrounding areas of each province (Pp_{s-1}).

Similarly, nearly 59% of Ps_s variance is explained by the function based on natural logarithms, but Ps_{s-1} explains up to 31% of the same variance.

4. Conclusions

In this study, we demonstrate that spatial dependence is a key topic in the research strand that aims to delve into the determinants of the transition to the renewables, specifically the solar photovoltaic energy. The results we achieve pose at least two issues that call for further investigations. The first concerns the nonlinearity of the relationships between dependent and independent variables, because the goodness of fit of the logarithmic functions ($0.53 < \text{Adj. } R^2 < 0.59$) is higher than in the linear models ($0.35 < \text{Adj. } R^2 < 0.37$). The second issue consists of the formulation of the proximity structure. The nearness between the units of observation may be measured using several indicators, such as distances, shared boundaries, and so forth. Hence, it should be analyzed whether and how much different nearness indicators lead to diverging results.

References

[1] Copiello S. Building energy efficiency: A research branch made of paradoxes. *Renew Sustain Energy Rev* 2017;69:1064–76.
[2] International Energy Agency. *Technology Roadmap - Solar Photovoltaic Energy*, Paris; 2014.
[3] International Energy Agency. *World Energy Outlook*, Paris; 2016.
[4] Balcombe P, Rigby D, Azapagic A. Motivations and barriers associated with adopting microgeneration energy technologies in the UK. *Renew Sustain Energy Rev* 2013;22:655–66.
[5] Westacott P, Candelise C. A novel geographical information systems framework to characterize photovoltaic deployment in the UK: Initial evidence. *Energies* 2016;9.
[6] Faiers A, Neame C. Consumer attitudes towards domestic solar power systems. *Energy Policy* 2006;34:1797–806.
[7] Keirstead J. Behavioural responses to photovoltaic systems in the UK domestic sector. *Energy Policy* 2007;35:4128–41.
[8] Zhang Y, Song J, Hamori S. Impact of subsidy policies on diffusion of photovoltaic power generation. *Energy Policy* 2011;39:1958–64.
[9] Sardianou E, Genoudi P. Which factors affect the willingness of consumers to adopt renewable energies? *Renew Energy* 2013;57:1–4.
[10] Bonifaci P, Copiello S, Stanghellini S. Assessing policy measures on building energy efficiency through a multi-Actor multi-criteria analysis, in: P. Hájek, J. Tywoniak, A. Lupíšek, K. Sojková (Eds.), *CESB 2016 - Cent. Eur. Towar. Sustain. Build. 2016 Innov. Sustain.* Futur., Grada Publishing, Prague, 2016: pp. 1343–1350.
[11] Dharshing S. Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy Res Soc Sci* 2017;23:113–24.
[12] Balta-Ozkan N, Yildirim J, Connor PM. Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach. *Energy Econ* 2015;51:417–29.
[13] Bollinger B, Gillingham K. Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Mark Sci* 2012;31:900–12.
[14] Müller S, Rode J. The adoption of photovoltaic systems in Wiesbaden, Germany. *Econ Innov New Technol* 2013;22:519–35.
[15] Graziano M, Gillingham K. Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment. *J Econ Geogr* 2015;15:815–39.
[16] Rode J, Weber A. Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. *J Environ Econ Manage* 2016;78:38–48.
[17] Palm A. Local factors driving the diffusion of solar photovoltaics in Sweden: A case study of five municipalities in an early market, Energy *Res Soc Sci* 2016;14:1–12.
[18] Schaffer AJ, Brun S. Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. *Energy Res Soc Sci* 2015;10:220–7.
[19] Anselin L. *Spatial Econometrics: Methods and Models*. Dordrecht: Springer Kluwer; 1988.
[20] C. Grillenzoni, Adaptive spatio-temporal models for satellite ecological data, *J Agric Biol Environ Stat* 2004;9:158–180.
[21] Copiello S, Grillenzoni C. Is the cold the only reason why we heat our homes? Empirical evidence from spatial series data. *Appl Energy* 2017;193:491–506.