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UNIVERSITÄT DUISBURG ESSEN

Open-Minded

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by Jan Paul Baginski* and Christoph Weber

Abstract

The share of solar energy in German electricity generation has increased strongly over recent years. This is largely due to guaranteed feed-in tariffs together with decreasing prices for solar panels. Residential PV systems play a decisive part providing households with a possibility to contribute to the *Energiewende* and benefit from the use of renewable energy. Their regional distribution varies distinctly across Germany implying different requirements in distribution grids as well as uneven utilization of national policy measures. Our paper focusses on the spatial diffusion of roof mounted PV systems and the underlying drivers in Germany. We extend previous findings not only by including additional explanatory variables but also by considering cross-regional spillover using spatial econometric models. Estimation results show that spatial dependence is a relevant determinant for explaining regional clusters of PV adoption. Recurrent visual perception or peer-effects might explain spatial autocorrelation as potential adopters follow decisions by actors in the proximity. Another reason for spatial dependence might be a concentration of craft skills or solar initiatives, which leads to an accelerated diffusion in a region and its surroundings. Whereas the first explanation corresponds to the specification of a spatial lag model, the latter is in line with a spatial error specification. However, our results indicate that although spatial lag is present, spatial dependence in the residuals has higher explanatory power. Hence, we suppose that spatial spillover is not mainly driven by social imitation but by unobserved regional characteristics. Notably, high values for solar radiation, the share of detached houses, electricity demand and inverse population density of a region favour the PV uptake.

Keywords: residential photovoltaic; spatial econometrics; spatial spillover

JEL-Classification: C21 Q28 Q42

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Content

1 Introduction

The limited availability of fossil resources and more importantly their contribution to climate change have driven the deployment of sustainable electricity generation technologies. Numerous countries have rolled out policies to encourage the use of renewable energies (REN21 2017). Germany was among the first countries to introduce a feed-in tariff (FIT) for photovoltaic panels (PV) by the Renewable Energy Sources Act (EEG). As a result, Germany became a pioneer for PV and still has the highest installed PV capacity per capita worldwide (REN21 2017), despite solar radiation being rather low compared to other countries. The share of German electricity demand covered by solar energy systems has risen from below 1% in the year 2008 to around 6% in the year 2016. A distinctive feature of PV panels is their scalability, making them attractive at the utility, commercial and residential scale. Residential customers, who are in the focus of this study, can easily install roof mounted PV panels and become small-scale producers (Groote et al. 2016). From a households' perspective, PV systems bundle both investment opportunities (the net present value of the generated electricity) and an apparent support of renewable energies (the common knowledge a house becomes "greener") (Dastrup et al. 2012). From a political perspective, these characteristics may considerably contribute to the social acceptance of renewable energy and induce a commitment of private households (Schaffer and Brun 2015). In Germany, small-scale PV installations (below 10 kW_p) account for about 5.4 GW as of December 2015, representing 14% of total capacity.

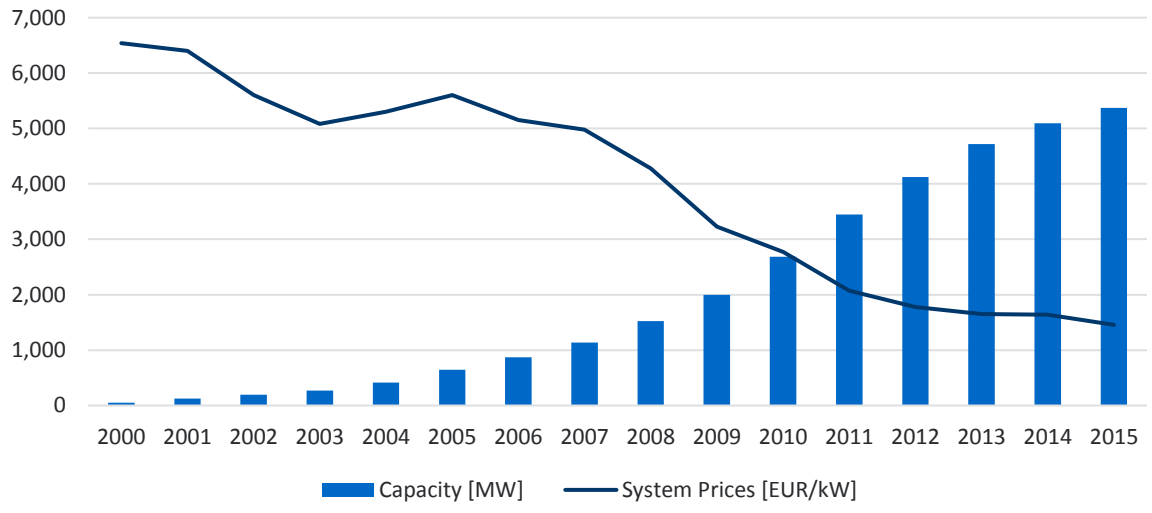

Figure 1 PV Capacity and System Prices for small-scale systems (below 10 kW_p) in Germany from 2000 to 2015. Own illustration and calculation based on data from German TSOs (2016) and IEA (2016)

Besides guaranteed FIT, decreasing PV system prices enhance their popularity among households, leading to a growing capacity over the years (c.f. Figure 1). However, only about 2.4% of Germany's 38 million households have installed PV panels. Mainzer et al. (2014) estimate the total technical residential building roof potential in Germany to be above 200 GW.

Considering this huge potential for small-scale roof mounted PV installations, the maturing PV sector and the ambitious renewable energy targets, two related questions arise: How do residential PV systems spread over space and what drives the regional uptake?

A variety of studies has discussed barriers and drivers for the adoption or non-adoption of residential PV. They use qualitative methods, such as interviews (Schelly 2014) and case studies (Braito et al. 2017) or quantitative methods, including (log-)linear regression analysis (Groote et al. 2016) based on data from large surveys (Rai et al. 2016) or publicly available data. From an economic perspective, a household will invest in a PV system, if it is profitable meaning it has e.g. a positive net present value (Klein and Deissenroth 2017). Ceteris paribus, higher solar irradiation increases yields making it more likely to invest in PV panels in locations with high irradiation (Schaffer and Brun 2015). However, findings indicate that beyond solar irradiation and economic motives, the built environment (Graziano and Gillingham 2015), knowledge of grants and costs (Vasseur and Kemp 2015), administrative burdens (Palm 2018), regional policies (Zhang et al. 2011), ecological attitudes (Braito et al. 2017), peer effects (Palm 2017), and the influence of installers (Rai et al. 2016) determine the decisions to install roof mounted PV panels.

Investigating accumulated PV uptake at a regional level, different degrees of PV adoption in, at first glance, similar regions are obvious und clusters in adjacent regions become apparent. Spatial clusters might be induced by different forces, such as peer effects (Palm 2017) or the concentrated know-how of craftsmen or regional solar initiatives (Schaffer and Brun 2015). As the presence of solar panels on rooftops is conspicuous, others in the same region know PV adopters and this community level re-enforcement may further spread the uptake of PV panels (Dastrup et al. 2012). Notably it is relevant whether social imitation effects or rather economic or ecological considerations essentially drive PV expansion. In the former case, regional disparities are likely to be self-reinforcing, at least in the mid-term. This has obvious implications for regional policy initiatives, business strategies as well as grid planning. Here, the identification of the underlying issues for PV uptake are important to foresee potential problem situations. The accumulation of decentral PV systems in specific regions, can cause bidirectional flows in the distribution grid, which can for instance cause voltage problems (Balta-Ozkan et al. 2015). This issue was often not accounted for when designing the (rather old) grid infrastructure and has to be met with either reinforcements or some flexibility options. A recent strategy in German energy policy is to favour self-consumption by funding battery storage systems (Wittenberg and Matthies 2016). However, with increasing electricity generation coming from decentral PV, to preserve grid stability in certain regions becomes more challenging.

Previous studies have failed to cover the spatially dependent nature of PV diffusion. They ignore potential neighbourhood effects in line with spatial proximity. Addressing this issue, an arising stream of literature (Dharshing 2017; Balta-Ozkan et al. 2015; Schaffer and Brun 2015) considers potential spatial relations, invoking Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things" (Tobler 1970, p. 236). In this context, our paper focusses on the underlying processes for PV diffusion over space, while controlling for regional differences in adopter characteristics and settlement structure. We extend previous findings on the regional diffusion of roof mounted PV systems in Germany not only by including additional explanatory variables but also by considering multiple forms of cross-regional spillover using spatial econometric models. The analysed PV sample comprises all installations with a capacity up to 10 kW_p erected by the end of 2015. By normalizing the entire dataset to households, a coherent specification and interpretation of model results is achieved. Another advance of our study is the consideration and comparison of various spatial model specifications to select the model, which performs best to fit the data and to capture the underlying spatial process. Further, we differentiate between direct and indirect effects (LeSage and Pace 2009), which has no precedent in the literature regarding PV adoption analysis with spatial econometric models. We thus contribute to the literature by deepening the interpretation of spatial model estimations in the context of residential PV diffusion research, by providing new results including unprecedented variables as well as aligning our results with previous findings. Our results indicate that solar irradiation, electricity demand, detached housing and inverse population density positively relate to the uptake of residential PV systems. The impact of environmental attitude and income seem to be negligible. Significant spatial parameter estimates indicate spatial dependence is a relevant determinant for explaining regional clusters of adoption.

The remainder of this paper is structured as follows: Section 2 outlines the relevant literature. Section 3 describes the methodological approach for the spatial regression analysis including the identification of direct and indirect effects. Section 4 provides data and descriptive statistics. Estimation and test results of the spatial econometric analysis are described in section 5. The final chapter concludes.

2 Related Literature

The here mentioned articles share the use of spatial econometric models (c.f. section 3) to identity determinants for residential PV adoption (c.f.Table 1). They agree that spatial spillover is a major determinant for explaining residential PV uptake. Another common driver is solar irradiation. Higher irradiation entails higher electricity generation and consequently greater PV

expansion.[1] Further, the built environment and settlement structure has a strong influence on residential PV adoption. Building density (residential buildings per sqm) is identified as a positive influence by Schaffer and Brun (2015). They argue that for rooftop installations, roof space is a prerequisite and hence greater building density induces higher PV adoption.[2] Graziano and Gillingham (2015) and Balta-Ozkan et al. (2015) find that adoptions decrease with population density, implying multi-storey buildings with limited roof space. Density measures do not capture building features, which usually supplement the analysis. Balta-Ozkan et al. (2015) embraces the share of detached houses as a predictor for PV adoption and finds a positive influence. Compared to terraced houses, detached houses offer better access to possibly larger rooftops, which simplifies construction work. Dharshing (2017) presumes that owners of single-family houses are often the target for PV marketing and more likely to install PV systems.[3] However, the author does not discover a significant effect. Similarly, researchers anticipate PV adoption to increase with the share of owner-occupied buildings. Owner-occupiers might be financially well off and have savings to invest in PV systems. In addition, the planning and installation process is easier to manage as owner-occupiers can decide freely whether to install PV. They might show a higher willingness to invest in building technologies as they directly profit from anticipated yields. In contrast renters may not have permission to install PV panels (Graziano and Gillingham 2015) and the presence of the user/investor-dilemma hampers PV uptake.[4] Schaffer and Brun (2015) ascertain a positive impact of owner-occupied buildings and similarly Graziano and Gillingham (2015) find a negative impact of rented dwellings. Yet, Balta-Ozkan et al. (2015) surmise an opposing effect. Despite continuously decreasing solar panel prices, initial costs still impede the diffusion of residential PV systems. Households' disposable income might increase the propensity to invest in a PV system. Balta-Ozkan et al. (2015) and Zhang et al. (2011) do not find a significant effect of per-capita income. In contrast, Dharshing (2017) and Schaffer and Brun (2015) reveal a positive influence of (per-capita) income. However, Schaffer and Brun (2015) use the Gross Regional Product to control for income, which may not be a suitable indicator to reflect household income. It remains unclear whether, high-income households are more likely to adopt PV panels. The merit of PV systems to generate electricity environment friendly, without CO2-emissions during operation, may incite environmental aware households

[1] Electricity is usually fed into the grid and remunerated under a FIT (the EEG in Germany). FIT for small-scale PV systems were in place in the considered countries and timeframes, except in Graziano and Gillingham 2015, who analyse a data sample with different support policies in place.
[2] However, building density does not capture building type e.g. specifying dwellings per building.
[3] Dharshing 2017 controls for new constructions as a predictor variable and deduces a negative influence on PV uptake, indicating that owners of older buildings might install PV systems during renovation activities.
[4] In multi-family houses, with the owner occupying one dwelling, the decision is rather straightforward as well. In condominiums with several owner-occupied flats, a common decision about installing PV cells on the roof is necessary which raises the barrier to action. However, condominiums are a building segment of limited relevance in Germany.

to adopt the PV technology. Zhang et al. (2011) find a positive effect of environmental consciousness on PV installations. Schaffer and Brun (2015) results show no significant impact of ecological attitudes and Dharshing (2017)'s results are ambiguous. Balta-Ozkan et al. (2015) find that households' PV adoption increases with a higher electricity demand. This might build on incentives to reduce electricity costs, to reduce the environmental impact of a high electricity demand or the desire to become more self-sufficient.

Table 1: Corresponding Literature

Authors	Dataset & Spatial Resolution	Methodological Approach & explained variable	Key Findings
Allan and McIntyre (2017)	269,449 domestic PV systems with an average capacity of 3.45 kWp in the UK (only England) in 326 local authorities	Cross-sectional spatial model; number of PV systems per household	• Local socio-economic factors, including wealth, housing type and population density explain uptake of FIT • "Green" attitudes are not important • Significant spatial coefficients
Balta-Ozkan et al. (2015)	384,043 PV systems in the UK, under 10 kWp installed until June 2013 in 134 NUTS3 regions	Cross-sectional spatial model; (log of) absolute number of PV installations	• Electricity demand, population density, pollution levels, education and detached housing affect PV adoption • Rather than income, accumulated capital and financial savings are key drivers for PV uptake in the UK • Significant spatial spillover effects
Dharshing (2017)	589,202 PV Systems in Germany (2000-2013), with a capacity between 1 and 10 kWp in 402 NUTS3 regions	Spatial panel model; number of PV installation per owner-occupied building	• Differences in economics influence spatial and temporal patterns of PV adoption • Socioeconomic status has an impact on PV adoption, but effect of environmental attitude and settlement structure is ambiguous • Significant spatial spillover effects between neighbouring counties
Graziano and Gillingham (2015)	3833 PV systems in Connecticut, USA installed between 2005 and September 2013, with a capacity below 5 kWp on block group level	Fixed effects panel model including spatial parameters; number of PV systems	• Spatial clustering beyond distribution of income or population • Positive relationship between previous PV installations nearby as well as built environment and PV adoption • Spatial effect decreases with distance and time
Rode and Weber (2016)	576,056 German PV systems installed from 1992 until the end of 2009 smaller or equal to 30 kWp with exact location	Epidemic diffusion model; PV systems per building (proxy for potential number of adopters)	• Imitation behaviour is important factor for diffusion of PV • Decreasing influence of distance on localized imitation
Schaffer and Brun (2015)	Over 820,000 PV systems in Germany installed between 1991 and 2011, with a capacity under 16 kWp in 402 NUTS3 regions	Cross-sectional spatial model; PV capacity per square kilometre	• House density, homeownership, solar radiation and per-capita income explain PV uptake • Ecological attitude has no impact on investment decision • Significant cross-regional spatial spillover

3 Methodology: Spatial Econometric Models

Either a specific-to-general or vice versa a general-to-specific approach can be chosen to arrive at a suitable model to capture spatial interaction effects (Florax et al. 2003; Mur and Angulo 2009; Elhorst 2010). The latter approach starts the analysis with a non-spatial linear regression[5], the standard approach in empirical work. It presumes that the manifestation of the dependent variable in a region is independent from the manifestation of the dependent variable in regions nearby. The approach proceeds by testing whether or not the model specification needs to be extended with spatial interactions effects (Elhorst 2010). Omitting possible spatial dependence may lead to biased and inconsistent parameter estimates (Anselin, Bera 1998). The former approach means to start with a general spatial model that contains a series of simpler models representing all the alternative economic hypotheses worth considering. According to Manski (1993) these are: (i) endogenous interactions, where the decision of a spatial unit depends on the decision taken in other spatial units; (ii) exogenous interactions, where the decision of a spatial unit to act in some way depends in independent explanatory variables of the decision taken by other spatial units; and (iii) correlated effects, where similar unobserved characteristics result in similar decision. The Manski model, also known as the general nesting spatial model, includes all three proposed spatial interactions and nests several reduced models. Figure *2* provides formulas of relevant spatial specifications and their connectedness.

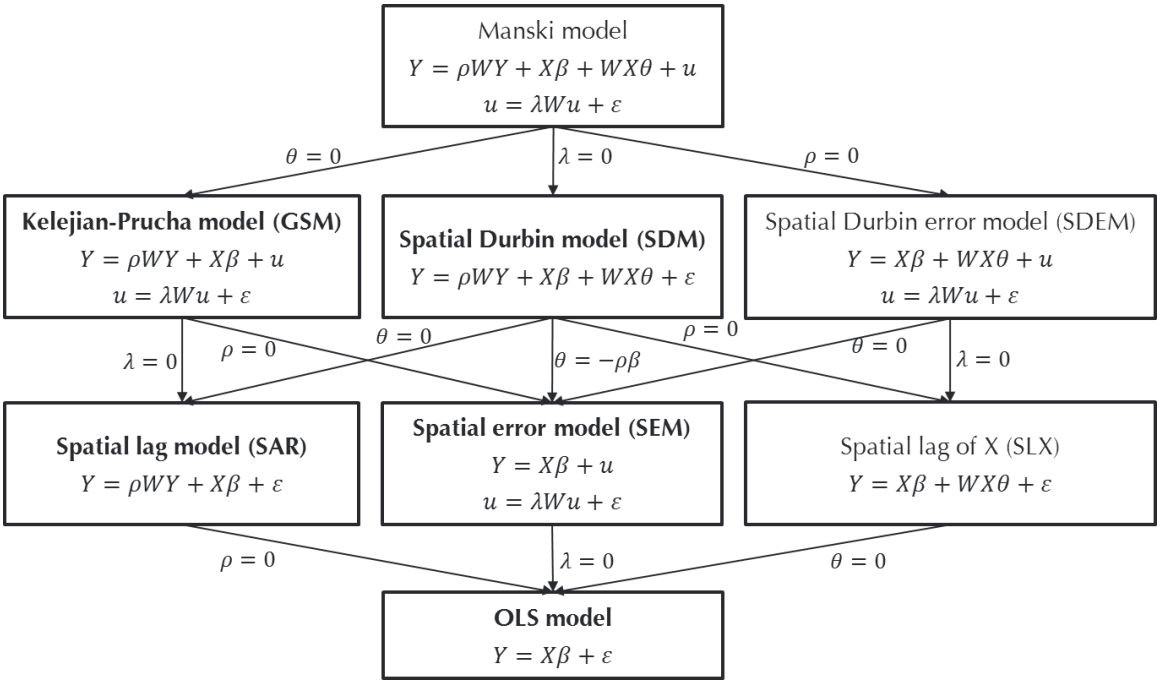

Figure 2: Different spatial model specifications and their connectedness (tested models in bold print) (own illustration based on (Elhorst 2010))

[5] As the linear regression is usually estimated by ordinary least squares (OLS), we label this regression and its results as OLS.

Thereby Y denotes a $N \times 1$ vector of observations on the dependent variable and X is a $N \times K$ matrix of observations on the explanatory variables with an associated $K \times 1$ vector of regression coefficients β. The variable Wy denotes endogenous interactions among the dependent variable, associated with ρ, the spatial autoregressive parameter. It measures the effect of spatial lag in the dependent variable. WX captures exogenous interactions among independent variables, with the $K \times 1$ vector θ representing spatial lag in the predictor variables. Wu denotes interactions among the residuals of spatial units, associated with λ, the spatial autocorrelation parameter. ε represents an independently and identically distributed error term with zero mean and constant variance σ^2. W is a $N \times N$ matrix (spatial weights matrix) reflecting the spatial structure of the units in the sample. There are different options to define the spatial weights matrix based on concepts of contiguity and distance or a combination of both (Anselin and Bera 1998). In the "queen contiguity" the matrix elements are set to one, if spatial units are neighbours[6] and zero otherwise (Eq. 2a). In distance-based approaches, the matrix elements are commonly defined as the inverse distances of the spatial units (Eq. 2b). By convention, the diagonal elements of the weights matrix ($w_{i,i}$) are set to zero as no spatial unit is viewed as its own neighbour and row elements are standardized such that they sum to one. Additionally, a cut-off point d^* can be introduced to limit spatial units as neighbours to a given distance (Eq. 2c)

$$w_{i,j} = \begin{cases} 1, if\ neighbour\ to\ j \\ 0, otherwise \end{cases} \quad (1a)$$

$$w_{i,j} = \frac{1}{d_{i,j}} \quad (1b)$$

$$w_{i,j} = 0, if\ d > d^* \quad (1c)$$

In this study, a queen contiguity matrix is used and its spatial structure for German NUTS3 region is presented in Figure *3*. Since the selection of the spatial weights matrix W is to some extent arbitrary, it has become a common practice to examine whether the results are robust to the specification (Elhorst 2010). Thus, we have also specified the inverse distance weights matrix and have estimated the same spatial models. We use the NUTS3 centres to calculate the distances. As we expect the effect of spatial units on the entity of interest to decrease with distance and eventually vanish, we introduce a cut-off distance at 65 km. Thereby we ensure that each region has at least one neighbour. As results have shown no significant differences,

[6] Neighbour means an entity that shares a common side or vertex with the region of interest (Le Sage 1999, p. 12).

we just provide graphical illustration of the used weights matrices (c.f. Figure *3*).[7] When only direct neighbours are considered, the number of neighbours is rather small. If instead neighbours are defined based on distance, urban areas have multiple neighbours, which gets obvious in the meshed structure.

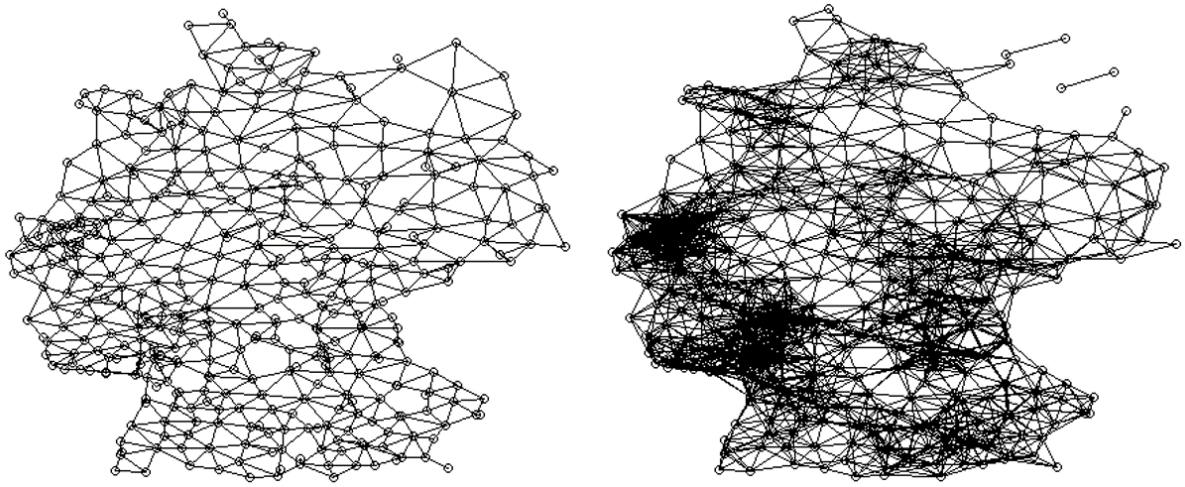

Figure 3: Neighbourhood structure of queen contiguity spatial weights matrix (left) and inverse distance spatial weights matrix with cut-off distance at 65 km (right) of German NUTS3 regions

Following the suggestion of Florax et al. (2003) and Elhorst (2010), we start our analysis with an OLS regression and then expand the model with a spatially lagged dependent variable, leading to the spatial lag or spatial autoregressive model (SAR) (c.f. Figure *2*). Then we specify the spatial error model (SEM), incorporating a spatial autoregressive process in the error term. Under most circumstances, LeSage and Pace (2009) propose using a spatial Durbin (SDM) model, since spatial dependence among the dependent and independent variables is considered. The advantage of this model over others is the capacity to generate unbiased parameter estimates, regardless of the underlying spatial process (Elhorst 2010; LeSage and Pace 2009; Botzen 2016). Further, estimating a SDM model is still appropriate if spatially correlated variables are omitted (Bowen and Lacombe 2017). As the underlying spatial process is usually unclear, another approach is to employ an even more general model combining all three spatial effects (Manski-Model). However, Elhorst (2010) proves that one of the components has to be excluded in order to distinguish between spatial coefficients from each other and to interpret the results. Hence, we exclude the lag of predictor variables and estimate the Kelejian-Prucha (Keleijan and Prucha 1989) or general spatial model (GSM), controlling for both a spatially lagged dependent variable and a spatial autoregressive process in the error term.

[7] Results for inverse distance matrix are provided upon request. Elhorst (2010) suggests that if a model is estimated for different spatial weight matrices, the matrix exhibiting the highest log-likelihood function value should be selected.

To support the interpretation of the β coefficients in spatial econometric models, associated measures are necessary (Bivand and Piras 2015). LeSage and Pace (2009) show that point estimates may lead to erroneous conclusions and partial derivative interpretations of the impacts represent a more valid basis.[8] The change in a single region associated with any explanatory variable that affects the region itself is called direct impact whereas the potential effect on all other regions is called indirect effect (LeSage and Pace 2009). The sum of both effects leads to the total effect. Impact measures can be determined for any model including a spatially lagged variable (either the dependent variable WY or the explanatory variables WX). In an OLS and SEM, the β coefficients are similar to direct effects, and indirect effects are zero (Elhorst 2010).

4 Data, Descriptive Statistics and Model Specification

4.1 Solar PV Installation Data

Following the approach of previous studies, our analysis relies on NUTS3 data.[9] In the classification scheme of the European Union a NUTS3 region corresponds to a German county.[10] The PV data is retrieved from a transparency platform, which contains renewable energy plant data of the four German transmission grid operators (Amprion, Tennet, Transnet and Hertz 50 (2016)).[11] Renewable plants other than PV systems are removed from the dataset. As this paper focusses on household PV investments, the considered capacity should mirror the boundaries for rooftop installations on residential buildings. The academic literature uses either a 10 kW_p boundary (c.f. Dharshing 2017; Balta-Ozkan et al. 2015), a 16 kW_p boundary (Schaffer and Brun 2015) or a 30 kW_p boundary (Mainzer et al. 2014; Rode and Weber 2016) to delineate small-scale roof top installations. These power boundaries are deduced from assumptions on the average available roof top space of residential buildings and differ consequently. According to the EEG, a higher feed-in tariff is granted for systems smaller or equal to 10 kW_p.[12] Taking this as a basis, we use a 10 kW_p threshold as the condition for small-scale rooftop PV installations and consider all PV systems installed before 2016. After cleaning the data, 892.452 PV installations across Germany with an average capacity of 6 kW_p are considered. Since NUTS3 regions differ in size and population, the absolute domestic PV capacity is hardly comparable. Hence, installed power should be normalized to increase comparability between regions and reduce heteroscedasticity of residuals in the regression analysis. The decision to purchase a PV system is usually made at the household level. As we

[8] For mathemtical prove see LeSage and Pace 2009 and for examples see Elhorst 2010.
[9] This is mainly due to data availability. Data on smaller units e.g. postcode regions is not available for all variables.
[10] The German term is „Landkreis“.
[11] www.netztransparenz.de/EEG/Anlagenstammdaten
[12] C.f. EEG 2017, § 48, Section. 2, Number.1: Renewable Energy Sources Act as of 21st July 2014 (BGBl. I p. 1066), last changed by Section 1 of this law from 7th July 2017 (BGBl. I p. 2532)

want to explain the diffusion of PV systems among households, we normalize the PV capacity to the number of households. Notably, not every decision-maker (household) is in the position to install PV panels. This mainly is true for households in multifamily houses, or in general, households living in rented apartments. Nonetheless, this approach is advantageous, since it allows not only normalizing the PV capacity to the number of households but also the predictor variables. This enables a consistent specification and interpretation of the model. In this vein, the impact of households living in rented dwellings is captured through the (complementary) share of owner-occupied apartments in total dwellings. Household data is obtained from the German 2011 census. Such comprehensive population and building surveys are only conducted every ten years, yet only limited changes in the number of households per county are expected between 2011 and 2015 given inert population dynamics. Figure *4* shows the dependent variable of this study, the cumulated capacity of small-scale PV installations per household.

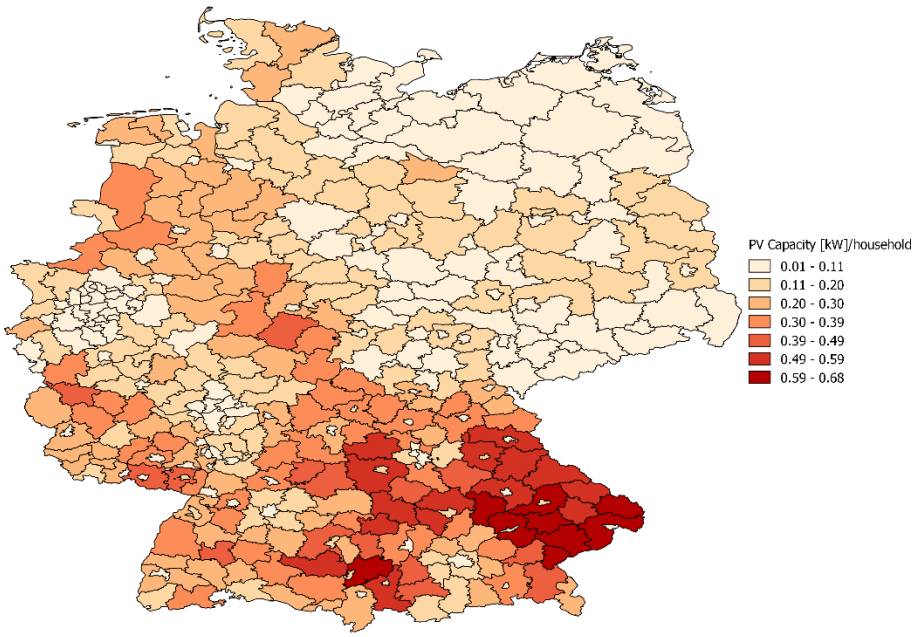

Figure 4: Accumulated installed capacity of small-scale installations (kWp/household) in German counties by the end of 2015. Own calculations and illustration based on data from German TSOs (2016).

The average household PV capacity in NUTS3 regions shows significant differences ranging from 0.01 kW to 0.68 kW. The spatial pattern of households' PV uptake shows a downward gradient from south to north. A divide between East and West Germany, with lower capacity levels in the East is also visible. Cities show rather low adoption levels as well, presumably related due to the high denominator, the number of households. High capacity levels occur especially in South Germany revealing spatial clusters, e.g. in Bavaria. As FIT defined by the EEG are applicable in every NUTS3 region, the differences in regional distribution are due to other determinants (c.f. Section 4.2).

4.2 Explanatory Variables - Determinants for PV Adoption

First, a region's cumulated installed capacity is expected to increase with solar irradiation. We capture solar radiation using the sum of global solar irradiation at NUTS3 region centres. The data are retrieved from the German Weather Service (DWD 2015). To characterise adopters of PV systems, we include share of Green voters, share of welfare recipients, household electricity demand and disposable household income. Following previous approaches, we use the share of voters for the Green party (labelled "Green voters" subsequently) in the 2013 federal election to capture environmental attitude and expect a positive impact on PV uptake. As no official electricity consumption data is available for NUTS3 regions, electricity demand has not been analysed as a predictor variable for PV uptake in Germany before. We use information from a comparison portal that evaluated 200.000 electricity contracts in 2014 and provides the annual per capita electricity consumption for 120 German cities (c.f. preisvergleich.de (2015)). Several cities correspond directly to NUTS3 regions, hence 120 of 402 data points are available. The missing data is approximated: For each state, the weighted average per capita electricity consumption is calculated based on the data within that state. We estimate the missing NUTS3 data points for electricity demand by multiplying the per-capita consumption within that state with the NUTS3 population. It could be argued that households who already adopted PV have a lower electricity demand, as more electricity is produced locally and not purchased. This would lead to an endogeneity problem. However, electricity generation from PV rooftop installations is measured by a second meter (under the EEG) and thus does not interfere with household electricity demand. Hence, there should not be a problem using the data. Disposable household income in NUTS3 regions of the year 2014 is retrieved from regional account data provided by the German Federal Statistical Office. As not only income, but also financial assets in general, determine the possibility to purchase PV systems, we try to capture the effect of prosperity. In general, it is difficult to find proxies for wealth, since data is hardly available. As one indicator, we use the share of owner-occupied dwellings, as home-ownership generally indicates a higher financial status. Data bases on the 2011 census. As income from capital shows a clear divide between East and West Germany (Federal and State Statistical Offices 2014), we add an east-west dummy. Data on the income from capital might be a better indicator for financial assets than owner-occupied dwellings. Unfortunately, this data could not be obtained. In addition, the east-west dummy controls for differences in East and West Germany beyond income, e.g. possible different mind-sets. Achtnicht and Madlener (2014) find differences of East and West German households regarding energy efficient retrofits, indicating more price sensitive households in East Germany. Accordingly, we expect a negative impact of East German regions on PV uptake. As a (negative) control variable for prosperity in a region, the share of welfare recipients is included, containing beneficiaries of unemployment benefits as well as other social benefits.

The sensitive financial situation might not offer the possibility to purchase the PV technology. Data is retrieved from the German Federal Statistical Office for the year 2014. To control for settlement structure we include the share of detached houses, share of single-family houses and the share of owner-occupied dwellings and presume positive impacts on PV uptake. The data bases on the 2011 census. As correlation between these variables may be high, it is tested for in the analysis. As we normalize to the number of households, we do not consider household size or population density. However, we include the county area, which normalized to the number of households yields the inverse of the household density. We expect the area per household to have a positive impact on cumulated installed capacity in a region. Descriptive statistics for all variables are presented in Table *1*. Other influences, such as age or education variables are omitted in this study, as we do not want to overload the analysis and presume that the main drivers for PV adoption are covered. Yet, previous studies capture the effect of population age and find a negative impact for the share of population under 20 years (Dharshing 2017). The effect of other age variables, e.g. people above 60 remains unclear. Similarly, Graziano and Gillingham (2015) do not find a significant effect of age. Both, Balta-Ozkan et al. (2015) and Dharshing (2017) suggest a positive impact of education on the regional PV uptake.

Table 1: Descriptive statistics of model variables

Variable	Description	Mean	Std. Dev.	Min.	Max.
PV Capacity	kWp/household	0.187	0.148	0.011	0.683
Solar Radiation	Global radiation [kWh/m2a]	1,115	60	987	1,262
Green Voters	Share of Green party voters	0.090	0.035	0.027	0.239
Electricity Demand	Electricity demand/household	3.620	434	2,469	4,976
Available Income	EUR/household	46,306	7,642	29,509	92,251
Welfare Recipients	Share of welfare recipients	0.171	0.075	0.038	0.423
Owner-Occupier	Share of owner-occupiers	0.519	0.144	0.128	0.769
Single Family Houses	Share of single family houses	0.388	0.152	0.085	0.753
Detached Houses	Share of detached dwellings	0.627	0.208	0.122	0.974
County Area	County area [m2]/household	13,108	10,763	424	57,929

4.3 Model Specification

To investigate the determinants of PV adoption across the 402 German NUTS3 regions (n) the following model is applied:

$$PV_n = \beta_0 + \beta_1 solar_n + \beta_2 green_n + \beta_3 elec_n + \beta_4 income_n + \beta_5 welfare_n + \beta_6 owner_n + \beta_7 detach_n + \beta_8 area_n + u_n. \quad (2)$$

$$u \sim N(0, \sigma^2 I_n)$$

The dependent variable in Equation (1) is the PV capacity of installations under 10 kW normalized to the number of households. The explanatory variables encompass solar irradiation ($solar$), share of green voters ($green$), household electricity demand ($elec$), household income ($income$), share of welfare beneficiaries ($welfare$), share of owner-occupied dwellings ($owner$), share of detached buildings ($detached$) and area per household ($area$). Except solar radiation, all variables are normalised to the number of households in NUTS3 regions.

5 Estimation Results and Discussion

As single-family houses are often detached and occupied by the owner, the use of all variables leads to collinearity problems.[13] Collinearity causes instability in parameter estimation and must be avoided. We exclude the share of single-family houses as a regressor.[14] Standardized coefficient estimates of the OLS model are presented in the first column of Table 3. Results reveal that solar radiation, electricity demand, share of detached houses and area per household have a positive impact on the regional uptake of PV installations. Available income, welfare recipients, green voters and the east dummy variable turn out to affect negatively the adoption of PV. Ownership seems to be negligible. The negative impacts of available income and green voters are rather surprising and rise questions on the validity of the specification although the obtained R^2 of 0.75 indicates a rather good model fit. To test for spatial correlation, we calculate Moran's I (Moran, 1950) and carry out Lagrange multiplier (LM) tests. Moran's I test statistic is a global indicator of spatial association.[15] The positive values (c.f. Table 2) indicate spatial dependence of PV capacity as well as OLS residuals. Also, Moran's scatter plots in Figure *5* and Figure 6 show positive spatial correlation between neighbouring regions.

[13] We use the the variance of inflation factor (VIF) to detect collinearity. The VIF is based on the square of the multiple correlation coefficients resulting from regressing a predictor variable against all other predictor variables. A VIF greater than 10 signals a collinearity problem in the model. We also excluded detached houses or single-family houses, which lead to a smaller R2 and justifies the omission of the owner-occupier rate.

[14] Results including single-family houses are provided upon request.

[15] Moran's I: $I = \frac{N \cdot \sum_{i=1}^{N} \sum_{j=1}^{N} [w_{ij} \cdot (y_i - \bar{y}) \cdot (y_j - \bar{y})]}{\sum_{i=1}^{N} \sum_{j=1}^{N} [w_{ij} \cdot \sum_{i=1}^{N} (y_j - \bar{y})^2]}$

We use a row standardized queen contiguity weights matrix for the tests and the subsequent spatial models. LM_{error} and LM_{lag} tests, in addition to their robust versions, test the null hypothesis of no spatial dependence against alternatives of spatial error and spatial lag dependence respectively (Anselin, 1988; Florax et al., 2003).[16] LM tests (c.f. Table 2) indicate that the null hypothesis of no spatial dependence should be dismissed. OLS regression seems inappropriate and may result in biased estimates, as spatial forces driving PV adoption are not confined by NUTS3 borders but are likely to spill over to proximate regions. Given the positive and significant values of LM_{error} and LM_{lag} tests and their robust versions, the OLS model is rejected in favour of both the SAR and the SEM. Hence, also the SDM should be estimated (Elhorst 2010). In addition, we employ a GSM, incorporating both spatial lag and error correlation, but neglecting spatial dependence in explanatory variables. Table 3 provides estimation results. In addition, Table 5 shows impact measures of the SDM and GSM.

Table 2: Test for spatial dependence in the OLS regression

Test	
Moran's I for PV capacity	0.596
Moran's I for residuals	0.316
LM_{error}	86.28***
Robust LM_{error}	22.67***
LM_{lag}	72.40***
Robust LM_{lag}	8.78**

*** Significance level at 0.1%
** Significance level at 1%.

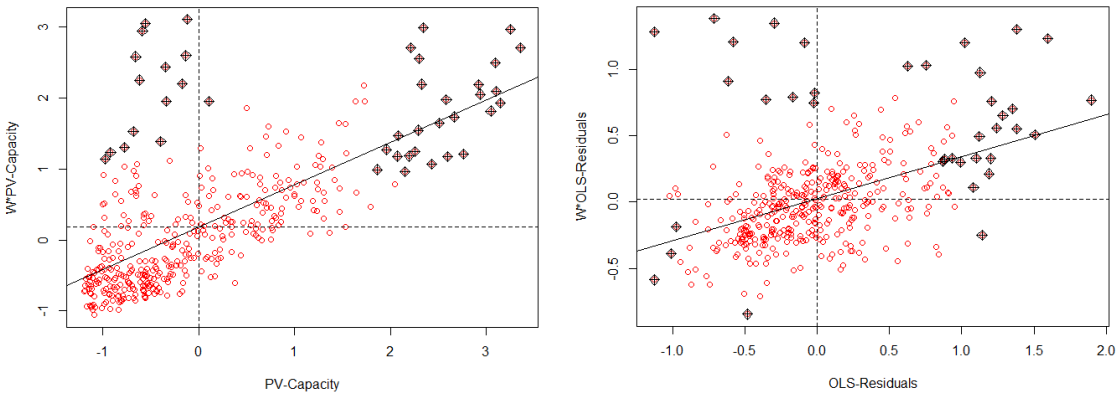

Figure 5 and Figure 6: Moran's I Scatter Plots (PV capacity (left) and OLS residuals (right))

[16] Tests for a missing spatially lagged dependent variable (LM lag) test (in the specification of equ. (1)) that $\rho = 0$; tests for spatial autocorrelation of the error (LM error) test whether $\lambda = 0$. RLM error tests for error dependence in the possible presence of a missing lagged dependent variable. RLM lag tests for a missing spatial lagged dependent variable in the possible presence of spatial error dependence.

Table 3: OLS and spatial model estimation results

Variable	OLS	SAR	SEM	SDM		GSM
	Estimate	Estimate	Estimate	Estimate	θ Estimate	Estimate
Intercept	0.000	-0.061.	-0.031	-0.027		-0.033
	(1.000)	(0.010)	(0.546)	(0.299)		(0.464)
Solar Radiation	0.298***	0.176***	0.230***	0.144	-0.027	0.227***
	(0.000)	(0.000)	(0.000)	(0.230)	(0.840)	(0.000)
Green Voters	-0.092**	-0.009	0.038	0.014	-0.155*	-0.046
	(0.009)	(0.772)	(0.292)	(0.745)	(0.019)	(0.225)
Electricity Demand	0.322***	0.273***	0.306***	0.288***	-0.125	0.297***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.178)	(0.000)
Income	-0.156**	-0.082.	-0.118*	-0.087.	0.037	-0.110*
	(0.001)	(0.061)	(0.011)	(0.071)	(0.697)	(0.018)
Welfare recipients	-0.233***	-0.113*	-0.128*	-0.103.	-0.037	-0.16**
	(0.000)	(0.016)	(0.010)	(0.074)	(0.698)	(0.003)
East Dummy	-0.179***	-0.005	-0.053	-0.073	-0.006	-0.102.
	(0.000)	(0.920)	(0.373)	(0.443)	(0.959)	(0.089)
Ownership	0.061	0.178**	0.093	0.067	0.047	0.070
	(0.365)	(0.004)	(0.184)	(0.381)	(0.672)	(0.326)
Detached	0.201**	0.147**	0.234***	0.260***	-0.193.	0.224**
	(0.001)	(0.008)	(0.000)	(0.000)	(0.055)	(0.001)
County Area	0.201***	0.157***	0.213***	0.222***	-0.139*	0.210***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.000)
ρ		0.317***		0.468***		0.038
		(0.000)		(0.000)		(0.615)
λ			0.528***			0.493***
			(0.000)			(0.000)
R^2 /adj. R^2	0.746/0.741					
Log Likelihood	-294.65	-265.42	-255.90	-248.88		-255.81
AIC	611.29	554.85	535.79	539.76		537.63
BIC	655.25	602.80	583.75	623.68		589.58
Breusch Pagan Test	72.45	78.02	49.67	86.37		51.38

Note: The values in parentheses are p-values.
*** Significance level at 0.1%
** Significance level at 1%.
* Significance level at 5%
. Significance level at 10%

Considering the results of the OLS regression model as a benchmark, the findings are partly revised when spatial models are estimated. All models including spatial terms offer a better model fit (Log Likelihood, AIC, BIC) than OLS estimation. Results point to strong spatial correlation between PV adoption levels in adjacent counties, confirming residential PV forms local clusters in certain regions. The positive and statistically significant estimate of ρ in the SAR and SDM indicates spatial lag of PV adoption. It implies that levels of solar panel uptake tend to spill over NUTS3 borders and facilitate PV adoption in neighbouring regions. Recurrent visual perception, intensified social interactions and peer-effects might explain spatial autocorrelation as potential adopters follow decisions by actors in the proximity. The positive and statistically significant parameter estimate of λ in the SEM indicates spatial dependence in the residuals. Hence, similar unobserved characteristics result in similar decisions in neighbouring NUTS3 regions. A local concentration of craft skills, solar initiatives (Schaffer and Brun 2015), local PV supplier activities or advertising campaigns, might lead to an accelerated PV diffusion in a region and its surroundings. Admittedly, the interpretation of the spatial association is tentative and may certainly relate to other than the discussed factors. Combining both results, an influence of PV installations in one county on PV installations in neighbouring counties as well as a remaining unexplained spatial dependence indicated by the residuals is present. Consequently, the GSM should best fit to capture the spatial processes. The GSM results show positive estimates of both ρ and λ indicating a combined spatial dependence similar to an ARMA time series specification. However, in contrast to the SAR and SDM, ρ becomes insignificant. Since the models are estimated by maximum likelihood, we can perform a likelihood ratio (LR) test to examine whether the SDM or GSM can be reduced to the SAR or SEM (c.f. Figure 2). LRs indicate that neither the SDM nor GSM should be reduced to a SAR (c.f. Table 4). In contrast, the SDM model could be reduced to a SEM as the LR test is insignificant. Further, a model reduction of the GSM to a SEM seems plausible as the LR is small and insignificant, notably visible in the only infinitesimal different log likelihood. Hence, the effect of spatial lag does not offer additional explanatory power when considering spatial dependence in the residuals.[17] Also, log-likelihoods and AIC (Akaike Information Criterion) show that SEM and SDM model perform best and improve upon to the OLS and SAR models (c.f. Table 3). In terms of BIC (Bayesian information criterion) the SEM shows the best results, lending credence to its choice. Breusch–Pagan test indicates the presence of heteroscedasticity in residuals of all models, although it is somewhat reduced in the spatial estimations. SEM and GSM, taking spatial dependence of residuals into account, show the best results.

[17] Although this is indicated by the robust LM_{lag} test (c.f. Table 2).

Table 4: Likelihood rations for nested spatial models

SDM vs. reduced model		GSM vs. reduced model	
SAR ($\theta = 0$)	33.01*** (0.000)	SAR ($\lambda = 0$)	19.12*** (0.000)
SEM ($\theta = -\rho\beta$)	14.04 (0.121)	SEM ($\rho = 0$)	0.063 (0.687)

Regarding the β estimates, a difference between the OLS and spatial models are the generally smaller coefficients in the spatial models. This implies that their direct influence is less pronounced than estimated earlier, and partly attributable to spatial association. In this vein, the east dummy is insignificant in spatial models. As expected solar radiation maintains a positive influence on PV uptake in the spatial models.[18] Yet in our analysis solar radiation is not the predominant factor, as other variables show higher coefficients. Contrary to expectations, ecological attitude has a negative influence on PV uptake (OLS) or is insignificant (SAR, SEM und GSM). In the SDM the estimate is positive whereas the lag estimate is negative. This finding is supported by the impact analysis (c.f. Table 5). It suggests that a high share of Green voters in a region negatively influences PV adoption in adjacent regions, which has no plausible interpretation. Yet, by visualising the share of Green voters in NUTS3 regions, it becomes obvious, that the share of Green voters is especially high in cities. Here, the PV capacity per household is rather low, which might entail a negative relation. In less densely populated suburbs, meaning regions adjacent to cities, the PV uptake under consideration is rather high, which again might explain the negative spatial lag impact. Admittedly, the use of other indicators for environmental awareness than Green party voters might involve different results, in particular that environmental motivation favours PV uptake. E.g. Wittenberg and Matthies (2016) finds that the use of green electricity tariffs and energy efficient appliances is higher for PV adopters, indicating higher environmental awareness than average households.

A major predictor for PV uptake is household electricity demand. It has the highest positive coefficient estimates. Simiarly, Wittenberg and Matthies (2016) find that electricity consumption of PV adopters is medium to high compared to the German average. A household's comparatively higher demand may entail higher environmental concerns and lead to a the desire to compensate the higher demand by green electricity production (Balta-Ozkan et al. 2015). The decision could also be motivated by the financial consideration to reduce the household's comparatively higher electricity costs or the wish to become self-sufficient.

A negative impact of household income on cumulated PV capacity is suggested by spatial estimation results suggest and supported by the impact analysis (c.f. Table 5). This implies that high income is no precondition for meeting the upfront costs of PV systems. For high-

[18] The effect of solar radiation is statistically insignificant in the SDM, which has no plausible interpretation.

income households, the potentially profitable purchase of a PV system may not be a concern, as saving money (or energy costs) is not an issue. Also, higher incomes are potentially paid in densely populated areas, where limited roof potentials hinder the growth of installed capacity per household. Obviously, there is an indirect effect of income on PV uptake through the increased probability for living in a detached and owner-occupied house. However, the positive impact of homeownership is only significant in the SAR specification and insignificant in the remaining models. We assume the reason to be the high correlation of detached and owner-occupied dwellings. If detached houses are excluded as a regressor, the impact of owner-occupied dwellings is positive in all models. Similarly, including single-family houses instead of detached or owner-occupied dwellings, a positive impact is found. Hence, detached houses in our data (building on the German 2011 census) are to some extent congruent with owner-occupied dwellings as well as single-family houses. However, the explanatory power of detached houses is the highest. They are a main driver for PV adoption indicated by high β estimates in all models. In addition, county area per household essentially favours PV uptake.[19] This again hints at a positive impact of rural areas with larger properties and higher shares of detached single- or double-family houses. Detached houses improves solar exploitation of PV panels, since they usually encounter no shadowing and have larger roofs (Dharshing 2017). Further, construction work is easier compared to terraced houses (Balta-Ozkan et al. 2015). The share of welfare recipients mitigates regional PV uptake, hence capturing a positive relationship between socio-economic status and PV uptake, which could not be obtained from the income variable. In this vein, initial investment costs seem to detain socially deprived households (who are also more likely to rent) from adopting PV systems. Although FIT offer or increase profitability of PV systems, they do not reduce the high capital costs. Balta-Ozkan et al. (2015) use the findings of Graziano, Gillingham (2015) on the importance of accumulated capital for PV uptake and suggest that the early adopters of PV panels seem to be post-family householders capable to cover the high upfront costs. Notably, in older post family households (two-person, retired), electricity demand is rather high as more time is spent at home (Wittenberg and Matthies 2016). These households again are likely to characterize affluent regions, live in detached houses and entail enough capital savings to invest in PV panels.[20]

[19] Population density negatively affects household PV adoption, as county area per household has a positive impact in all models.
[20] In the appendix (c.f. Table 6), we summarise our results and compare them to literature findings.

Table 5: Impacts measures of SDM and GSM

	SDM			GSM		
Variable	Direct	Indirect	Total	Direct	Indirect	Total
Solar Radiation	0.149	0.072	0.221**	0.227***	0.009	0.236***
	(0.178)	(0.613)	(0.004)	(0.000)	(0.633)	(0.000)
Green Voters	-0.003	-0.262**	-0.266**	-0.046	-0.002	-0.047
	(0.920)	(0.003)	(0.002)	(0.198)	(0.753)	(0.200)
Electricity Demand	0.289***	0.017	0.306*	0.297***	0.012	0.309***
	(0.000)	(0.869)	(0.034)	(0.000)	(0.615)	(0.000)
Income	-0.087.	-0.006	-0.094	-0.110*	-0.004	-0.115*
	(0.059)	(0.939)	(0.537)	(0.022)	(0.682)	(0.021)
Welfare recipients	-0.113*	-0.150	-0.262.	-0.160**	-0.006	-0.166**
	(0.043)	(0.282)	(0.061)	(0.001)	(0.639)	(0.001)
East Dummy	-0.077	-0.071	-0.148	-0.102.	-0.004	-0.106.
	(0.381)	(0.681)	(0.283)	(0.094)	(0.775)	(0.086)
Ownership	0.076	0.138	0.213	0.070	0.003	0.073
	(0.270)	(0.399)	(0.201)	(0.325)	(0.677)	(0.327)
Detached	0.252***	-0.125	0.127	0.224***	0.009	0.233**
	(0.000)	(0.394)	(0.328)	(0.000)	(0.595)	(0.001)
County Area	0.218***	-0.063	0.155.	0.210***	0.008	0.218***
	(0.000)	(0.437)	(0.084)	(0.000)	(0.621)	(0.000)

Note: The values in parentheses are p-values.
*** Significance level at 0.1%
** Significance level at 1%.
* Significance level at 5%
. Significance level at 10%

The θ coefficients of the SDM, representing spatial lags of the independent variables, are only statistically significant for county area and green voters. Similarly, indirect impact measures of the SDM and GSM are only significant for Green voters and detached houses (c.f. Table 5).[21] This implies that spatial lag of independent variables and indirect impacts do not offer meaningful explanations of PV adoption. Hence, most effects are local, as mostly direct impacts are significant and outgun indirect impacts. Consequently, PV uptake in a region depends on its own adopter-characteristics and settlement structure, and less so on those of its neighbours. In addition, positive direct (or total) impact measures of the SDM and GSM

[21] The effects estimate for the SAR model gives a similar picture (cf. Table 10).

confirm that solar irradiation detached houses, electricity demand and county area favour PV uptake. Negative influences of income and welfare recipients are also substantiated.

To conclude, it is clear from the results that the data exhibits significant spatial dependence independently of the chosen specification. In the context of this study, we do not prefer a single model, but rather build implications on all model results. However, from coefficient estimates and test results the SEM performs best to interpret the impact of PV uptake within a region. This indicates that although spatial lag is present, spatial dependence in the residuals has higher explanatory power. Hence, we suppose that spatial spillover is not mainly driven by social imitation but by other regional characteristics not included in our model.

Detached houses in spacious regions offer favourable conditions for PV adoptions. Also, households living in (their own) detached buildings might have financial savings to invest in PV systems. The share of welfare recipients seem to be a suitable negative proxy for wealth, having an impeding influence on a regions PV uptake. We hence suggest that is not income but rather prosperity i.e. accumulated capital, which contributes to regional differences in PV uptake. Further, households with higher electricity demand are inclined to adopt PV panels. Neither disposable income nor ecological attitude qualify to explain higher levels of PV adoption and rather show an opposing impact. A supposed East German mind-set impeding PV adoption could also not be supported.

The availability and choice of data as well as the configuration of the spatial weights matrix (Mur and Angulo 2009) are crucial for the regression results and their interpretation. We have tested an inverse distance matrix and results are robust across this alternative specification.

6 Conclusion

Considering the finite nature of fossil resources and their effect on climate change as well as the huge potential for small-scale roof mounted PV installations and the support mechanisms in place, more small-scale PV installations are likely to emerge. This article studies the drivers and barriers influencing the diffusion of small-scale solar PV systems across space. We use cross-sectional data on PV installations in Germany, along with adopter characteristics, settlement structure and radiation data to find key determinants for accumulated capacity of small-scale PV systems in NUTS3 regions.

Spatial dependence is a significant explanatory factor for residential PV diffusion, implying positive spillover to adjacent regions and the manifestation of PV clusters in certain regions. Recurrent visual perception, intensified social interactions and peer-effects might explain spatial autocorrelation as potential adopters follow decisions by actors in the proximity. Another reason for spatial dependence might be a concentration of craft skills or solar initiatives, which leads to an accelerated diffusion in a region and its surroundings. Whereas the first explanation

corresponds to the specification of a spatial lag model (SAR) the latter is in line with a spatial error specification (SEM). When considering both spatial processes in a generalized spatial model (GSM), we find that although spatial lag is present, spatial dependence in the residuals has higher explanatory power. We suppose that spatial spillover is not mainly driven by social imitation but by rather on regional characteristics beyond the included predictor variables. Notably, high values for solar radiation, shares of detached houses, electricity demand and inverse population density of a region favour PV uptake. The number of welfare benefit recipients and available income have a negative impact on small-scale PV installations. The share of Green voters has a negative impact in the OLS model but is insignificant in spatial models. This indicates on the one side that neglecting spatial association leads to implausible results. On the other hand, our results suggest that neither high income nor ecological attitudes induce PV installations as a presumably "typical" ecological behaviour. Obviously, there is an indirect effect of income (or accumulated capital) on PV uptake through the increased probability for living in a detached house. Yet beyond this impact, no direct effect is measurable. Also our results indicate that there are no measurable effects of a specific "East German" mind set (or differing economic conditions) beyond the general spatial interdependences and economic factors.

The drivers for the regional distribution of PV installations are important for political and scientific discussions regarding the increasing share of PV generation in Germany. As 62% of German residential buildings are detached, there is further rooftop PV potential to be exploited. Potential new business models such as solar leasing or tenant (sub-) metering might grow and make rooftop PV accessible to a broader market. One implication pointed at by Dharshing (2017) is that regional differences lead to variations in the local benefits of policy measures. A better understanding of the regional impacts of policies can help to improve remuneration schemes and adjust national policies. In addition, the installation of PV systems in a region creates local jobs and revitalises artisanship, which might be important factors for urban development and planning.

Our findings deepen the understanding on the regional diffusion of small-scale PV but research is still needed, as spatial dependence in residuals hints at unobserved drivers for regional uptake. E.g. editing data on local solar initiatives in NUTS3 regions and taking it as a predictor variable might account for some of the spatial error correlation. Shortcomings of our research which could be addressed include the following: Notably we do not account for innovation diffusion effects over time, as proposed by Rogers (2003). Hence, a temporal dimension could be integrated in the analysis leading to a spatial-temporal model. Klein and Deissenroth (2017) analyse when household's invest in PV systems and find that not only profitability, but also the change in profitability compared to the status quo determines the uptake. Yet a precondition for including time effects is the availability of the data. However, we do not want to capture

effects over time (e.g. cost decreases) but rather (nearly) time invariant features of different regions and thus employed cross-sectional data instead of panel data. Time invariant variables are incorporated in the fixed effects (FE) of standard FE panel models, which complicates evaluation of these variables. Rode and Weber (2016) find that imitation in household PV adoption is highly localised, but influence decreases over distance. Richter (2013) also notices stronger social effects of domestic solar PV for smaller spatial units. In light of these findings, our spatial units seem to be rather big to investigate social interaction between households. Considering smaller spatial units such as zip codes in the analysis may hence improve our findings on spillover effects. However, data availability at a zip code level for the predictor variables used in this study has limited the spatial disaggregation.

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Appendix

Table 6: Summary of effects on PV uptake

Variable	Literature findings	Our findings
Solar Radiation	Schaffer and Brun (2015) and Balta-Ozkan et al. (2015) propose a positive effect: Higher irradiation means higher electricity generation that is generally fed into the grid and remunerated under a FIT. Insignificant impact in Allan and McIntyre (2017).	High positive impact in most specifications: Households consider financial yields when deciding whether to adopt PV.
Green voters	Proposed to be insignificant by Schaffer and Brun (2015) and Allan and McIntyre (2017); inconsistent finding by Dharshing (2017).	Inconclusive; negative effect in the OLS estimation and insignificant in spatial models. Not only ecological conscious households adopt PV.
Electricity Demand	Balta-Ozkan et al. (2015) find a positive effect: Households with higher demand may be more interested in becoming self-sufficient.	High positive impact: Higher interest to reduce comparatively high electricity costs or desire to compensate higher demand by green electricity production.
Available Income	Schaffer and Brun (2015) and Dharshing (2017) find a positive influence of income: higher income households may be more capable to manage high upfront costs of PV systems.	Small negative effect: Income is no precondition to adopt PV. Finding in line with Balta-Ozkan et al. (2015), Zhang et al. (2011) and Graziano and Gillingham (2015). Supposedly, accumulated capital more important than income.
Welfare recipients	Dharshing (2017) finds negative effect of unemployment rate, indicating poor local economy hampers PV adoption.	Negative impact: Sensitive financial situation of households does not offer the chance to purchase PV; Effect of accumulated capital bigger may be bigger than effect of income.

Home ownership	Balta-Ozkan et al. (2015) find a negative effect in the UK and claim cumulated capital is more important.	Positive effect (but due to correlation with detached houses insignificant except in SAR model): Homeowners are more likely to invest in building technologies and planning is easier as they can freely decide what to put on their roof; in line with Schaffer and Brun (2015).
Detached Houses	Balta-Ozkan et al. (2015) find a positive effect: Compared to terraced homes or block development, construction work could be easier.	High positive impact: Detached houses may offer more suitable roof space for rooftop PV installations and do not suffer from shadowing. Higher explanatory power than single-family houses and owner-occupied dwellings in our analysis.
Single-Family Houses	Dharshing (2017) finds positive impact in panel SEM model, but insignificant effect in FE and panel SAR model. Impact remains unclear.	Due to correlation between detached, owner-occupied and single-family houses excluded form regression.
County Area per Household (Inverse Population Density)	Schaffer and Brun (2015) find positive influence of house density: Scalable roof-top PV may be suitable for densely populated regions and rural areas with little inhabitation offer less roof potential.	High positive impact: More county area per household indicates larger properties with presumably larger roof spaces, characterised by a higher share of single and double family homes. Finding in line with Balta-Ozkan et al. (2015).

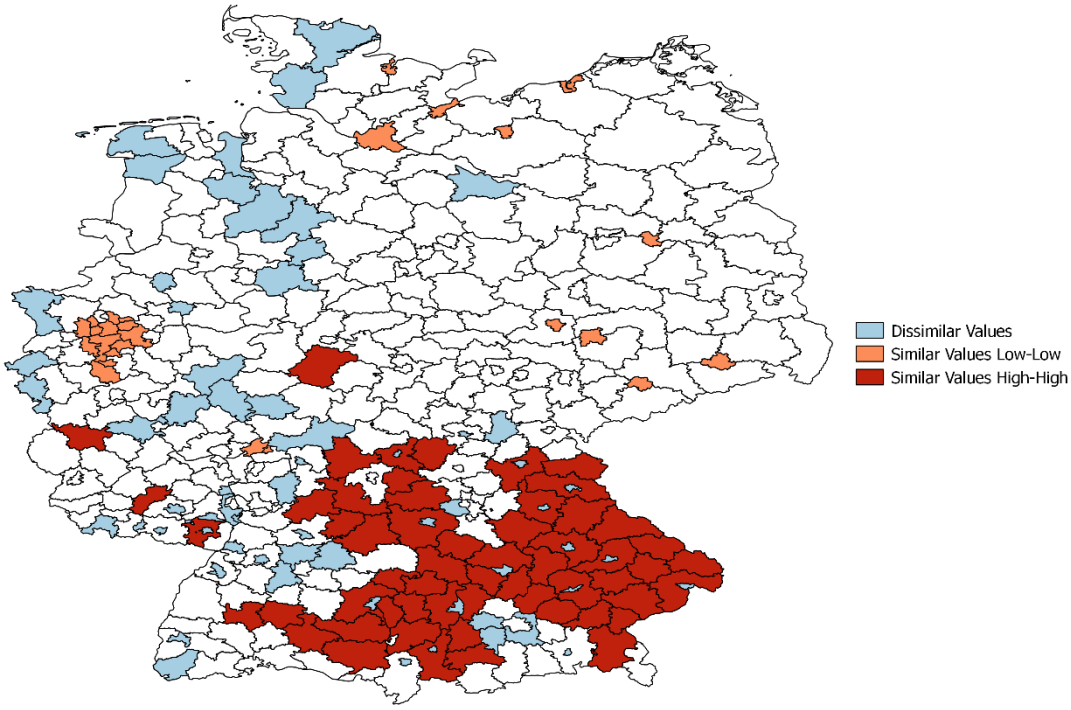

Figure 7: Local Moran's I showing similar and dissimilar values in neighbouring counties

Table 7: OLS estimation results with whole data set

Variable	Coefficient	Std. error	t-value	p-value	VIF
Intercept	0	0.025	-0.002	0.998	
Solar Radiation	0.281***	0.035	8.031	0.000	1.889
Green Voters	-0.153***	0.034	-4.462	0.000	1.815
Electricity Demand	0.331***	0.058	5.751	0.000	5.117
Income	-0.151**	0.047	-3.199	0.001	3.426
Welfare recipients	-0.267***	0.051	-5.241	0.000	4.013
East Dummy	-0.199***	0.050	-3.946	0.000	3.908
Ownership	0.056	0.088	0.636	0.525	12.010
Detached	-0.014	0.072	-0.189	0.850	8.027
County Area	0.198**	0.060	3.277	0.001	5.612
Solar Radiation	0.191***	0.042	4.537	0.000	2.726

Note: The values in parentheses are p-values.
*** Significance level at 0.1%
** Significance level at 1%.
* Significance level at 5%
. Significance level at 10%

Table 8: Correlation Matrix

Variable	Sol.	Green	Elec.	Inc.	Wel.	East	Own.	Sing.	Det.	Area
Solar Radiation	1.00									
Green Voters	0.07	1.00								
Electricity Demand	-0.02	0.25	1.00							
Income	0.27	0.38	0.70	1.00						
Welfare recipients	-0.49	-0.23	-0.51	-0.69	1.00					
East Dummy	0.02	-0.55	-0.69	-0.59	0.32	1.00				
Ownership	0.01	-0.05	0.70	0.57	-0.62	-0.30	1.00			
Single	-0.15	-0.14	0.63	0.38	-0.42	-0.14	0.89	1.00		
Detached	0.02	-0.01	0.60	0.50	-0.65	-0.24	0.88	0.77	1.00	
County Area	-0.01	-0.35	0.17	0.03	-0.26	0.29	0.57	0.65	0.60	1.00

Table 9: Direct and indirect effects of SAR model

Variable	Direct	Indirect	Total
Solar Radiation	0.179*** (0.000)	0.078*** (0.000)	0.257*** (0.000)
Green Voters	-0.073* (0.019)	-0.031* (0.021)	-0.104* (0.017)
Electricity Demand	0.275*** (0.000)	0.119*** (0.000)	0.394*** (0.000)
Income	-0.077. (0.066)	-0.033* (0.067)	-0.110* (0.062)
Welfare recipients	-0.142** (0.002)	-0.062** (0.003)	-0.204** (0.002)
East Dummy	-0.046 (0.302)	-0.020 (0.332)	-0.066 (0.307)
Ownership	0.150* (0.013)	0.065* (0.028)	0.215* (0.014)
Detached	0.158** (0.002)	0.068** (0.006)	0.226** (0.002)
County Area	0.159*** (0.000)	0.069** (0.001)	0.228*** (0.000)

Note: The values in parentheses are p-values.
*** Significance level at 0.1%
** Significance level at 1%.
* Significance level at 5%
. Significance level at 10%

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