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Something new under the sun. A spatial econometric analysis of the adoption of photovoltaic systems in Italy

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ABSTRACT

This paper analyses the adoption of photovoltaic systems (PV) in Italy. We employ a spatial econometric approach applied to province-level data for 2015–2021 to identify the main determinants of PV adoption and to gauge both the potential bias deriving from spatial dependence and the spillover effects affecting neighboring areas in PV diffusion. We test different spatial econometric models and different types of economic, social and demographic variables. We add new regressors to consider the role of housing market dynamics (volume of sales and price of transaction) as a possible driver of PV adoption. We find that the housing market and electricity consumption are important positive determinants of PV adoption, whereas social capital and socio-demographic indicators do not provide statistical evidence of being major drivers of PV adoption. We confirm that other economic factors, like average income, can explain PV diffusion, whereas solar irradiation does not show to play a critical role. We do not find an important role of policies on energy efficiency and renewable energy in the housing sector, but our data timeframe covers a period after the very high incentives from the 'Conto Energia' and, at the same time, prevents us from observing the possible effects of the 'Superbonus 110' introduced in 2021. Moreover, our findings indicate that spatial dependence exists between neighboring areas in PV adoption, suggesting that spatial econometric models can be robust empirical approaches for interpreting PV deployment in studies at the regional or sub-regional level.

1. Introduction

In the EU, the European Green Deal (EGD), further reinforced by the macro recovery policies of Next Generation EU (NGEU), is pursuing a transition strategy that implies a new phase of long-term structural change for the European economy (EU Commission, 2023a). Decarbonizing the EU energy system is the cornerstone of the EGD and the EU's climate policy, which aims to achieve a 55% cut in GHG emission by 2030 and Net Zero by 2050. The main objectives of the EGD are related to energy security by ensuring a secure and affordable energy supply for the EU, based mainly on renewable sources. Moreover, the EGD aims to develop an integrated, interconnected, and digitalized EU energy market, increase energy efficiency (i.e., buildings, transports) and introduce innovations in the energy market (i.e., promote innovative technologies, eco-design of products and modernization of energy infrastructures). Another important goal of the EGD is to mitigate the social impact of the energy market, by empowering consumers and reducing energy poverty in the EU member states (EU Commission, 2023a).

Photovoltaic solar systems (PV) can provide an important contribution to achieve the Net Zero by 2050 (IEA, 2022a) and PV deployment has increased substantially in recent years (IEA, 2022a, 2022b), even though the renewable energy sector still represents a small share of global energy supply (Alipour et al., 2021; Bourcet, 2020).

At the end of 2022, the EU Commission approved the REPowerEU which sets out a series of measures to reduce dependence on Russian fossil fuels and foster green transition by increasing the European energy system's resilience on fossil energy sources (EU Commission, 2023b). The program also includes the EU Solar Energy Strategy which aims to speed up the EU's clean energy transition with the massive diffusion of PV systems throughout Europe (320 GW by 2025 and 600GW by 2030) as a direct replacement of gas imports for electricity production.[1] REPowerEU has among its objectives to increase the EU's solar power ambitions (SolarPowerEurope, 2023). PV diffusion, therefore, will be

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[1] The new PV uptake will reduce natural gas imports by 9 billion cubic meters (EU Commission, 2023b).

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crucial for the EU to ensure a sustainable energy transition.

Even though these policy impulses are crucial for the transition, energy saving and green energy solutions in the residential sector are mainly driven by individual decision-making (Heiskanen and Matschoss, 2017; Schulte et al., 2022) which may be influenced by several factors (e.g. market conditions and energy price expectation, uncertainty on actual energy savings). Understanding the main drivers and barriers of PV diffusion can be extremely important for designing tailored policies to improve PV deployment at every territorial level (i.e., global, national, regional), thus contributing to decarbonization and energy security.

The literature on PV deployment and diffusion is extensive and relevant, but it is mainly based on surveys on observed adoptions and attitudes towards adoption (Alipour et al., 2021). Recently, some scholars have focused on regional patterns underlying PV uptake by including in their analyses spatial spillovers between regions, which are seen as an important aspect to consider and have found interesting aspects linked to spatial reciprocity across regions in the deployment of PV.

Spatial dependence is an important aspect in regional sciences because it can be an important driver of regional development especially in terms of technological diffusion due to the geographical interdependency of neighboring regions. This aspect has also been highlighted in the energy economics literature (Balta-Ozkan et al., 2015; Graziano and Gillingham, 2015; Kosugi et al., 2019) with contributions that emphasize how spatial dependence can contribute to mutual interactions of social, economic and cultural dimensions that increase the degree of technology diffusion between adjacent regions, with highly localized factors such as peer-effect, imitation, herd behavior and network interactions (Welsch and Kühling, 2009).

As highlighted by Schaffer and Brun (2015) and Dharshing (2017), PV diffusion can be strongly affected by spatial dependence since PV deployment in one region can be affected by the level of penetration of PV systems in neighboring regions. These authors define 'solar clusters' as the spatial dependence of PV deployment which may derive from structural physical features of a region such as solar irradiation, or the level of competences of specific regional agglomerations. Spatial dependence can therefore influence adjacent regions in terms of spillover effects through social or knowledge externalities, by inspiring and supporting the development of similar initiatives in neighboring areas (Dharshing, 2017).

This paper contributes to the energy economics literature on regional diffusion of PV systems by providing a case study of Italy. The paper uses a spatial econometric approach to identify the main determinants (either drivers or barriers) linked to PV adoption at the provincial level. The spatial-spillovers and spatial interconnections are considered both to reduce the biases due to standard econometric approaches, which overlook these aspects, and to consider the effects of spatial interconnections in PV diffusion.

The paper is structured as follows. In Section 2 the information background on PV systems in Italy is presented with a short literature review of research on PV deployment. Section 3 describes the method of analysis and the data that is used. The results are presented in Section 4 and in Section 5 the results are discussed, and some final remarks are proposed.

2. Background and literature review

2.1. Photovoltaic systems in Italy

In its energy strategy agenda, Italy included a massive development of renewable energy sources (RES) that, together with energy efficiency, is one of the pillars of Italy's green transition strategy. After a series of ineffective and controversial experiences in the 1990s, Italy started deploying structured national RES policies after the Directive 2009/28/EC (EU Parliament and Council, 2009). Within the EU's overall target of having an energy mix with 20% of gross final energy consumption from RES by 2020, the Italian national action plan (PAN) foresaw 17% of RES in gross final energy consumption and 10% in transport (PAN, 2010). After the 2020 deadline, and after having gone beyond the PAN objectives (RES in 2020 were 20.4% of gross final energy consumption), the new Italian National Energy and Climate Plan was implemented introducing new targets to be achieved by 2030 (30% of gross final energy consumption from RES) (PNIEC, 2019). In 2021, RES accounted for 38% of total internal gross electricity final consumption, which represents an overall increase of 133% from 2005 (GSE, 2023a). In 2021, the share of PV over the total amount of gross electricity consumption was 8%, while the shares of the other RES were: hydropower 15.4%, wind 6.4%, geothermal 2%, biomass 2.1%, biogas 2.6%, and liquid biofuels 1.5%. Therefore, the increase of solar technologies share has been impressive considering that in 2005 PV represented only 0.01% of total gross electricity final consumption. In Fig. 1, the evolution of the RES mix as a share of gross electricity final consumption is depicted.

The Italian governments have provided incentives to deploy RES with a special focus on solar energy by adopting a mix of mechanisms: (i) feed-in-tariffs from 2006 to 2012, under *I-IV Conto Energia* (with an additional constant premium rate compared to the energy market prices for all types of PV); from 2012 to 2013 under *V Conto Energia* (with additional constant premium rate differentiated by PV lower and higher than 1 MW) (GSE, 2023b); (ii) incentives for self-production and self-consumption electricity (*Scambio sul Posto*) (GSE, 2023c); (iii) incentives through auction mechanisms (*Decreto FER*) and (iv) fiscal incentives such as tax reliefs and discounts for energy efficiency of private buildings including the implementation of PVs (*Eco-Bonus* and *Superbonus 110*).

The installation of PV systems has increased steadily in Italy from 34,805 plants with an installed capacity of 483 MW in 2008 to 1,016,083 plants with an installed capacity of 22,594 MW in 2021. The rapid growth before 2013 was due to generous incentives from the *Conto Energia*, followed by a phase of consolidation that was characterized by a slower PV deployment both in terms of number of plants and installed capacity (GSE, 2021). On average, the scale of PV plants is relatively small and equal to 22.2 kW per plant. Small-scale PV with power lower than or equal to 20 kW make up around 93% of total installations in terms of number of plants, but they represent merely 23% of total installed capacity. Conversely, the remaining 77% of total installed capacity comes from medium and large PVs which represent 7% of the number of plants (GSE, 2023a; IEA, 2021). Therefore, although small-scale systems contribute only partially to the national PV installed capacity, they account for the majority of the PV systems installed in the country and have experienced a remarkable growth since 2015, with an average annual growth rate of 6.7%, while total cumulative capacity has grown at a slower pace of around 2.8% (GSE, 2023a).

Fig. 2 shows the distribution of the total number of PV systems by plant size and cumulative installed capacity from 2015 to 2021. In Fig. 3, the growth rate of both the number of plants and cumulative installed capacity in Italy are shown.

The economic size of the PV sector at the national level is important. The value added generated by the sector in 2021 was estimated by GSE at 764 million euros, with a total investment in the photovoltaic sector of 1.05 billion euros (GSE, 2022). Moreover, PV electricity production also contributed to reducing national CO_2 emissions: according to IEA the PV installations in Italy avoided a total of 15 MT of CO_2 (IEA, 2022b).

As in many other socio-economic aspects of the Italian system, there are significant regional differences in PV penetration, in terms of both number of installations and total capacity (GSE, 2020). According to the IEA report (2021), in 2021 two Northern regions (Lombardy and Veneto) hosted 30.4% of the plants installed nationwide, while the record for regional installed capacity, 13% of the total national capacity, was held by Apulia, a region in the South of Italy.

Figs. 4 and 5 respectively show the distribution of PV plants at the

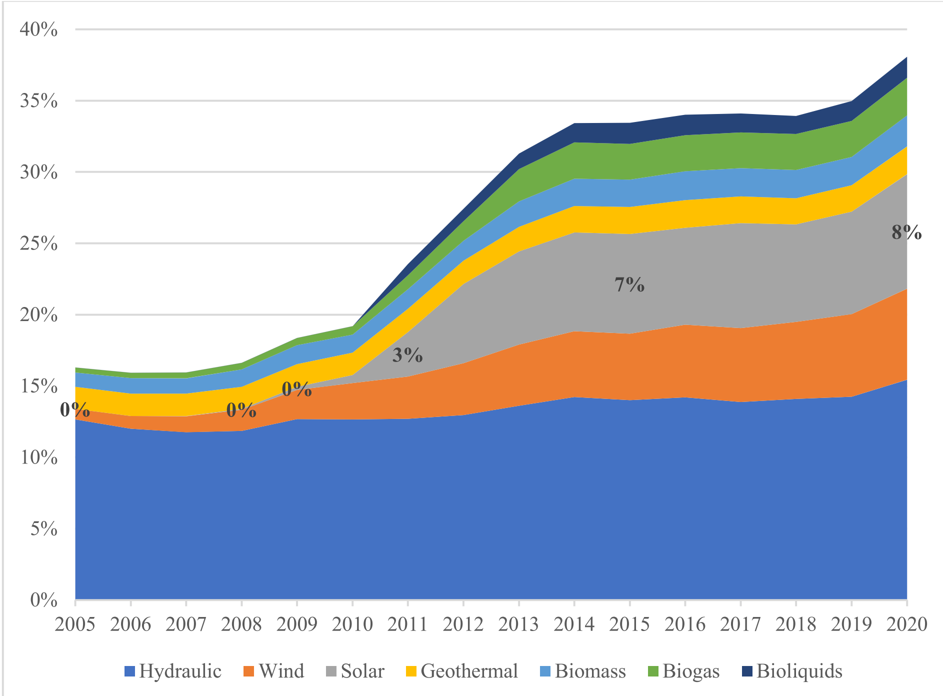

Fig. 1. RES production as share of total gross electricity final consumption, in %. Source: Authors' elaborations from GSE data. Note: the numbers refer only to the % shares of PV.

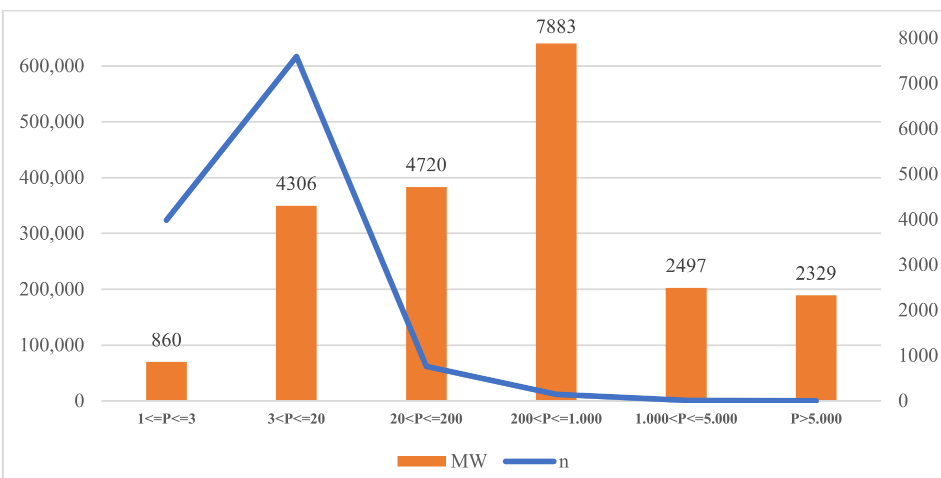

Fig. 2. Distribution of the cumulative PV plants (vertical axis on the left) and cumulative installed capacity in MW (vertical axis on the right) in Italy from 2015 to 2021. Source: Authors' elaborations on GSE (2023a) data.

provincial level (NUTS3) and the installed capacity as a share of the total national figures.

2.2. Literature on the adoption of photovoltaic systems

The research literature on PV adoption and diffusion has recently increased and it has now become vast and varied. Scholars have mainly focused on the different determinants influencing either the actual adoption, the attitude towards PV (i.e. willingness and acceptance) or the intention to adopt PV using a diversified set of frameworks (i.e., dynamic models, cointegration analysis, GMM, SEM, ANOVA, spatial analysis) (Alipour et al., 2021; Bourcet, 2020). Many analyses used as a dependent variable the PV percentage of the total energy mix, while in terms of independent variables, in a recent literature review, Alipour et al. (2021) identified two main categories of variables: economic and non-economic. The first category includes subsidies (e.g. feed-in-tariffs, fiscal incentives), policy and legislation to reduce installation costs, financial availability, energy prices, efficiency of the technology. The second category includes all other aspects which are not strictly linked to economic factors influencing adoption such as aesthetic value, mass media and information, peer effects, education, social aspects (Alipour et al., 2021). Most of the authors agree that economic factors are strongly relevant in increasing the propensity of PV adoption, whereas a clear shared conclusion on the role of non-economic factors does not emerge.

Bourcet (2020) provides another taxonomy of the determinants of PV adoption which also includes regulatory variables, environmental variables (e.g., CO_2 and emissions of other pollutants), political variables (e.

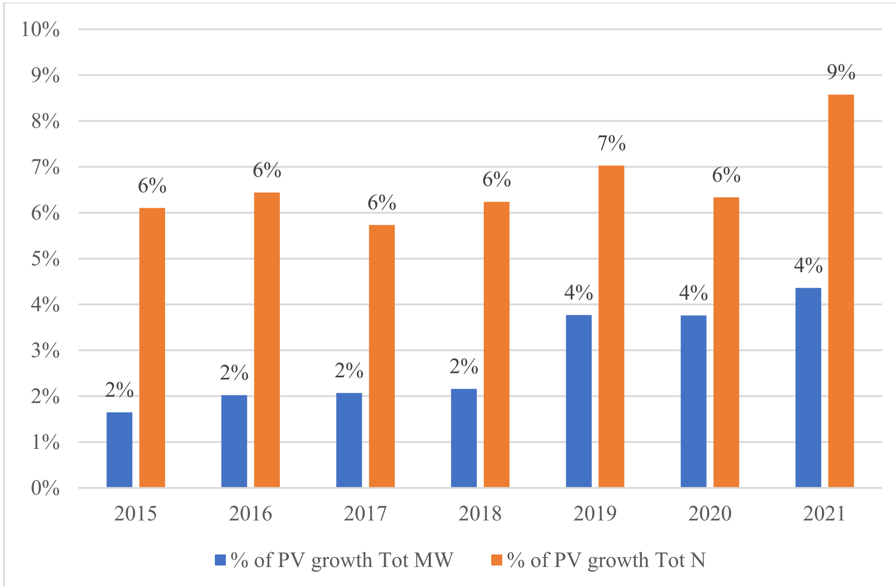

Fig. 3. Growth rate of the cumulated number of PV installations and cumulated installed capacity from 2015 to 2021 (%). Source: Authors' elaborations on GSE (2023a) data.

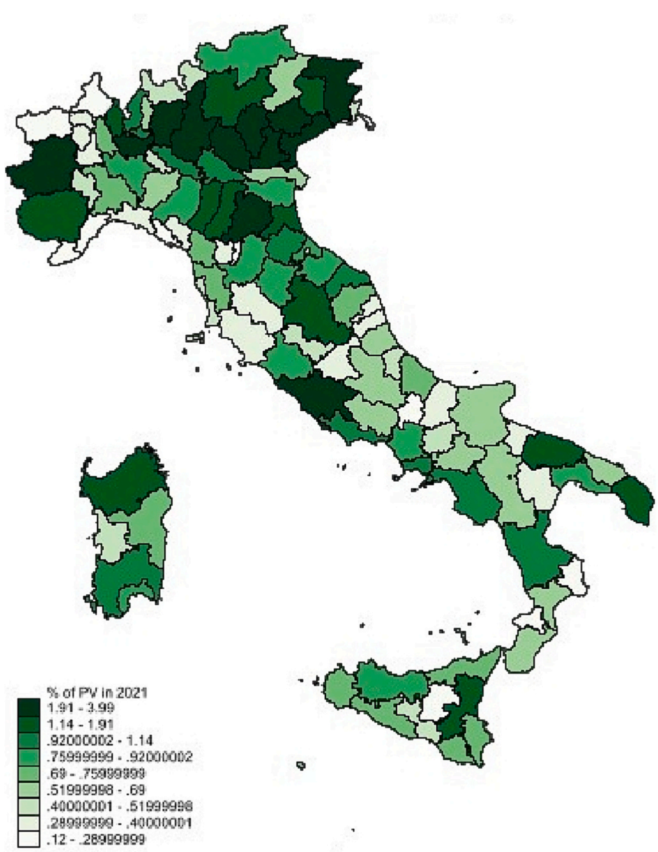

Fig. 4. Number of PV installations at provincial level as share of the total number at national level in 2021 (%).
Source: Authors' elaborations on GSE (2023d) data.

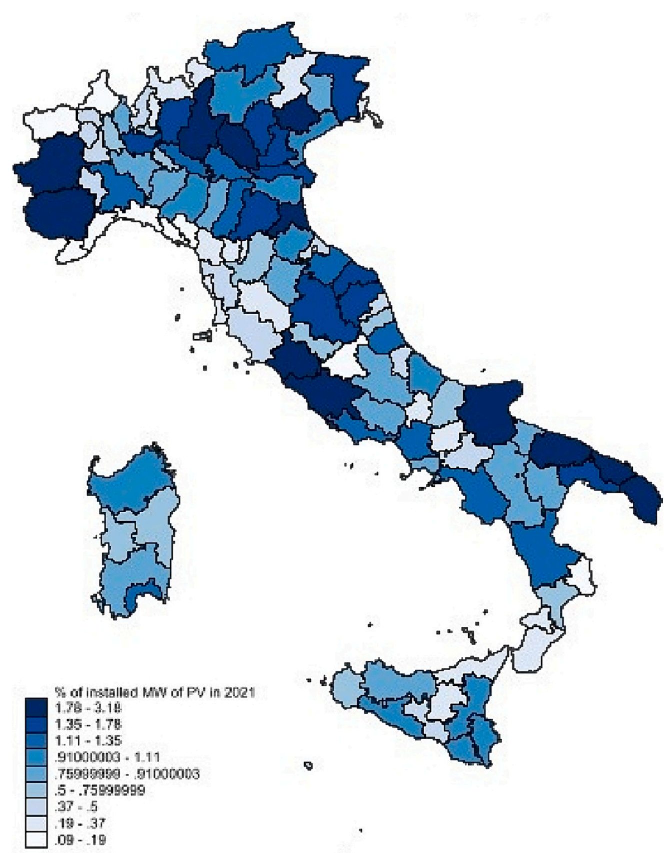

Fig. 5. Installed PV capacity at provincial level as share of the total national capacity in 2021 (%).
Source: Authors' elaborations on GSE (2023d) data.

g., institutional quality, government ideology) and demographic variables (e.g., population, size, education). In another literature review of 173 studies on the adoption behavior of PV on residential rooftops, Alipour et al. (2020) identified 333 predictors of PV deployment in the literature and divided them into three main categories: individual (142), social (104) and informational (87), which were further broken down into twenty subcategories. Even though the most common type of independent variables used are socio-demographic, Schulte et al. (2022)

and Alipour et al. (2020) showed in their meta-analysis that they are seldom explicative of the decision for PV adoption. The same authors identify personal traits and individual motivations as positive factors for PV deployment, as well as general attitudes towards the environment or pro-environmental behaviors.

Palm (2020) includes, among the factors worthy of interest for PV diffusion, predictors linked to the built environment such as detached homes, ownership and home value indicating that they are likely to be more important than socio-economic and household demographic features. The same author indicates in his literature review that voting behavior or political affiliation, which is used in many studies as Green party share or Green party support, are seldom relevant in explaining PV diffusion. Moreover, in Palm's review, information availability and peer effects are identified as important aspects of PV diffusion (Palm, 2020). Education has been identified as a factor positively influencing higher levels of PV uptake (Heiskanen and Matschoss, 2017).

Surprisingly, within the ample literature on PV uptake, only eleven studies analyzed the topic through a spatial lens taking into account spillovers between territories.

The first studies on PV adoption with a spatial focus were by Bollinger and Gillingham (2012), Müller and Rode (2013) and Richter (2013), who analyzed the peer effects and social interactions on PV uptake at the household level, respectively in California, Germany and the UK. All the studies highlighted that actual households adoption decisions were driven by social interactions, networks and peer-effects which in turn are strongly induced by relative closeness and spatial distance.

Also Graziano and Gillingham (2015) analyzed PV diffusion in Connecticut (US) focusing on neighbors peer effects. They used census track level data associated with prior adoption in the nearby blocks and found strong evidence of neighboring effects. Moreover, the authors also considered different distances between neighboring blocks for PV uptake and found that the spatial effect decreases with distance. They also found that the neighboring effect diminishes with time, suggesting that prior installations have less influence on putting in new installations as time goes by. Another interesting finding is that smaller centers contribute more than larger urban areas to PV adoption and the share of renters has a decreasing effect on adoption. High localization and imitation patterns of household PV adoption have been further confirmed by Rode and Weber (2016) who extended the Graziano and Gillingham analysis to the national level, again confirming strong peer effects which diminish with increasing distance.

Other scholars focused more on a regional approach to understand the main drivers of PV uptake. Schaffer and Brun (2015) analyzed the issue in Germany at the county level from 1991 to 2012. The authors used as the dependent variable the cumulated capacity of small-scale PV installations per km^2 to consider diversities in the size of German counties. They found a variety of PV uptake rates across counties with solar irradiation, income per capita, house density and spillover effects as important drivers for adoption, whereas their study does not provide evidence of the environmental attitude of households (in terms of % of Green party voters in that county) (Schaffer and Brun, 2015).

Residential PV uptake in Germany has been studied also by Dharshing (2017) with county level data covering 14 years (2000–2013), using the percentage of owner-occupied buildings installing a domestic PV system in the time period observed. The author found a clear correlation between the socio-economic and demographic conditions of the household (income, level of education), age (population under 20) and the profitability of the technology (return on investment) as drivers of PV adoption. The author found statistically significant spillover effects for neighboring counties with 'Solar clusters', while the environmental attitude (% of Green party voters) and the housing type (single family homes) had unclear effects on PV adoption (Dharshing, 2017).

Balta-Ozkan et al. (2015) used cross-section data (PV installation in 2013) to analyze the determinant of residential PV installations in the UK at NUTS3 level (134 spatial units). They employed as a dependent variable the logarithm of the number of domestic PV installations under 10KW. The authors provided evidence that the level of education, CO_2 emissions, solar irradiance level, demand for electricity and housing type (shared or detached) are all positive determinants of PV uptake, whereas they did not find any clear statistical effect on regional gross income. The findings on spatial spillover effects of the average number of households, share of owned houses and population density are not clear since they provide only estimations of the main coefficients without showing the indirect effects of their estimations.[2]

Kosugi et al. (2019) analyzed factors influencing the diffusion of domestic PV in the city of Kyoto (Japan) with spatial panel data (neighborhood block) using as a dependent variable the ratio between installed PV per year and the stock of detached houses. In the analysis, the authors considered different socio-economic aspects of households as well as one on income differences by household groupings. They used as independent variables classical socio-economic indicators such as population density and demographic characteristics (proportion of young and elderly population living on the block, and number of household members). Moreover, they added some variables never used before in literature such as the PV payback period (undiscounted payback period for each year of adoption) and the proportion of the population living on the block for at least 5 years or for 20 years or longer (Kosugi et al., 2019). Their results indicate the following factors have a positive boost on the diffusion of PV in neighborhoods: low population density, a younger population, number of households members, and length of time living in the neighborhood. In terms of spatial spillovers, they found that a lower ratio of detached houses and lower population densities in nearby blocks can positively influence the diffusion of PV in the observed block, while the spillover effect due to PV adoption in nearby neighborhoods is statistically significant only if the range of distance[3] is between 500 and 1000 m (Kosugi et al., 2019).

Graziano et al. (2019) focused their analysis on the effects of spatial peer effects and the built environment (e.g. detached homes, single family properties) on PV uptake in Hartford, the capital of the State of Connecticut (USA). Using a mixed spatial approach analysis (fixed effects panel, spatial models), they confirmed the evidence that strong spatial effects exist on PV uptake decisions in neighboring areas, whereas the effect of the built environment was weaker than in other studies.

Finally, Kucher et al. (2021) studied residential solar PV adoption in the Mid-Atlantic region of the US at county level with a panel spanning from 2005 to 2016. Their dependent variable was the PV capacity installed in the county, using as predictors socio-economic factors (i.e., education, house density and detached homes, age), but added policy measures (i.e., solar carve-out, sales tax exemption) and electricity market measure which could affect PV adoption (i.e., size of PV, cost of PV, electricity price). They found that energy and policy variables (i.e., increase of electricity prices, cost of PV, and tax exemptions) were prevailing drivers for PV installations, while socio-economic variables were weak predictors of adoption except for education which was a statistically significant predictor of PV uptake (Kucher et al., 2021). Moreover, they found a statistically significant autocorrelation coefficient and spillover effect indicating that spatial dependence between neighboring counties was due to the degree of PV penetration in adjacent areas.

The Italian case has been addressed by a number of works. Most of the authors had focused on the effects of the feed-in-tariffs schemes and other subsidizing policies introduced in Italy on the national PV uptake,

[2] The estimated coefficients did not provide the marginal effect of the regressors using the Spatial Durbin Model (LeSage and Pace, 2009), while they should have provided the direct, indirect and total effects of each regressor.

[3] They used different models considering the distance between the centroids of the blocks (from <200 m to <2000 m).

and employ descriptive methods such as Antonelli and Desideri (2014), Orioli and Di Gangi (2015) and Bianco et al. (2021). Rogna (2020) and Bocca et al. (2015) analyzed the most important factors for identifying the best sites for the implementation of industrial PV. The former employed a multi-attribute filtering method based on Pareto efficiency of the identified location (Rogna, 2020), whereas the latter used Geographical Informative Systems to select the most suitable locations considering the yearly solar radiation, the average temperature and the type of possible installation (Bocca et al., 2015). They both agree that the profitability of the investment for industrial PV depend on the irradiation of the sites which strictly affect the potential production of the systems shortening the length of the investment payback. Only the study of Copiello and Grillenzoni (2021) employed a spatial statistical method based on the nearest neighbor approach applied to a sample of PV units installed in Italy between 2006 and 2011. Although they do not explicitly use a standard spatial econometric analysis, in their OLS they consider spatial and time dependence in the dependent variable and in the independent variables (very similar to a SDM approach). They study the determinants of adoption looking at drivers already explored by the above mentioned literature. Their main dependent variable is the cumulative installed PV capacity in each municipality that had at least one PV plant benefitting from the feed-in-tariff scheme in place in their period of analysis. As possible determinants affecting PV uptake, they selected: i) a set of physical factors such as elevation (altitude), latitude, land area, the built environment (i.e., houses built before 1981 and after 2006); ii) a set of socio-economic variables such as employment rate, number of firms normalized by population, education, disposable income per capita, and a commuting indicator (students and workers) to indirectly consider potential spatial spillovers (i.e., they use this indicator as a proxy of imitation and peer-effects). Their results confirmed serial and spatial dependence in the data indicating the installed PV capacity is positively affected by the simultaneous and antecedent installations in the surrounding areas, thus supporting the hypothesis of peer and neighboring effects. Moreover, they found that physical variables (altitude, latitude) have not explanatory power for describing the PV uptake process in Italy, highlighting that solar irradiance and weather effects (latitude is a proxy of solar irradiance) are not important drivers of adoption. Moreover, they found that the built environment and population are the most important drivers of adoption, whereas the other socioeconomic factors considered were not. Interestingly, they found a strong, but negative, relationship between disposable income and PV uptake and concluded that the feed-in tariff schemes in place in the period under study were supporting PV adoption in less wealthy areas (Copiello and Grillenzoni, 2021).

3. Methods and data description

3.1. Econometric strategy

The aim of this paper is to investigate the main determinants of the adoption of PV systems in Italy. We adopt a spatial econometric approach which allows us to deal with spatial dependence, which commonly emerges from regional data. Econometric literature, with interesting empirical applications in energy economics studies, (Balta-Ozkan et al., 2015; Dharshing, 2017; Kucher et al., 2021; Schaffer and Brun, 2015; Zhao et al., 2021), introduced some robust econometric models for dealing with bias caused by spatial dependence, thus providing interpretations for marginal effects in terms of spatial spillovers.

Spatial dependence can be defined as a situation where values observed in one location (or region) depend on the values of neighboring observations in nearby locations (or regions). This implies a simultaneous data generating process in which the independence assumption is violated, and this can cause biased and inconsistent estimations when using standard econometric methods since the residuals are not independently and identically distributed (Anselin, 1988; LeSage and Pace, 2009). Especially in regional studies, the presence of a spatial lag is plausible and realistic since neighboring areas tend to resemble each other, showing similar characteristics (e.g. income, employment) due to mutual influence, to spatial externalities and spillover effects (LeSage and Pace, 2010).

Following Elhorst (2014), three different types of spatial interactions can be identified. The first is endogenous interaction effects where the dependent variable of the specific spatial unit depends on the dependent variable of another spatial unit and vice versa. The second is exogenous interaction effects where the dependent variable of a specific spatial unit depends on the independent variables of other spatial units. The third type of interactions occur when spatial dependence is present among the error terms of different spatial units (Elhorst, 2014).

In all three cases, the two dependent variables are jointly determined and identified by spatial patterns between units based on: 1) location; 2) degree of connectivity; 3) strength of the spatial dependence (respectively for the endogenous and exogenous variables, and error terms) (LeSage and Pace, 2009). Spatial econometric models can help solve problems arising from spatial interactions by adding spatial lags to standard models for terms affected by spatial dependence using a spatial weighted normalized matrix (W) to account for neighboring relations among observations (Anselin, 2003). Following Elhorst (2014), a full model with all types of interaction effects takes the form of the general nesting spatial model (GNS) as in Eq.1:

$$Y = \alpha I_N + \rho WY + \beta X + \theta WX + u \tag{1.a}$$

$$u = \lambda Wu + \varepsilon \tag{1.b}$$

where WY is the endogenous interaction effects of the dependent variables between the observed region and its neighboring regions, simply called the spatial lag; it represents a linear combination of the values, variable y, combined with the values of the dependent variable in neighboring observations. WX is the exogenous interaction effects of independent variables from nearby regions and Wu is the spatial interaction effects in the disturbance term. αI_N is the costant term. Their respective coefficients to be determined are the spatial autoregressive coefficient, ρ, a set of spatial exogenous correlation effects, θ, and the spatial autocorrelation coefficient, λ. The spatial parameters (ρ, θ, λ) define the strength of spatial dependence in the sample of observations (LeSage and Pace, 2009). The spatial structure of the data is reflected by the spatial weight normalized matrix, W. Its elements are $W_{i,j}$=1 if observations i and j are neighboring regions sharing a common border (Queen contiguity),[4] otherwise they are set to 0. Then the W matrix is row-normalized, that is, when all the row elements sum to unity (dividing by row of all the ones by the number of neighbors) (Elhorst, 2014).

The spatial model used can take on different specifications depending on the type of spatial dependence assumed. The spatial dependence considered in our model reduces the general model presented in eq.1 to restricted versions which depend on the values assumed for each spatial term (i.e., ρ, θ, λ). There are four special cases of spatial models as restricted versions of the GNS[5]: 1) if all the spatial interactions are set to zero, assuming there is no spatial dependence in the model (i.e., $\rho = 0$, $\theta = 0$, $\lambda = 0$), we have a standard linear regression model; 2) if only the spatial autoregressive interaction is considered (i.e., $\rho \neq 0$, $\theta = 0$, $\lambda = 0$) we have a spatial autoregressive model (SAR); 3) if only the spatial interaction term of the regressors is considered (i.e., $\rho = 0$, $\theta \neq 0$, $\lambda = 0$) we have a spatially lagged-X model (SLX); 4) finally, if the spatial lag considered is in the error term (i.e., $\rho = 0$, $\theta = 0$, $\lambda \neq 0$), we obtain a

[4] We used a Queen contiguity approach to create the W matrix. The elements on the diagonal are set to zero since we do not consider that a region can be considered its own neighbor.

[5] Usually, GNS models are not used because they suffer from over-parameterization problems (Elhorst (2014)).

spatial error model (SEM) (Elhorst, 2014; Golgher and Voss, 2016).

Generally, empirical works employ combinations of the above-mentioned spatial models since they allow more flexibility in managing spatial dependence issues which can occur simultaneously in the data. The spatial Durbin model (SDM) combines SAR and SLX, while the spatial Durbin Error model (SDEM) combines SLX and SEM, whereas the spatial-autoregressive model with spatial-autoregressive disturbances (SAC or SARAR) combines the SAR and SEM models to control for the spatial dependence both in the autoregressive and in the disturbance term (Elhorst, 2014).

The first empirical step is to check for spatial dependence in the dependent variable to look for potential spatial autocorrelation by using the Moran's I Test which can detect the presence of spatial correlation in the dependent variable, thus suggesting the introduction of the spatial autoregressive term. The Moran's I test return values ranging between −1 and 1, where negative values stand for negative spatial correlation and positive values suggest positive spatial dependence; it is explicated in Eq. 2

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i-\overline{X})(X_j-\overline{X})}{\sum_{i=1}^{n}(X_i-\overline{X})^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{2}$$

where X_i and X_j denote, respectively, the observation of the ith and jth provinces, $\overline{X}$ is the mean of the relevant variable and w_{ij} is the element in the spatial weighted matrix W at the ith row and jth column. Positive levels of the Moran's I test indicate spatial clustering in nearby observations.

Elhorst (2014) proposed a specific-to-general approach to proceed in spatial analysis by starting from non-spatial linear regression testing for potential extensions of the baseline specification, adding spatial interaction effects to design the best specification of the model for dealing with the specific caveats caused by spatial dependence in the data. We followed this approach starting with a standard linear panel fixed-effects model and, after detecting a spatial dependence in the dependent variable using the Moran's I tests, we opted for a spatial econometric approach. We then run several spatial models SDM, SEM, SAR and SAC to compare all the models in terms of robustness and to consider how each model can deal with the spatial dependence as previously identified. After estimating our models, we performed a robustness check using the Akaike (AIC) and Bayesian Information Criterion (BIC) test on other spatial models (SAR, SEM, SDM) to find the best fit of the data generation process as suggested by LeSage and Pace (2009) and Elhorst (2014). The AIC and BIC tests recommend to choose the models with the lowest values of both statistics, then, in our case, they suggest to exclude the SEM and SAR model since their values are clearly higher then SDM and SAC. Unfortunately, these tests cannot provide us a clear picture on which is the best model between the SDM and SAC as they are not in accordance (i.e. the lowest AIC indicate SDM while the lowest BIC indicate SAC), but just indicate that SDM and SAC are better than the other models in describing the data generation process. The final choice is using the SAC model, because of the two models, it is the only one showing statistically significant values of the spatial lag term (ρ), whereas this term is not statistically significant using the SDM model, suggesting that the SAC model is better for taking into account the spatial dependence already identified in the Moran's I tests (the results of all the models are presented in the Section 4).

Moreover, we opted for the SAC model since it was the best choice for our data generating process since it also identifies the potential spatial dependence in the error terms due to unobserved factors. In fact, it is plausible to assume that regions are spatially correlated in the unobservable components and this may lead to spatially lagged error terms (Anselin, 2003).

Thus, SAC allows to simultaneously consider spatial lags either in the dependent variable or in the error term (LeSage and Pace, 2009). Furthermore, using this approach, it is possible to obtain the average direct and indirect effect of each regressor. The latter can be considered as the average spillover effect of one province to all the other provinces due to contiguity and spatial interactions among provinces. Whereas the former can be considered as the effect of a regressor from the province under observation plus the feedback effect from adjacent provinces (Golgher and Voss, 2016).

The baseline model specification is shown in Eq. 3

$$Y_{it} = \rho\sum_{j=1}^{N} w_{ij}Y_{jt} + \sum_{k=1}^{K} x_{itk}\beta_k + \tau_t + \gamma_i + u_{it}; u_{it} = \lambda\sum_{j=1}^{N} w_{ij}u_{it} + \varepsilon_{it} \tag{3}$$

where ρ is the spatial autoregressive coefficient indicating the influence of the dependent variable from the nearby jth province on the ith province, weighted by the their level of contiguity synthetized by the w_{ij}th element of the spatial W matrix, x_{itk} is the set of K regressors with β_k coefficients, λ is the spatial autocorrelation coefficient in the disturbance term by which the error of the nearby jth province spatially interacts with the ith province disturbance through the w_{ij}th element of the W matrix[6], whereas ε_{it} is the idiosyncratic component of the error term with a 0 mean and σ^2 variance (LeSage and Pace, 2010). The variable τ_t is used to capture the time fixed effects, and thus controls for all exogenous factors which may affect the estimation in the time frame considered such as macroeconomic shocks or specific policies aimed at boosting PV uptake (e.g., economic downturns, inflation, energy policies such as *Conto Energia*, *Superbonus 110*). The term γ_i is the provincial fixed effects as used in the standard fixed effects setting to control for unobserved cross-section heterogeneity which may lead to biased estimations. The SAC model is estimated using the Maximum Likelihood technique, employing the method developed by Belotti et al. (2017)[7] that uses fixed effects for addressing cross-sectional heterogeneity.

3.2. Data description

3.2.1. The dependent variable

Our geographical unit of observation is the Italian province (NUTS3 level). Italy has 107 provinces that represent the intermediate level of government between municipalities and Regions. The provincial level is the lowest of the administrative data that allow us to apply a panel-type analysis. Data at the lowest administrative level (i.e. municipalities) are available but only in the form of cross-section data.

We employed as a dependent variable the net uptake of PV systems in terms of the net number of installed systems at provincial level. The data on the total number of cumulative PV installations in each Italian province for the 2014–2021 timeframe was obtained from the dataset of the National Energy Service Operator (GSE, *Gestore Servizi Energetici*). The GSE data includes both small residential and non-residential systems, without distinction in size or power of the system installed. It is worth remembering, as also noted in Section 2, that the total number of residential PV installations smaller than 20kWh make up 93% of total national installations (GSE, 2021). Therefore, we can consider the number of PVs installed to be a good proxy for describing households' PV adoption decision.

We opted for the net uptake per year to consider both new PV installations and dismantling of old PV systems to get a measure of the actual yearly adoption flow at the provincial level. Following other

[6] We adopted the same matrix for all the spatial lagged terms. To calculate and normalize the matrix of spatial weight we used the Stata *spmat* command developed by Drukker et al. (2013). We used a Queen contiguity matrix which considers areas that share a common border or a single common point as neighbors. The matrix has been row normalized in which each element in a row is divided by the sum of the row's elements (LeSage and Pace, 2009).

[7] To run the spatial estimator we used the *xsmle* command developed by Belotti et al. (2017).

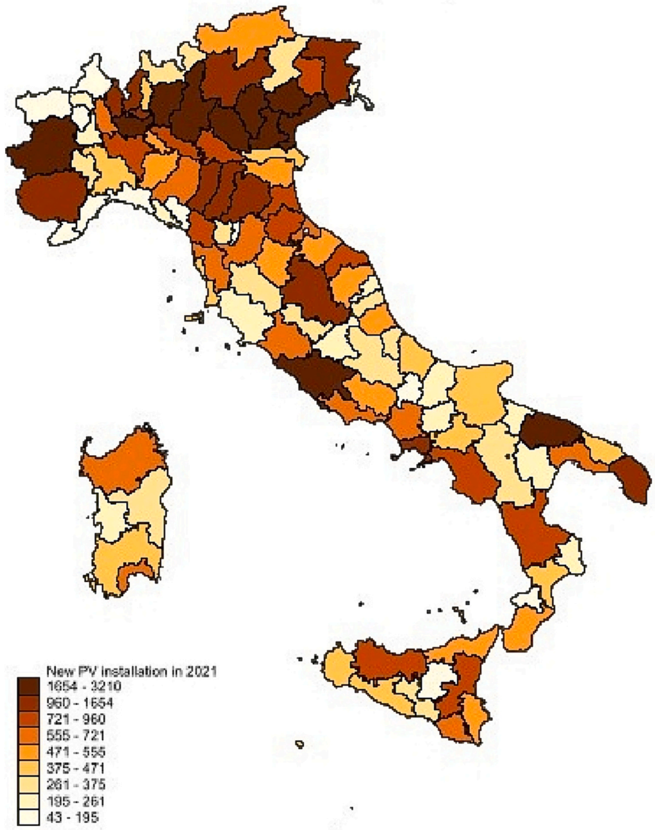

Fig. 6. Geographical distribution of Net installations of PV systems per squared kilometer by Province in 2021. Source: Authors' elaboration on GSE data.

empirical studies on PV uptake, such as Kosugi et al. (2019) and Dharshing (2017), who standardized the dependent variable to have a smooth distribution of the data and make the different provinces comparable, we adopted the same approach using the provincial area (km^2), as in Schaffer and Brun (2015), to achieve comparability among observations that may greatly differ by size. Therefore, our dependent variable is the net flow of installations resulting from the difference in the installed stock from *t* and *t-1*, as in eq. 4.

$$NetPV = \frac{PV_t(n) - PV_{t-1}(n)}{Provincial\ Area\ (sq.Km)} \tag{4}$$

where PV_t and PV_{t-1} are the stock of PV systems installed at the provincial level respectively in the year *t* and *t-1*. The difference in the stock is then divided by the area of the province from Eurostat data (Eurostat, 2022) to standardize the value obtained. Therefore, our dependent variable is the flow of net installed systems per squared kilometer for each Italian province in year *t*. The variable *NetPV* is positive when the net PV installations in year (*t*) are higher than the number of dismantled PV installations in the same year, and vice versa, it is negative if the installations in year (*t*) are less than the number of dismantled PVs in the same year. In the observed data, there is only one negative value.[8] The geographical distribution of our dependent variable is shown in Fig. 6.

Fig. 6 depicts a clear geographical distribution of the dependent variable in which net PV installation is highly clustered (e.g., West Piedmont, Emilia-Romagna, Lombardy, Veneto, Apulia and Lazio).

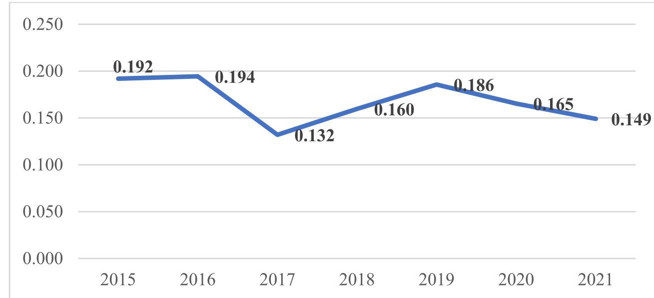

Fig. 7. Moran index for the dependent variable Net PV for the years 2015–2021.
Source: Authors' elaboration on GSE data. *Note: all the values of the Moran index are statistically significant at 1% level of significance except for 2017 which is significant at 5% level.*

Similarly, the central part of the country shows a similar pattern, but with the opposite sign, with clusters of low levels of installed net capacity (e.g., Abruzzo, Molise, Basilicata, Southern Calabria and Central-Western Sicily).

To confirm the presence of spatial dependence in the dependent variable, we ran a Moran's I test as described in Eq. 2. The test indicates a statistically significant spatial correlation[9] for the *NetPV* variable in nearby provinces suggesting a spatial econometric approach can be used to deal with this issue. The Moran's I tests are graphically described in Figs. 7 and 8. The first graph considers the Moran index trend for all the periods considered, indicating that the Moran index was always positive and statistically significant (every year at 1% except for 2017 when it was 5%; the Moran test is provided in Table A.1 in the appendix). The second graph depicts a Moran scatter plot for all the observations in the year 2021, showing a strong clustering in the third quadrant (counter-clockwise), which indicates spatial dependence[10] (LeSage and Pace, 2009). The Moran Indexes are positive and always highly statistically significant, but it is possible to note that there are slight fluctuations in spatial autocorrelation through time. In particular, it is clear a slight reduction in the year 2017 (0.132) and 2021 (0.139). We cannot provide a clear explanation for that since this might depend on exogenous effects which should have reduced the spatial correlation of PV uptake between Italian provinces despite an increase trend in overall PV adoption. We can only assume that the implementation of the Italian strategic energy policy ("*Nuova strategia energetica nazionale*") in 2017 and the introduction in 2021 of the incentivizing policy "*Superbonus 110*" might have boosted the adoption of PV in new areas where adoption rates were low before. This might have contributed to the slight reduction in spatial

[8] It is the case of the province of Cagliari in the Sardinia region in 2017, which was the result of the 2016 reforms of the province, when Cagliari was transformed into a 'metropolitan area' that led to the loss of some municipalities under its jurisdiction, which passed to the new province of Sud Sardegna.

[9] All the Moran Index *NetPV* variable values for the years considered are higher than 0 (between 0.132 and 0.192) indicating spatial dependence exists between nearby provinces. In this case the spatial dependence indicates that both high values and low values of PV uptake are more spatially clustered suggesting that similar values of PV uptake among adjacent geographical regions and that the spatial distribution of PV uptake is not random.

[10] Spatial dependence is evident in a Moran graph if clusters arise in the first and third counter-clockwise quadrants, since the distances from the mean in the *i*th and *j*th provinces move in the same direction. The quadrants of the plots indicate how the residuals of the dependent variables distribute (horizontal axis) considering the spatial lags (vertical axis). The quadrants indicate the relation between the deviation from the mean of the observed province and the average distance from the neighbors' mean. In quadrant I the *NetPV* residuals are above the mean where the average *NetPV* of neighboring provinces is also greater than the mean. In quadrant III, the *NetPV* residuals are below the mean and the average *NetPV* of neighboring provinces is also below the mean. This suggests spatial correlation. Conversely, in quadrants II and IV, the deviation from the mean of residuals and the neighbors' average deviation move in opposite directions, suggesting a negative spatial correlation (LeSage and Pace, 2009).

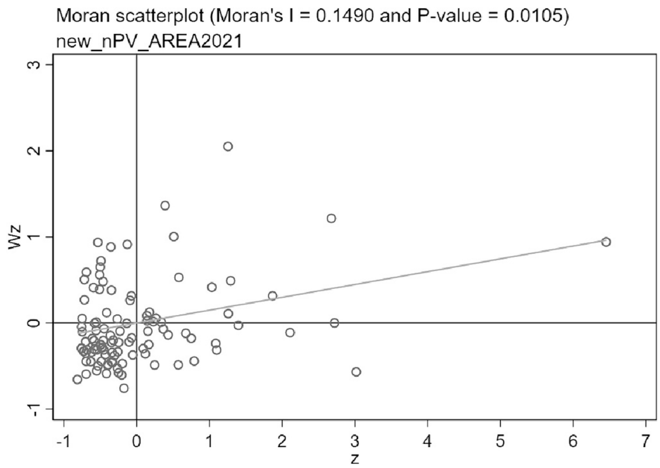

Fig. 8. Graph of the Moran index for the dependent variable Net PV in scatterplot form for 2021. Source: Authors' elaboration on GSE data.

correlation between regions where clusters of PV uptake were in place.

3.2.2. The independent variables

The independent variables were selected following the empirical literature on PV uptake we reviewed above. In the literature, one of the most prominent factors directly influencing PV adoption and diffusion at the household level is income, which reflects the financial constraints and risk-bearing possibilities of households (Balta-Ozkan et al., 2015). We used provincial aggregated data from the database on income statements at the municipal level released by the Ministry of Economy and Finance (MEF, 2023) to obtain the average provincial income in thousands of euros (*Income*).

We introduce the housing market as another potential driver of PV uptake. Indeed, a more active real estate sector may influence real estate market in provinces, that can be linked to the construction sector and housing renovations, which in turn can positively influence the adoption of energy-saving systems such as PV (both private and business). To consider this factor, we used provincial housing transaction data from the housing market observatory (*Osservatorio del Mercato Immobiliare*) of the Italian Revenue Agency (*Agenzia delle Entrate*) (OMI, 2023). The variable *House_Trade* is defined as the sum of the total housing market transactions in the province divided by the area (km^2) of the province in order to obtain size comparability among provinces.[11]

Another important aspect related to the real estate market is the value of houses, since this can influence the adoption of PV. Indeed, a home with a high value can favour the decision to adopt PV and other green solutions, while a low value can hinder PV adoption and pro-green choices. To consider home values, we used the variable *House_Value*, calculated as the difference between the maximum and minimum average house price per square meter in the province (original data are at municipal level), using data from the Italian real estate market provided by OMI aggregated at the provincial level (OMI, 2023). By using the difference between high and low prices we can control for heterogeneity in the housing market, but we can also smooth out peaks due to relatively high prices in specific areas such as metropolitan or tourist cities (e.g., Milan, Rome, Venice, Bologna) where average house values are very high and may be closely correlated with income. There are no multicollinearity problems between the two variables (i.e. *House_Trade* and *House_Value*), as defined, because the correlation between the two variables is low (0.39). In addition, to consider this aspect, we ran our final model with different specifications excluding one variable at a time; all results of this robustness check are stable, the statistical significance and the magnitude of the coefficient of both variables when the other is excluded are stable. The introduction of the housing market variables (*House_Trade* and *House_Value*) is an element of novelty in our work, as these aspects of housing have never been used before in research works on PV diffusion.

Among the factors directly driving PV uptake is the physical capacity of a territory to produce electricity through solar irradiation (Balta-Ozkan et al., 2015). To control for this factor, we used the average annual cumulative solar irradiation by province measured in kWh per m^2 on horizontal surface to measure the potential solar capacity of Italian provinces (*Solar_irradiation*). Solar irradiance is defined as the amount of electromagnetic energy incident on a surface received from the sun per unit time and per unit area (Wang et al., 2012). Solar irradiance data are derived from estimates obtained from the image processing of the Meteosat Second Generation weather satellite operated by Eumetsat (EUMETSAT, 2023), using the RADSAF methodology (Alessandrini et al., 2013; Collino and Ronzio, 2021) developed by the RSE (*Ricerca sul Sistema Energetico*) (RSE, 2023).

The level of electricity consumption can be another variable that can influence PV deployment since higher levels of energy consumption can increase energy costs, both for households and for other sectors. PV uptake can be considered as a form of energy cost abatement, since it allows for self-produced electricity, thus reducing the share of electricity bought on the market. To consider this factor we used the publicly available data from the national grid operator for electricity transmission TERNA on total annual electric provincial household consumption divided by the area of the province, expressed in GW per Km^2 (TERNA, 2023).

Following Kosugi et al. (2019), we add population density to consider agglomerative factors and to control for different levels of urbanization between provinces. This variable was transformed using its natural logarithm in order to smooth the distribution of data which is characterized by strong skewedness.

Other socio-demographic factors can influence the adoption and diffusion of PVs, as highlighted by previous studies like Kosugi et al. (2019) and Kucher et al. (2021). We controlled for this factor by using the provincial dependency ratio provided by Eurostat (Eurostat, 2022) which measures the percentage of young and old people on the total working population[12] (*Dependency_ratio*); the higher the ratio, the greater the presence of the non-working age (i.e., young and old people) population in the province.

Human and social capital are other important aspects which may influence pro-green behavior and thus the adoption of green energy technologies such as PVs. The first can be proxied by the investment of an individual in years of education (Faggian, 2019), while the latter can be defined as all the networks, connections, social norms and relations which make people trust and cooperate with each other to pursue common social benefits (Paldam, 2000). To measure human capital, we use the percentage of graduated students residents in year (t) divided by the number of total residents in the province, exploiting the data from the Italian Ministry of University and Research (MUR, 2023). To measure social capital, we used the percentage of recycled municipal waste in the province, from ISTAT data, which can be considered as a proxy for social participation in the provision of public goods that reflects social capital endowment (ISTAT, 2023). Other authors have used the Green Party's share of voters as a proxy for pro-environmental citizen behavior, but unfortunately this statistic is not available at the provincial level and, moreover, the Italian Green Party is usually in a coalition with other parties and does not receive many votes.

[11] Housing market transactions consider all the houses traded in the province as a sum of the housing transactions in the administrative district of the province and the housing transactions in the rest of the province.

[12] The dependency ratio (3rd Eurostat variant) is calculated as the sum of people younger than 20 and older than 65 divided by the population between 20 and 64 years old (Eurostat, 2022).

Another factor that may influence PV uptake is the level of provincial public services and the quality of local governance, which can influence the overall local perception of citizens towards public goods and environmental behaviors. As a proxy for the quality of governance and public services we employed the ratio of children aged 0–3 receiving day care services with respect to the total population of children of the same age residing in the province (*Kindergarten*). Moreover, as a general indicator of the quality of the local economy and social conditions, we also considered the provincial unemployment rate which can be used as a proxy for the "health" of the local socio-economic system (Eurostat, 2022).

Another aspect which can influence PV uptake is the stock of PV already installed in the province. In fact, this can potentially drive the adoption of new PV adoption in two ways. One is the potential effect of increasing PV adoption due to imitation, peer effects and bandwagon effects (Battisti and Stoneman, 2003; Geroski, 2000) as already documented by several authors (Graziano et al., 2019; Graziano and Gillingham, 2015; Müller and Rode, 2013; Richter, 2013; Rode and Weber, 2016). Another way can be the saturation effect of the current PV potential: high existing levels of PV stock may reduce the flow of new installations because the peak in the diffusion curve is being achieved. In other words, the benefits enjoyed by a new adopter will fall when the number of users increases and the later marginal adopters will have lower gains than earlier adopters (Rogers, 1971; Stoneman and Battisti, 2010). This effect could depend also on a lower level of incentives, less favourable tariffs or simply the actual saturation of the PV installation potential. To consider this aspect, we could not employ the actual or the lagged PV stock since these were already used to build our main dependent variable (*NetPV*) resulting in an extremely high correlation between the two (0.94 and 0.93 respectively). To overcome this problem, we used the ratio of the provincial PV stock to the total national stock *(PV_Ratio)* as a proxy of the cumulative level of provincial PV stock in each year, which show a lower correlation with the dependent variable (0.44). The use of this variable can provide important information because its coefficient, if positive, can be interpreted in terms of potential increase of PV uptake due to an existing presence of PV stock in the province and in the adjacent territories while, if negative, it could be interpreted as a limiting factor discouraging PV adoption due to a saturation process caused by an already high adoption of the technology occurred in the previous years.

Finally, since no policy-specific data are available to consider the effects of policies on PV adoption, time dummy variables are considered. They have the double task of controlling for exogenous shocks and of indicating whether the introduction of new policies has influenced the level of PV adoption. In Table 1 the summary statistics of the variables used in the econometric analysis is presented.

4. Results

4.1. Spatial model selection

We employed a general to specific approach, as suggested by LeSage and Pace (2009) and Elhorst (2014), by testing several spatial econometric models to find the best solution to fit the data. We run five models comparing all the estimated coefficients and employing the Akaike (AIC) and Bayesian Information Criterion (BIC) to compare goodness of fit for the models (Belotti et al., 2017). We started our comparison by using a non-spatial model with a standard panel linear regression, then we employed the SDM, SEM, SAR and SAC spatial models.

The estimated coefficients of all the models (FE, SDM, SEM, SAR, SAC) are shown in Table 2, from which is possible to see that there are not important diversities that arise: all the sign and magnitude of the coefficients are stable using all the models. Also the statistical significance of the coefficients remain stable when changing the model. The main difference is that the *Perc_Graduated* variable used for measuring human capital is statistically significant at 90% with strong economic significance, ranging between 19.06 in the SDM to 19.81 in the SAR. This is in line with Kucher et al. (2021), Dharshing (2017) and Balta-Ozkan et al. (2015), but since these models (OLS, SDM, SEM, SAR) have been found to be weaker in describing the data generation process, we did not consider this variable as a key determinant of PV adoption, and we leave this factor for analysis in further studies. Moreover, the variable *Solar_irradiation* is statistically significant only for the panel linear model (at 90% level), with a negligible magnitude of the coefficient. When considering spatial dependence, (i.e. using SDM, SEM, SAR, SAC) the coefficient of *Solar_irradiation* stops to be statistical significant, thus suggesting that solar irradiance is not a strong driver of PV installation, as also emerged from other studies such as Schaffer and Brun (2015) and Dharshing (2017). Energy consumption (*Energy_Consumption*) is strongly statistically significant with a positive coefficient only for the spatial models, suggesting that, when considering spatial dependence that variable can be considered a driver of PV uptake in Italy. Also the average level of income (*Income*) and the value of houses (*House_Value*) in the province start to be significant with an important magnitude only when considering spatial dependence while they are not significant using the standard linear panel model.

Other differences among the models are emerging from the year dummies for the years 2017 and 2021, which can describe various exogenous events or policies that might have influenced PV uptake. The former shows a statistically significant negative coefficient at the 95% level for the SEM, SAR and SAC model only, whereas the latter has a positive and statistically significant coefficient at 99% level only for the SEM and SAR model. Therefore, there are not clear and consistent suggestions attainable from the analysis of those variables, and therefore

Table 1
Descriptive statistics of the variables used in the analysis.

Variable	Unit of measure	Source	Obs	Mean	Std. Dev.	Min	Max
NetPV	N of PV per Km^2	GSE	749	0.22	0.26	−0.73	2.81
PV_Ratio	Ratio of the provincial PV stock over total national	GSE	749	0.93	0.72	0.12	3.99
Solar_Irradiation	KWh per m^2 on horizontal surface	RSE	749	1415.42	135.67	1050.36	1762.033
Energy_Consumption	GW per Km^2	TERNA	749	0.29	0.4	0.02	2.519
Income	Thousands of €	MEF	749	19.87	3.18	13.64	29.81
House_Trade	n. of transaction per km^2	OMI	749	2.75	4.39	0.23	45.447
House_Value	€ per m^2	OMI	749	341.89	153.04	114.66	841.511
Log_PopDensity	Natural logarithm of the n. of residents per Km^2			5.25	0.79	3.65	7.89
Recycling_rate	% of recycling MSW	ISTAT	749	48.06	24.92	0.18	88.307
Kindergarten	% of 0–3 children receiving daycare service on total population of children 0–3	ISTAT	749	13.51	7.77	0.3	39
Dependency_ratio	% of 0–19 and over 64 population on 20–64 population	Eurostat	749	69.77	3.69	58.4	80.2
Perc_Graduated	% of new graduates on total population	MUR	749	0.005	0.001	0.002	0.008
Unemployment	% of unemployed workers on total workforce	Eurostat	749	10.98	5.72	2.87	31.456

Table 2
Estimated Coefficients of the OLS FE model, SDM, SEM and SAR model.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Model 1.1 Non spatial, Net PV installed	Model 1.2 SDM Net PV installed	Model 1.3 SEM Net PV installed	Model 1.4 SAR Net PV installed	Model 1.5 SAC Net PV installed
PV_Ratio	0.415***	0.378***	0.419***	0.412***	0.392***
	(2.962)	(7.339)	(7.897)	(7.743)	(7.712)
Solar_irradiation	0.000234*	0.000155	0.000239	0.000226	0.000202
	(1.894)	(1.102)	(1.630)	(1.543)	(1.434)
Energy_Consumption	1.436	1.347***	1.483***	1.405***	1.459***
	(1.446)	(5.213)	(5.524)	(5.250)	(5.787)
Income	0.0839	0.0773***	0.0859***	0.0824***	0.0804***
	(1.590)	(4.624)	(5.004)	(4.800)	(4.959)
House_Trade	0.0305**	0.0314***	0.0330***	0.0290***	0.0347***
	(2.484)	(6.126)	(5.938)	(5.525)	(6.662)
House_Value	0.000524	0.000376**	0.000539***	0.000506***	0.000480***
	(1.123)	(2.051)	(2.914)	(2.720)	(2.772)
Log_PopDensity	0.244	0.339	0.247	0.253	0.291
	(1.135)	(1.558)	(1.101)	(1.131)	(1.356)
Recycling_Rate	−0.000105	−0.000200	−0.000126	−9.77e-05	−0.000162
	(−0.347)	(−0.573)	(−0.348)	(−0.270)	(−0.478)
Dependency_Ratio	−0.0194***	−0.0220***	−0.0193***	−0.0196***	−0.0189***
	(−2.650)	(−4.824)	(−4.178)	(−4.266)	(−4.222)
Perc_Graduated	19.58	19.06*	18.68	19.81*	16.30
	(1.634)	(1.693)	(1.595)	(1.696)	(1.459)
Unemployment	0.000989	0.000280	0.00138	0.000730	0.00155
	(0.415)	(0.167)	(0.782)	(0.418)	(0.935)
Kindergarten	0.00118	0.000762	0.000989	0.00134	0.000766
	(0.812)	(0.288)	(0.362)	(0.489)	(0.297)
Dummy_2016	0.00515	−0.0216	0.00433	0.00421	−0.00124
	(0.231)		(0.342)	(0.319)	(−0.114)
Dummy _2017	−0.0449	−0.0722	−0.0469**	−0.0434**	−0.0434**
	(−1.179)		(−2.545)	(−2.318)	(−2.566)
Dummy _2018	−0.0122	−0.0830	−0.0150	−0.0133	−0.0257
	(−0.245)		(−0.512)	(−0.450)	(−0.947)
Dummy _2019	−0.00312	0.00411	−0.00535	−0.00670	−0.0211
	(−0.0465)	(0.0627)	(−0.192)	(−0.239)	(−0.803)
Dummy _2020	−0.0212	0.00112	−0.0236	−0.0240	−0.0358
	(−0.286)	(0.0147)	(−0.752)	(−0.762)	(−1.198)
Dummy _2021	0.0925	−0.0269	0.0880***	0.0832***	0.0411
	(1.275)		(2.942)	(2.731)	(1.382)
Rho				0.0759	0.298***
				(1.473)	(4.690)
Lambda			−0.0781		−0.373***
			(−1.249)		(−4.363)
Constant	−2.888**				
	(−2.062)				
AIC	−1758.133	−1803.248	−1755.702	−1756.277	−1770.381
BIC	−1674.995	−1655.448	−1663.327	−1663.903	−1673.387
Observations	749	749	749	749	749
R-squared	0.476	0.591	0.595	0.602	0.601
Number of id	107	107	107	107	107

Note: Robust t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

it is difficult to state whether some policies were relevant for PV uptake in Italy in the time span considered.

The variables that present similar results in all the specifications are *PV_Ratio*, *House_Trade* and *Dependency_Ratio,* all with a statistical significance at 99%. The first two have shown positive coefficients suggesting that they are drivers of PV uptake in Italy, whereas the third has shown negative coefficients in all the models, which suggest that they can be considered as a barrier of adoption. All the results will be further commented in the next subsections.

An important point to highlight from our results is that only the SAC model presents spatial coefficients that are statistically significant, whereas all the other spatial models never show statistically significant spatial terms. This suggest that the only spatial model that can account for the spatial dependence identified by the Moran's I test is the SAC model, which seems to be the most suited model to be used for our analysis.

Both the autoregressive coefficient ρ (Rho) and the autocorrelation coefficient λ (lambda) are statistically significant at the 99% level. This confirms that the use of a spatial approach for this analysis was appropriate, and suggests that using a SAC model, which allows us to control for spatial dependence in neighboring provinces in both the dependent variable and the disturbance, avoids biased estimates due to spatial relationships and interconnections between adjacent provinces. Moreover, the positive sign of the ρ coefficient indicates that PV adoption in a province is influenced by the level of PV adoption in neighboring provinces. Less straightforward to understand is the negative sign of λ. It indicates a non-clustering spatial distribution of the error term, which can be interpreted as an inter-provincial competition for the components of the unobserved factors included in the error terms (Griffith, 2019). This is translated into a repulsive force and competitive mechanisms among neighboring areas to common shocks modelled by the error term (Kopczewska et al., 2017). The same result, even if not statistically significant, is also reported in the SEM model, and this suggests that a negative spatial autocorrelation in the error term is persistent in the data generating process.

In Table 2 the results of AIC and BIC estimators are shown. The comparison of those statistics can help in choosing the model which, among different others, is the best in fitting the data generating process. The selection rule when comparing two models is: choose the one with the lower value of both statistics. In our case, we have contrasting evidence between SDM and SAC since the former shows a lower value of AIC, whereas the BIC is higher than SAC. This method allows us to consider those two models as superior to the others (SEM, SAR), but it does not allow us to consider one better than the other overall for the data generation process (Elhorst, 2014). Our final decision fell on SAC, selecting it as the main model of analysis for this study because the estimations using the SDM showed non-statistical significance of the spatial autoregressive parameter, ρ, which suggests that this model cannot capture the spatial dependence of the dependent variable identified with the Moran tests. Only the SAC model shows strong statistical significance (99%) for the spatial terms, both ρ and λ, whereas the other spatial models showed non-statistical significance of the spatial lags.

4.2. Effects within provinces

In this subsection we comment the main result of our analysis considering only the findings of the SAC model that was chosen as principal spatial model for this paper. As already mentioned in the previous sub-section, the results of all the spatial models employed are consistent with the results of the SAC model.

In this subsection we consider the internal effects of regressors, that is the specific effect of a change in an independent variable on the dependent variable within the same observed province (i.e. without considering spillover and feedback effects arising from spatial dependence) (Golgher and Voss, 2016). The results are shown in Table 3 in column 1.

The results are in line with our expectations: as drivers of PV uptake, the socio-economic variables show greater importance than socio-demographic variables. In any case, all variables have small coefficients magnitudes due to the fact that the dependent variable is expressed in numbers of PVs installed per Km^2 (see Table 1).

The role of income as an element critically relevant for the number of net new PV installations is totally supported by our results. The income variable coefficient is statistically significant at 99% level, and although its magnitude is relatively small (0.08), its average impact can be strong on PV uptake if we consider the average size of an Italian province (2807 Km^2). In fact, for each additional thousand euros of average income in the province, the PV adoption in the same province increase by 0.08 unit installed per Km^2, which can be considered a strong economic significance: an increase of one thousand euros in the average provincial income can increase the average uptake by 0.08 PV per Km^2 which is equivalent, on average, to 225 PV per year per province. This is impressive if we consider that the average annual PV uptake in Italy was 491 PV per province per year in the time span considered. Therefore, every increase in 100 euros in the average income can increase the provincial annual PV uptake by an amount of 22 new installed PV in the year per province.[13] This finding is contrasting the evidences produced by Schaffer and Brun (2015) and Balta-Ozkan et al. (2015), who state that this factor is not a strong driver having found small magnitudes or non-statistically significance of the income variable. Instead our study support the results of Kosugi et al. (2019), Dharshing (2017) and Jacksohn et al. (2019) who found income as a strong driver of PV adoption. The link between income and PV adoption can be quite straightforward, since a higher level of available income can induce higher levels of investments in home PV projects because the risks of adopting new technologies are lower.

The results of our analysis suggest that the housing market can be an important driver of PV adoption increase. The housing market variables, that is total transactions per Km^2 (*House_Trade*) and house selling prices (*House_Price*), are statistically significant, both at 99% level. The number of housing transactions appear to have higher magnitude than the selling value of houses in influencing the adoption of PV within provinces (0.0347 vs 0.000480), but this may be due by the different unit of measurement of the two variables (number of transactions per Km^2 vs house prices per m^2). In fact, the first variable is a proxy of the volume of house transactions occurring in the province per Km^2, while the second variable is a proxy of the value of houses in the province per m^2 (considered as the average value of the difference between the maximum and minimum price per m^2). Both the volume of the housing market and the value of houses can increase PV uptake. This is quite straightforward since housing transactions can be linked to renovation activities, which may consider also saving energy choices of the new buyers, while high housing values may be related to a higher propensity of house owners to invest in green energy.

Solar irradiance has a weak explanatory power and it is not a strong driver of PV installation, as has also emerged from other studies such as Schaffer and Brun (2015) and Dharshing (2017).

Household electricity consumption emerges as an important driver of PV adoption with strong statistical and economic significance. The coefficient of the *Energy Consumption* variable is significant at 99% and the magnitude of the coefficient is the highest among all the variables included in the econometric model (1.46), thus indicating that each additional GW of energy consumed per Km^2 in the province can boost the uptake of PV in the same province 1.46 PV per Km^2. The importance of the electricity market as a factor of PV uptake confirms the results of Balta-Ozkan et al. (2015), Graziano and Gillingham (2015) and Kucher et al. (2021) who find similar results in their studies in the UK and the US.

Population density is not statistically significant (it is never significant in all the models, see Table 2), and this indicates that factors linked to urbanization and agglomeration are not drivers of PV adoption in Italy. In this case, it must be noted that Italy is the third most densely populated country in the EU after Germany and Switzerland (excluding Luxembourg and Malta) with no major differences between provinces (only Sardinia and mountain areas show a lower level of population density). Considering these aspects, Italian provinces are not the most suitable level of data aggregation to analyze urban-rural differences in relation to PV adoption. More granular data might be more useful for this purpose.

Among the socio-demographic variables, the only statistically significant is the dependency ratio, which displays a negative sign and a significance level of 99%. That variable is a proxy for the proportion of

[13] Effect on provincial PV adoption due to an average income increase of 100 euros. β income = 0.08; ΔIncome = 0.1 thousand euros; average provincial extension = 2807 Km^2; ΔNewPV = 0.1*0.08 = 0.008; average provincial net uptake =0.008*2807 = 22 PV.

Table 3
Results of the SAC model.

	(1)	(2)	(3)	(4)
VARIABLES	SAC Net Power installed	Direct Effects	Indirect Effects	Total Effects
PV_Ratio	0.392***	0.404***	0.160***	0.564***
	(7.712)	(7.631)	(3.226)	(6.694)
Solar_irradiation	0.000202	0.000201	7.96e-05	0.000281
	(1.434)	(1.441)	(1.262)	(1.418)
Energy_Consumption	1.459***	1.521***	0.604***	2.125***
	(5.787)	(6.134)	(2.968)	(5.458)
Income	0.0804***	0.0826***	0.0328***	0.115***
	(4.959)	(5.157)	(2.845)	(4.782)
House_Trade	0.0347***	0.0356***	0.0142***	0.0498***
	(6.662)	(7.005)	(3.086)	(6.094)
House_Value	0.000480***	0.000498***	0.000195**	0.000693***
	(2.772)	(2.883)	(2.323)	(2.895)
Log_PopDensity	0.291	0.298	0.119	0.417
	(1.356)	(1.302)	(1.190)	(1.293)
Recycling_Rate	−0.000162	−0.000179	−6.84e-05	−0.000247
	(−0.478)	(−0.531)	(−0.485)	(−0.522)
Dependency_Ratio	−0.0189***	−0.0191***	−0.00757***	−0.0267***
	(−4.222)	(−4.326)	(−2.712)	(−4.122)
Perc_Graduated	16.30	17.39	6.911	24.30
	(1.459)	(1.530)	(1.299)	(1.493)
Unemployment	0.00155	0.00156	0.000627	0.00219
	(0.935)	(0.947)	(0.897)	(0.945)
Kindergarten	0.000766	0.000937	0.000362	0.00130
	(0.297)	(0.340)	(0.327)	(0.339)
Dummy_2016	−0.00124	−0.00196	−0.000981	−0.00294
	(−0.114)	(−0.185)	(−0.222)	(−0.198)
Dummy _2017	−0.0434**	−0.0447***	−0.0179**	−0.0625***
	(−2.566)	(−2.827)	(−2.065)	(−2.713)
Dummy _2018	−0.0257	−0.0289	−0.0116	−0.0404
	(−0.947)	(−1.018)	(−0.929)	(−1.005)
Dummy _2019	−0.0211	−0.0232	−0.00978	−0.0330
	(−0.803)	(−0.922)	(−0.862)	(−0.918)
Dummy _2020	−0.0358	−0.0375	−0.0154	−0.0529
	(−1.198)	(−1.285)	(−1.150)	(−1.269)
Dummy _2021	0.0411	0.0399	0.0147	0.0546
	(1.382)	(1.345)	(1.281)	(1.358)
Rho	0.298***			
	(4.690)			
Lambda	−0.373***			
	(−4.363)			
Observations	749	749	749	749
R-squared	0.601	0.601	0.601	0.601
Number of id	107	107	107	107

Note: The estimated coefficients are in Column 1, whereas from column 2 to 4 the effects of each regressor are shown, respectively Direct, Indirect and Total effects. All standard errors are Robust to consider Heteroscedasticity. The regression includes provincial Fixed Effects and Year fixed effects; z-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

children and elders as a percentage of the working age class (aged between 20 and 65). The result indicates that the higher the level of 'non-working' age categories as a ratio to 'working' age categories, the lower the level of net PV adoption, with an internal impact in the province under observation of −0.019 PV per Km^2 for each positive unit increase in the dependency ratio indicator in the same province. This result is very plausible, since long term green investments, such as PV uptake, may be made by those with income-generation capacity and future prospects, who are usually households and individuals in the working age group (20–65).

All other socio-demographic variables capturing human capital (*perc_Graduated*), social participation (*Recycling_rate*), social conditions (*Unemployment*) and public services (*Kindergarten*) are not relevant drivers or barriers to PV net capacity uptake since their estimated coefficients are never statistically significant, even using other spatial models.

The time dummies do not show statistical significance apart for the dummy for the year 2017, with a statistical significance of 99% with a magnitude of −0.04. This result indicates a small downturn in the upward trend in photovoltaic adoption that occurred for 20 years, and it is difficult to interpret the negative sign of the dummy as a consequence of the new national energy strategy released in the same year.

The no-statistical significance of the dummy for the year 2021 does not provide evidence that the strong government intervention to support eco-efficient housing though renovation incentives (*Superbonus 110*) has been ineffective. This missing effect might be explained by the fact that the policy started in 2021 and lasted (with some modifications) until 2023. Therefore, with respect the timeframe of our data, the policy was still an ongoing process. Whether this policy has been effective or not, also for the adoption of PVs at the household level, can be the object of future studies.

4.3. Spillover effects

Spatial econometric models provide a straightforward average measure of the spillover effects of each regressor due to the spatial reciprocity of the provinces.[14] These effects are shown in Table 3 (columns from 2 to 4). They are respectively: i) the average direct effects, which consider the average internal effects with a province plus the feedback effects received from neighboring provinces; ii) the average indirect effects or the average spill-over effects on all other provinces; and iii) the total effects, which is the sum of the average direct and indirect effects of the regressor (Elhorst, 2014; LeSage and Pace, 2009).[15]

In general, what is evident from our findings is that spillover effects of the regressors are present, indicating that a change in an independent variable in a province does not affect only the same province, but also the neighboring provinces (indirect effects). Moreover, through spatial reciprocity the initial change in a province is augmented also by the feedback effect received from neighboring provinces, increasing the internal effects of the initial change (i.e. the direct effects). Therefore, by considering spillover effects, the overall impacts of a regressor on provinces (total effects) is higher than the average effects within a province (main coefficients in column 1 in Table 2) (Golgher and Voss, 2016).

Our results confirm that income levels have neighboring effects on nearby provinces, with provincial clusters of high and low incomes that influence differently PV diffusion. Having high income provinces as neighbors increases the level of PV adoption, whereas having lower income neighboring provinces reduces PV adoption.

Housing market variables, both the one accounting for the transaction (*House_Trade*) and the one considering the value of houses (*House_Value*), present significant spillover effects in nearby provinces. This may indicate that in terms of spillover effects, the vitality and the value of the housing market has a positive influence on PV installations in the observed provinces due to the feedback effects receiving from other provinces (direct effect) and has a statistically significant effect also from the housing market in nearby provinces (indirect effect).

The PV stock in the provinces has important spatial effects on PV uptake because it has both statistically significant direct and indirect effects. Following Elhorst (2014), the direct effect occurring in a region can be decomposed into two parts of the effects of the dependent variable, in this case the % of PV already installed in the province as a share of the total national PV stock in Italy. The first is the average effect observable in the province under study due to a change in the independent variable in the same province, as already commented in the previous section, which in this case is 0.39 (representing 69.5% of the total average effect). The second component is the feedback effect due to the endogenous interaction effect on the dependent variable ($\rho WY_{j,t}$): the initial impulse observed in the province under study is transmitted to surrounding provinces and then back again to the province that stimulated the change. In our case, the feedback effect of the pre-existing PV stock in the province averages 0.01 PV per km^2 in the province, which is a small part of the total effect (2.13% of the total effect). On the other hand, an important part of the total effect of the pre-existing PV stock is the indirect effects of the surrounding provinces, amounting to 0.16 PV per km^2, which represents 28.37% of the average total effect. This highlights how the accumulated stock of PV in the province is an important driver of adoption, but also how it influences PV deployment in other regions. The positive coefficient of the variable seems to suggest that the overall level of PV adoption in Italy is below the saturation point, the latter possibly being identified by a negative sign of the coefficient.

The average solar irradiance of a province (*Solar_Irradiation*) has no statistically significant effect on neighboring provinces (indirect effects), thus contradicting, in the case of Italy, the hypothesis of solar clusters mentioned in the German case study by Schaffer and Brun (2015) and Dharshing (2017). This is probably due to the geographical and structural weather differences between Germany and Italy, with the latter receiving on average higher levels of solar irradiance than continental European countries.

Electric household consumption has strong and statistically significant average spillover effects on nearby provinces which is high and accounts for the 28% of the total effect of the variable.[16] Our results suggest a strong presence of electric consumption clusters which drive PV adoption and that in general high levels of consumption at the provincial level may have strong effects on PV uptake in neighboring provinces and vice versa. Therefore, this finding confirm the results of Balta-Ozkan et al. (2015) and Kucher et al. (2021) who find similar results in their studies in the UK and the US on the importance of spatial spillovers related to the electricity market in neighboring areas in positively influencing PV uptake as an indirect effect. In other words, this means that an additional increase in electricity consumption in one province have an indirect effect in the PV adoption of adjacent regions, in our case the effect of the increase in the consumption of electricity 1 GW per Km^2 have an average increase in the adoption of 0.6 PV per Km^2.

The dependency ratio has an indirect statistically significant negative spillover effect (99% level) on other regions due to spatial dependence, therefore this variable, which hinders PV deployment at the provincial level, also has a spatial interaction effect with nearby provinces that negatively affect PV deployment in surrounding areas. The negative indirect effect on other regions is on average − 0.007 PV per Km^2.

4.4. Robustness tests

One of the most crucial aspects in spatial econometric analysis is the choice of weighting method which is selected by the researcher and it may influence the consistency of the results with different types of weighting matrix selections (LeSage and Pace, 2009). Another aspect which might slightly alter the analysis is the normalization method adopted.

In our study we adopted a Queen contiguity matrix, which is a standard choice in spatial econometric analysis, but other methods can be applied such as Rook contiguity or Inverse distance matrix. The first considers as neighboring areas only the units that share a common border (i.e. points or vertices are not considered), whereas the second considers the inverse of the Euclidean distance between points as weights, and by doing this larger influence is given to closer spatial units than farther units. An alternative method to row normalization is min-max normalization in which each element is divided by the minimum of the largest row sum and column sum of the matrix (Drukker et al., 2013).

For robustness test of our results, we repeated the analysis using the SAC model but altered the construction of the spatial weighting matrix using a Rook contiguity matrix and an Inverse-distance matrix. We have also changed the normalization method of the weighting matrix using min-max normalization instead of the row normalization used in the analysis. All the alterations did not change the estimated coefficients which remain stable both in terms of statistical significance and magnitude. The results of the robustness are presented in Table 4.

[14] Even if the spatial dependence of the regressors has not been taken into account directly as in the SDM method, the spatial effects of the regressors affects other provinces through the spatial lags of the autoregressive terms (Elhorst, 2014; Golgher and Voss, 2016).

[15] A good description of the three effects is provided by Golgher and Voss (2016) who defined the direct effect as the "*the expected average change across all observations for the dependent variable in a particular region due to an increase of one unit for a specific explanatory variable in this region*", whereas the indirect effect as the expected "*changes in the dependent variable of a particular region arising from a one unit increase in an explanatory variable in another region*" while the total effect is the sum of the direct and indirect effects.

[16] Effects of energy consumption (*Energy_Consumption*). Direct Effect: 1.52 (71,7%) of which Internal Effect: 1.46 (68.87%) and Feedback Effect: 0.06 (2.83%); Indirect Effect: 0.6 (28,3%), Total Effect: 2.12 (100%) (Elhorst, 2014).

Table 4
Estimated Coefficients of the OLS FE model, SDM, SEM and SAR model.

	(1)	(2)	(3)
VARIABLES	Robustness 1 ROOK contiguity	Robustness 2 MinMax normalization	Robustness 3 Inverse Distance W matrix
PV_Ratio	0.392***	0.400***	0.412***
	(7.712)	(7.896)	(7.883)
Solar_irradiation	0.000202	0.000204	0.000243*
	(1.434)	(1.443)	(1.660)
Energy_Consumption	1.459***	1.467***	1.490***
	(5.787)	(5.792)	(5.592)
Income	0.0804***	0.0752***	0.0894***
	(4.959)	(4.557)	(5.223)
House_Trade	0.0347***	0.0359***	0.0336***
	(6.662)	(6.822)	(6.360)
House_Value	0.000480***	0.000487***	0.000544***
	(2.772)	(2.787)	(2.941)
Log_PopDensity	0.291	0.309	0.231
	(1.356)	(1.443)	(1.032)
Recycling_Rate	−0.000162	−0.000154	−0.000121
	(−0.478)	(−0.445)	(−0.338)
Dependency_Ratio	−0.0189***	−0.0192***	−0.0196***
	(−4.222)	(−4.257)	(−4.275)
Perc_Graduated	16.30	15.24	17.87
	(1.459)	(1.350)	(1.536)
Unemployment	0.00155	0.00160	0.00152
	(0.935)	(0.952)	(0.876)
Kindergarten	0.000766	0.000500	0.000933
	(0.297)	(0.193)	(0.346)
Dummy_2016	−0.00124	0.00137	0.00260
	(−0.114)	(0.126)	(0.235)
Dummy _2017	−0.0434**	−0.0406**	−0.0491***
	(−2.566)	(−2.368)	(−2.923)
Dummy _2018	−0.0257	−0.0190	−0.0187
	(−0.947)	(−0.694)	(−0.634)
Dummy _2019	−0.0211	−0.0114	−0.0129
	(−0.803)	(−0.430)	(−0.406)
Dummy _2020	−0.0358	−0.0257	−0.0310
	(−1.198)	(−0.855)	(−0.900)
Dummy _2021	0.0411	0.0525*	0.0744
	(1.382)	(1.776)	(1.517)
rho	0.298***	0.492***	0.0716
	(4.690)	(4.248)	(0.312)
lambda	−0.373***	−0.759***	−0.805**
	(−4.363)	(−4.200)	(−2.358)
Observations	749	749	749
R-squared	0.601	0.515	0.594
Number of id	107	107	107

z-statistics in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results of the robustness test show a stable sign of the coefficients and the same statistical significance as the main drivers of PV adoption identified in our analysis. The only difference is that by using an inverse distance matrix, instead of a contiguity matrix, solar irradiance became statistically significant albeit at a small level of 90%. But in this last case, the coefficient of the spatial lag (ρ) is not statistically significant, which suggests that the inverse distance weighting matrix method is not suitable for considering the spatial dependence identified in our dependent variable.

5. Discussion and concluding remarks

Our study provides a detailed spatial analysis of the main determinants of PV adoption at the provincial level in Italy. The main results of our paper are in line with Schulte et al. (2022) and Alipour et al. (2020) who show that socio-demographic factors are less relevant than economic variables and the housing market for the deployment of PV. We introduced the value of houses, as suggested by Palm (2020), finding that the higher the average value of houses in a province, the higher the PV uptake. Moreover, we added among the regressors a measure to capture the vitality of the housing market, finding that this factor is important for PV uptake. On the other hand, we did not find evidence of explanatory power for the variables proxying human capital, social participation, social conditions and quality of public services, and the same applies to education, recycling, unemployment and kindergarten services that are never statistically significant, even when considering different spatial econometric modelling.

Moreover, our study provides evidence of the spatial interconnections which may slow down or boost the process of PV diffusion across the Italian provinces through spatial dependence due to observed and unobserved factors. The observed factors have been analyzed considering different variables (i.e., solar potential, income, energy consumption, housing market, human capital, social participation, social conditions and public services). The results confirm those of Copiello and Grillenzoni (2021), who have found spatial effects in PV uptake in Italy, suggesting the presence of peer and neighboring effects.

The unobserved factors, which are not explicitly considered in the regressions, are part of the disturbance term. Those factors can be important elements for the PV diffusion process, but they are simply not observable in an aggregate form such as peer-connections, imitation processes, herding behavior and bandwagon effect even though they may be relevant for describing the spatial dependence between provinces. However, our analysis suggests that, in our models, those non-observed factors are spatially correlated among each other (Elhorst, 2014; LeSage and Pace, 2009), and since the coefficient of the spatial error term (λ) is statistically significant but negative, they show a centrifugal or a repulsive effect (Kopczewska et al., 2017; Tolnay et al., 1996). This does not spatially affect PV uptake since λ only refers to the effects between the residuals of neighboring provinces, and, in this case, this relation is negative indicating that the residuals move in the opposite direction to each other (i.e. if a province has positive residuals its surrounding provinces can show negative residuals and vice versa) (Griffith, 2019; Griffith and Arbia, 2010).

An important point emerging from our results is that solar potential, as proxied by solar irradiance, does not have strong explanatory power as a driver of PV uptake in Italy. In fact, solar irradiance is positive but never statistically significant. This is in slight contrast with other studies in Northern European and the Continental Region countries such as the analyses of Balta-Ozkan et al. (2015) and Schaffer and Brun (2015) who suggest the idea of solar clusters in PV uptake. This may not apply to the Italian case due to the higher average solar irradiance in Italy than in Germany, where solar exposure is high only in specific and clustered areas, whereas in Italy it is more widespread. In any case, solar irradiance may become strategically important when considering commercial PV instead of household PV systems. Unfortunately, this difference cannot be examined in our study, which addresses mainly household PV, and could be further developed in future studies with appropriate data and modelling specifications suitable to explain commercial PV uptake.

Other authors have found similar results for Italy, where a higher level of PV was identified in the Northern areas of the country instead of the Southern ones, which are expected to be the most suitable locations due to better climatic conditions and then higher investment profitability with shorter payback period (Antonelli and Desideri, 2014; Copiello and Grillenzoni, 2021; Orioli and Di Gangi, 2015). Their analysis considered installed capacity, which mainly represents commercial PV, and they focused the feed-in tariff period (2006–2012), justifying the North-South divergence as a ‘distorting effect’ of the generous feed-in tariffs applied until 2012 that favored PV installation in Northern regions. In our case, instead, we have considered the net flow of PV adoption at household level in each year, in a time period (2014–2021) when the generous initial PV incentive policies had already ended. Therefore, we expect that it was already in place some inertial effects in adoption difference between North and South, which started in 2006 as described by Copiello and Grillenzoni (2021) and Antonelli and Desideri (2014).

As expected, the most important positive factors driving PV uptake are linked to income, the energy market and the housing market, with also important positive spill-over effects in neighboring provinces. Our results highlight income as an important driver of PV adoption by households, in contrast to the results of Copiello and Grillenzoni (2021), who found that income is not a major driving force for PV adoption. The differences between our results and those of their study are plausible, because they used cumulative installed capacity as dependent variable, which is more a proxy for commercial PV than for domestic PV. This difference also supports the hypothesis that the determinants of the two types of PV systems may be very different. In fact, while in the domestic sector the individual disposable income may be crucial for households' investment decision, this variable, as defined, can be not so critical for commercial PV uptake.

The importance of the housing market in PV adoption is in line with the findings of Kucher et al. (2021), Balta-Ozkan et al. (2015) and Kosugi et al. (2019), but differently from our study, those authors proxied the housing sector as a percentage of detached or stand-alone owned houses on total housing stock in the area. These findings are also in line with the study of Copiello and Grillenzoni (2021) who identified the built environment, as the percentage of residential buildings built after 1981, as a driving force of the PV installed capacity in Italy. Our results are quite innovative since our study measured the effect of the housing market and the value of houses and found that both are drivers of PV uptake. A potential extension of this work could include further variables related to the built environment and the housing stock (e.g., multi-storey buildings and single-family houses) to identify their effects on PV uptake.

Conversely, all social factors failed to emerge as important drivers of PV deployment. Moreover, our results show that the dependency ratio is a negative factor for PV uptake because it reduces both the level of adoption within a province and among the neighboring provinces. The fact that the working age population ($>19 < 65$) is the most inclined towards PV adoption, while younger and older age groups are less inclined, is probably linked to the higher disposable income of the working age groups and to the type of investment that can produce a payback only in the longer term, reasonably beyond the horizon of the older groups >65.

A crucial aspect is also the stock of PV already in place in the provinces, which works as a driver of diffusion within and between provinces, confirming the results of previous studies (Graziano et al., 2019; Graziano and Gillingham, 2015; Müller and Rode, 2013; Richter, 2013; Rode and Weber, 2016). Unfortunately, our data do not allow us to disentangle which is the main driver of this relationship between the flow of new PV and the cumulated PV stock. Aspects such as imitation, peer and bandwagon effects should be further analyzed in future analysis.

Furthermore, the results did not show that the introduction of incentives for energy efficiency in buildings (*Superbonus 110*), where the adoption of photovoltaics was an important component of eligibility to incentives, had beneficial effects in terms of photovoltaic adoption in Italian provinces. The time frame of our analysis ends in 2021, and therefore, the policy impulse may still be in place and a longer time frame should be considered. In order to possibly find evidence on the effects of this very strong policy, other methods of analysis could be used, for example counterfactual approaches or structural breaks analysis.

The main limitation of our study is the type of available data, which does not allow to distinguish between different PV sizes and thus mixes domestic and non-domestic PV systems. This problem is partially overcome by the fact that using the number of PV systems as the dependent variable can be a good proxy for small PV systems, since 93% of the PV systems installed in Italy at the end of 2021 were below 20kWh (GSE, 2023d) indicating that this variable mainly covers residential PVs. Therefore, the data pushed us, de facto, to focus PV adoption by households. In order to consider the drivers of non-domestic PV uptake, further studies need to be undertaken taking into account the structural differences in the drivers and constraints that characterize small and medium-sized photovoltaics, which possibly implies the use of different data (i.e. more granular data) and/or different econometric strategies. In fact, the determinants of adoption of commercial PV should be analyzed considering variables more linked to the profitability of the commercial investments, the suitability of the territory (e.g., acclivity, altitude, waterbodies), the cost of land, the type of land cover (e.g., industrial roofs) and natural risks (e.g., earthquakes, floods, landslides) or the presence of specific industrial incentives, whereas socio-economic variables could be expected to be less important. Moreover, the use of spatial modelling should be reconsidered since all the factor linked to imitation and diffusion should be dampened.

Moreover, due to the type of data we employed (aggregated at the provincial level without the possibility of differentiating between small and medium-large PVs), we could not test other potential explanations worthy of interest such as personal motivation, availability of information, shared PV ownership, political vision, and pro-environmental behavior. Those aspect can be investigated in the Italian case by employing ad-hoc surveys or municipality-level data.

Even with these limitations, the results allow us to provide some policy suggestions. In the time frame covered by this study (2014–2021), PV diffusion flows in Italy have been driven mainly by economic factors (income, housing market turnover and values, spatial density of energy consumption), in combination with incentives (such as *Eco-Bonus* and *Superbonus 110*) that can be mainly accessed by wealthy socio-economic actors. These factors brought to a relatively prominent role of the Northern provinces in the diffusion process of PV in Italy, in contrast with the geography of the solar irradiation density, of which the Southern provinces are relatively more endowed.

On the one hand, this apparent paradox implies that Italy has a huge unexploited natural potential for PV, which is a very important asset in front of the evolving EU energy and climate policies, driven by the EGD, the combination of RepowerEU and Fit-for-55 (with a proposed overall RES target of 45% in 2030),[17] the emerging priority of 'strategic autonomy' for energy and primary commodities, and the strategic turning point marked by the 'Green Deal Industrial Plan' of 2023. On the other hand, the socio-economic conditions (income, a lively housing market, etc.) that brought more intensive PV diffusion in the North, cannot be easily and rapidly transferred or generated in the South, and this can represent a structural barrier to the full deployment of the PV potential in Italy. The issue of well-designed incentives for RES, in particular after the radical revision of the mechanisms of *Superbonus 110* by the Italian government, the possibility of deploying large PV plants in the Southern regions, and the true potential associated to the mounting interest in Renewable Energy Communities, should be placed at the very core of PV policy strategies within the broader RES policies in Italy. However, in the case of Renewable Energy Communities, our results on the very limited role of social variables, including those on social participation for PV diffusion, seem to put a damper on the possibility of massively involving communities in large-scale RES strategies, especially in those Southern Italy provinces that are most endowed with solar irradiation.

CRediT authorship contribution statement

A. Pronti: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **R. Zoboli:** Conceptualization, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

None.

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Appendix A. Appendix

Table A.1
Moran'I Test.

Year	Moran Index	E(I)	Sd(I)	Z	*P*-value
2015	0.192	−0.0094	0.0636	3.1666	0.0015
2016	0.194	−0.0094	0.0637	3.2017	0.0014
2017	0.132	−0.0094	0.0643	2.201	0.0277
2018	0.160	−0.0094	0.064	2.6432	0.0082
2019	0.186	−0.0094	0.0622	3.1368	0.0017
2020	0.165	−0.0094	0.0611	2.8609	0.0042
2021	0.149	−0.0094	0.0619	2.5587	0.0105

[17] "*Under RED II, the EU is obliged to ensure at least 32% of its energy consumption comes from renewable energy sources (RES) by 2030. The revised RED II strengthens these provisions and sets a new EU target of a minimum 40% share of RES in final energy consumption by 2030, accompanied by new sectoral targets. As part of the REPowerEU plan (May 2022), the Commission proposes to further raise this RES target to a 45% share by 2030*", https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2021)698,781.

Table A.2
Correlation table.

	NetPV	*Solar_ irradiation*	*Energy_ Consumption*	*Income*	*House_ Trade*	*House_ Value*	*Log_ PopDensity*	*Recycling_ Rate*	*Dependency_ Ratio*	*Perc_ Graduated*	*Unemployment*	*Kindergarten*	*Dummy_ 2016*	*Dummy _2017*	*Dummy _2018*	*Dummy _2019*	*Dummy _2020*	*Dummy _2021*	*PV_ Ratio*
NetPV	1																		
Solar_irradiation	−0.1718	1																	
Energy_ Consumption	0.7064	−0.0208	1																
Income	0.4978	−0.6280	0.3896	1															
House_Trade	0.6226	−0.0997	0.8779	0.4706	1														
House_Value	0.0900	−0.1866	0.2862	0.3947	0.2679	1													
Log_PopDensity	0.7037	−0.0075	0.8086	0.4294	0.7265	0.2657	1												
Recycling_Rate	0.2235	−0.1484	0.0617	0.3148	0.0625	−0.0099	0.0633	1											
Dependency_Ratio	0.0058	−0.4310	−0.0678	0.4358	0.0637	0.3195	−0.0209	0.1023	1										
Perc_Graduated	−0.0719	0.4579	−0.0423	−0.5675	−0.0902	−0.4043	−0.1149	−0.1305	−0.4411	1									
Unemployment	−0.3002	0.7066	−0.0565	−0.7735	−0.1691	−0.2289	−0.0929	−0.3915	−0.5050	0.4897	1								
Kindergarten	0.1601	−0.4380	0.0916	0.6745	0.2418	0.3739	0.1421	0.1850	0.4975	−0.4885	−0.6231	1							
Dummy_2016	−0.0576	−0.0395	−0.0069	−0.0542	−0.0203	0.0067	0.0031	0.0673	−0.0993	−0.1024	0.0794	−0.0345	1						
Dummy _2017	−0.0782	0.1853	−0.0007	−0.0247	−0.0097	−0.0015	−0.0010	0.1214	−0.0429	−0.0762	0.0554	0.0026	−0.1667	1					
Dummy _2018	−0.0287	−0.2164	−0.0014	0.0144	0.0044	−0.0052	−0.0024	−0.7413	−0.0052	−0.0152	−0.0031	0.0304	−0.1667	−0.1667	1				
Dummy _2019	0.0351	−0.0310	0.0001	0.0486	0.0141	−0.0055	−0.0063	0.2311	0.0400	0.0714	−0.0423	0.0754	−0.1667	−0.1667	−0.1667	1			
Dummy _2020	0.0277	0.1031	0.0027	0.0680	−0.0037	−0.0080	0.0010	0.2652	0.0970	0.1295	−0.0916	−0.0104	−0.1667	−0.1667	−0.1667	−0.1667	1		
Dummy _2021	0.1883	−0.0687	0.0052	0.0460	0.0669	−0.0117	0.0010	0.0670	0.1729	0.1329	−0.0879	−0.0104	−0.1667	−0.1667	−0.1667	−0.1667	−0.1667	1	
PV_Ratio	*0.4382*	*−0.1525*	*0.2412*	*0.391*	*0.2352*	*0.009*	*0.3629*	*0,1625*	*−0.1745*	*−0.031*	*−0.2251*	*0.1401*	*0.0015*	*0.0015*	*0.0015*	*0.0015*	*0.0005*	*0.0015*	*1*

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107582.

References

Alessandrini, S., Collino, E., Decimi, G., 2013. Impatto della produzione eolica e solare sulla rete (Ricerca di sistema No. 13000895). RSE, Milano.

Alipour, M., Salim, H., Stewart, R.A., Sahin, O., 2020. Predictors, taxonomy of predictors, and correlations of predictors with the decision behaviour of residential solar photovoltaics adoption: a review. Renew. Sust. Energ. Rev. 123, 109749 https://doi.org/10.1016/j.rser.2020.109749.

Alipour, M., Salim, H., Stewart, R.A., Sahin, O., 2021. Residential solar photovoltaic adoption behaviour: end-to-end review of theories, methods and approaches. Renew. Energy 170, 471–486. https://doi.org/10.1016/j.renene.2021.01.128.

Anselin, L., 1988. Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity. Geogr. Anal. 20, 1–17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x.

Anselin, L., 2003. Spatial externalities, spatial multipliers, and spatial econometrics. Int. Reg. Sci. Rev. 26, 153–166. https://doi.org/10.1177/0160017602250972.

Antonelli, M., Desideri, U., 2014. The doping effect of Italian feed-in tariffs on the PV market. Energy Policy 67, 583–594. https://doi.org/10.1016/j.enpol.2013.12.025.

Balta-Ozkan, N., Yildirim, J., Connor, P.M., 2015. Regional distribution of photovoltaic deployment in the UK and its determinants: a spatial econometric approach. Energy Econ. 51, 417–429. https://doi.org/10.1016/j.eneco.2015.08.003.

Battisti, G., Stoneman, P., 2003. Inter- and intra-firm effects in the diffusion of new process technology. Res. Policy 32, 1641–1655. https://doi.org/10.1016/S0048-7333(03)00055-6.

Belotti, F., Hughes, G., Mortari, A.P., 2017. Spatial Panel-data Models Using Stata. Stata J. 17, 139–180. https://doi.org/10.1177/1536867X1701700109.

Bianco, V., Cascetta, F., Nardini, S., 2021. Analysis of technology diffusion policies for renewable energy. The case of the Italian solar photovoltaic sector. Sustain. Energy Technol. Assess 46, 101250. https://doi.org/10.1016/j.seta.2021.101250.

Bocca, A., Chiavazzo, E., Macii, A., Asinari, P., 2015. Solar energy potential assessment: an overview and a fast modeling approach with application to Italy. Renew. Sust. Energ. Rev. 49, 291–296. https://doi.org/10.1016/j.rser.2015.04.138.

Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Mark. Sci. 31, 900–912. https://doi.org/10.1287/mksc.1120.0727.

Bourcet, C., 2020. Empirical determinants of renewable energy deployment: a systematic literature review. Energy Econ. 85, 104563 https://doi.org/10.1016/j.eneco.2019.104563.

Collino, E., Ronzio, D., 2021. Exploitation of a new short-term multimodel photovoltaic power forecasting method in the very short-term horizon to derive a multi-time scale forecasting system. Energies 14, 789. https://doi.org/10.3390/en14030789.

Copiello, S., Grillenzoni, C., 2021. Robust space–time modeling of solar photovoltaic deployment. Technol. Mater. Renew. Energy Environ. Sustain. 7, 657–676. https://doi.org/10.1016/j.egyr.2021.07.087.

Dharshing, S., 2017. Household dynamics of technology adoption: a spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. Energy Res. Soc. Sci. 23, 113–124. https://doi.org/10.1016/j.erss.2016.10.012.

Drukker, D.M., Peng, H., Prucha, I.R., Raciborski, R., 2013. Creating and managing spatial-weighting matrices with the Spmat command. Stata J. 13, 242–286. https://doi.org/10.1177/1536867X1301300202.

Elhorst, J.P., 2014. Spatial Econometrics. From Cross-Sectional Data to Spatial Panels, Springer Briefs in Regional Science. Springer Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-40340-8.

EU Commission, 2023a. Energy and the Green Deal. Eur, Comm. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/energy-and-green-deal_en.

EU Commission, 2023b. REPowerEU: Affordable, Secure and Sustainable Energy for Europe. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/repowereu-affordable-secure-and-sustainable-energy-europe_en.

EU Parliament and Council, 2009. On the Promotion of the Use of Energy from Renewable Sources and Amending and Subsequently Repealing Directives 2001/77/EC and 2003/30/EC.

EUMETSAT, 2023. European Organisation for the Exploitation of Meteorological Satellites. https://www.eumetsat.int/.

Eurostat, 2022. Regional Statistics by NUTS Classification. URL https://ec.europa.eu/eurostat/web/regions/data/database.

Faggian, A., 2019. Human capital and regional development. In: Handbook of Regional Growth and Development Theories. Edward Elgar Publishing, pp. 149–171. https://doi.org/10.4337/9781788970020.00015.

Geroski, P.A., 2000. Models of technology diffusion. Res. Policy 29, 603–625. https://doi.org/10.1016/S0048-7333(99)00092-X.

Golgher, A.B., Voss, P.R., 2016. How to interpret the coefficients of spatial models: spillovers, direct and indirect effects. Spat. Demogr. 4, 175–205. https://doi.org/10.1007/s40980-015-0016-y.

Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. J. Econ. Geogr. 15, 815–839. https://doi.org/10.1093/jeg/lbu036.

Graziano, M., Fiaschetti, M., Atkinson-Palombo, C., 2019. Peer effects in the adoption of solar energy technologies in the United States: an urban case study. Energy Res. Soc. Sci. 48, 75–84. https://doi.org/10.1016/j.erss.2018.09.002.

Griffith, D.A., 2019. Negative spatial autocorrelation: one of the Most neglected concepts in spatial statistics. Stats 2, 388–415. https://doi.org/10.3390/stats2030027.

Griffith, D.A., Arbia, G., 2010. Detecting negative spatial autocorrelation in georeferenced random variables. Int. J. Geogr. Inf. Sci. 24, 417–437. https://doi.org/10.1080/13658810902832591.

GSE, 2020. Fonti Rinnovabili in Italia e nelle Regioni. 2012-2020 (Rapporto di Monitoraggio). Gestore Servizi Energetici.

GSE, 2021. Rapporto Statistico. In: Solare Fotovoltaico 2021. Energetici, Gestore Servizi.

GSE, 2022. Monitoraggio degli Impatti Economici e Occupazionali delle Fonti Rinnovabili e dell'efficienza Energetica. Analisi di monitoraggio economico, Gestore Servizi Energetici.

GSE, 2023a. National monitoring of renewable energies penetration. Gestore Serv. Energ. URL https://www.gse.it/dati-e-scenari/monitoraggio-fer/monitoraggio-nazionale/obiettivo-complessivo.

GSE, 2023b. Conto Energia. Gestore Serv. Energ. URL https://www.gse.it/servizi-per-te/fotovoltaico/conto-energia (accessed 2.7.23).

GSE, 2023c. Scambio sul posto. Gestore Serv. Energ. URL https://www.gse.it/servizi-per-te/fotovoltaico/scambio-sul-posto (accessed 2.7.23).

GSE, 2023d. Statistiche. Gestore Serv. Energ. URL https://www.gse.it/dati-e-scenari/statistiche.

Heiskanen, E., Matschoss, K., 2017. Understanding the uneven diffusion of building-scale renewable energy systems: a review of household, local and country level factors in diverse European countries. Renew. Sust. Energ. Rev. 75, 580–591. https://doi.org/10.1016/j.rser.2016.11.027.

IEA, 2021. National Survey Report of PV Power Applications in Italy 2021. National Survey Report of PV Power Applications in Italy 2021. International Energy Agency, Photovoltaic Power Systems Programme.

IEA, 2022a. World Energy Outlook 2022. Paris.

IEA, 2022b. Trends in Photovoltaic Applications 2022 (Photovoltaic Power Systems Technology Collaboration Programme, Report IEA PVPS T1–43:2022). International Energy Agency.

ISTAT, 2023. Indicatori territoriali per le politiche di sviluppo. Istituto Nazionale di Statistica. URL https://www.istat.it/it/archivio/16777.

Jacksohn, A., Grösche, P., Rehdanz, K., Schröder, C., 2019. Drivers of renewable technology adoption in the household sector. Energy Econ. 81, 216–226. https://doi.org/10.1016/j.eneco.2019.04.001.

Kopczewska, K., Kudła, J., Walczyk, K., 2017. Strategy of spatial panel estimation: spatial spillovers between taxation and economic growth. Appl. Spat. Anal. Policy 10, 77–102. https://doi.org/10.1007/s12061-015-9170-2.

Kosugi, T., Shimoda, Y., Tashiro, T., 2019. Neighborhood influences on the diffusion of residential photovoltaic systems in Kyoto City, Japan. Environ. Econ. Policy Stud. 21, 477–505. https://doi.org/10.1007/s10018-019-00239-5.

Kucher, O., Lacombe, D., Davidson, S.T., 2021. The residential solar PV in the mid-Atlantic: a spatial panel approach. Int. Reg. Sci. Rev. 44, 262–288. https://doi.org/10.1177/0160017620914063.

LeSage, J., Pace, K.R., 2009. Introduction to Spatial Econometrics. CRC Press Taylor and Francis Group, Louisiana (US).

LeSage, J.P., Pace, R.K., 2010. Spatial Econometric Models. In: Fischer, M.M., Getis, A. (Eds.), Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications. Springer, Berlin Heidelberg, Berlin, Heidelberg, pp. 355–376. https://doi.org/10.1007/978-3-642-03647-7_18.

MEF, 2023. Ministry of Economy and Finance. Department of Finance. In: Statistical analysis. Open Data Declarations. https://www1.finanze.gov.it/finanze/pagina_dichiarazioni/public/dichiarazioni.php.

Müller, S., Rode, J., 2013. The adoption of photovoltaic systems in Wiesbaden, Germany. Econ. Innov. New Technol. 22, 519–535. https://doi.org/10.1080/10438599.2013.804333.

MUR, 2023. Portale dei dati dell'Istruzione Superiore. In: Ministero Università e Ricerca [WWW Document]. http://datiustatmiuritdatasetlaureatiresource0ac215ca-6cd2-4935-Bf0e-14c66a13871f.

OMI, 2023. Osservatorio del Mercato Immobiliare, Agenzia delle Entrate, Ministero dell'Economia e delle finanze. https://www.agenziaentrate.gov.it/portale/aree-tematiche/osservatorio-del-mercato-immobiliare-omi.

Orioli, A., Di Gangi, A., 2015. The recent change in the Italian policies for photovoltaics: effects on the payback period and levelized cost of electricity of grid-connected photovoltaic systems installed in urban contexts. Energy 93, 1989–2005. https://doi.org/10.1016/j.energy.2015.10.089.

Paldam, M., 2000. Social capital: one or many? Definition and measurement. J. Econ. Surv. 14, 629–653. https://doi.org/10.1111/1467-6419.00127.

Palm, A., 2020. Early adopters and their motives: differences between earlier and later adopters of residential solar photovoltaics. Renew. Sust. Energ. Rev. 133, 110142 https://doi.org/10.1016/j.rser.2020.110142.

PAN, 2010. National action plan for renewable energy in Italy (PAN) of the Ministry of Economic Development.

PNIEC, 2019. Integrated National Plan for Energy and Climate of the Ministry of Economic Development. Ministry of Infrastructure and Transport and the Ministry of the Environment.

Richter, L., 2013. Social effects in the diffusion of solar photovoltaic technology in the UK. In: Camb. Work. Pap. Econ. 2013-07–12.

Rode, J., Weber, A., 2016. Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. J. Environ. Econ. Manag. 78, 38–48. https://doi.org/10.1016/j.jeem.2016.02.001.

Rogers, E.M., 1971. Diffusion of Innovations. The Free Press. ed, New York(US).

Rogna, M., 2020. A first-phase screening method for site selection of large-scale solar plants with an application to Italy. Land Use Policy 99, 104839. https://doi.org/10.1016/j.landusepol.2020.104839.

RSE, 2023. Ricerca sul Sistema Energetico. https://www.rse-web.it/.

Schaffer, A.J., Brun, S., 2015. Beyond the sun—socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. Energy Res. Soc. Sci. 10, 220–227. https://doi.org/10.1016/j.erss.2015.06.010.

Schulte, E., Scheller, F., Sloot, D., Bruckner, T., 2022. A meta-analysis of residential PV adoption: the important role of perceived benefits, intentions and antecedents in solar energy acceptance. Energy Res. Soc. Sci. 84, 102339 https://doi.org/10.1016/j.erss.2021.102339.

SolarPowerEurope, 2023. EU solar strategy explained. In: A New Dawn for European Solar [WWW Document]. URL https://www.solarpowereurope.org/advocacy/eu-solar-strategy.

Stoneman, P., Battisti, G., 2010. Chapter 17 - the diffusion of new technology. In: Hall, B. H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation. North-Holland, pp. 733–760. https://doi.org/10.1016/S0169-7218(10)02001-0.

TERNA, 2023. Statistical Publications. URL https://www.terna.it/it/sistema-elettrico/statistiche/pubblicazioni-statistiche.

Tolnay, S.E., Deane, G., Beck, E.M., 1996. Vicarious violence: spatial effects on southern lynchings, 1890-1919. Am. J. Sociol. 102, 788–815.

Wang, F., Mi, Z., Su, S., Zhao, H., 2012. Short-term solar irradiance forecasting model based on artificial neural network using statistical feature parameters. Energies 5, 1355–1370. https://doi.org/10.3390/en5051355.

Welsch, H., Kühling, J., 2009. Determinants of pro-environmental consumption: the role of reference groups and routine behavior. Ecol. Econ. 69, 166–176. https://doi.org/10.1016/j.ecolecon.2009.08.009.

Zhao, J., Zhao, Z., Zhang, H., 2021. The impact of growth, energy and financial development on environmental pollution in China: new evidence from a spatial econometric analysis. Energy Econ. 93, 104506 https://doi.org/10.1016/j.eneco.2019.104506.