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**Working Paper**

## Disentangling small-scale solar photovoltaic adoption: A spatial analysis of decision factors and localized interactions in Germany

HEMF Working Paper, No. 06/2023

**Provided in Cooperation with:**

University of Duisburg-Essen, Chair for Management Science and Energy Economics

*Suggested Citation:* Stein, Tobias; Sieger, Lisa; Weber, Christoph (2023) : Disentangling small-scale solar photovoltaic adoption: A spatial analysis of decision factors and localized interactions in Germany, HEMF Working Paper, No. 06/2023, University of Duisburg-Essen, House of Energy Markets & Finance (HEMF), Essen

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# Disentangling Small-Scale Solar Photovoltaic Adoption: A Spatial Analysis of Decision Factors and Localized Interactions in Germany

HEMF Working Paper No. 06/2023

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Oktober 2023

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*Open-Minded*

# Disentangling Small-Scale Solar Photovoltaic Adoption: A Spatial Analysis of Decision Factors and Localized Interactions in Germany

by Tobias Stein, Lisa Sieger and Christoph Weber

## Abstract

The existence of spatial patterns in the adoption of small-scale solar photovoltaic (PV) systems is widely accepted in the academic literature. The diffusion of these systems depends on decisions of heterogeneous units, often households, that form their decision based on unit characteristics and attitudes, the built environment, economic and physical factors, as well as peer effects. When including several of these factors, many studies use macro-level datasets, which have a limited ability to capture ‘real’ small-scale spatial patterns. Using data on a 1 km<sup>2</sup> grid level for Germany, we identify spatial patterns of adoption while also controlling for highly localized explanatory variables. Spatial dependence is estimated and tested with spatial econometric models. Using this set of small-scale data, we show that spatial clustering affects the adoption of residential PV systems, which is increasing with larger neighborhood sizes. Further, the presence of large-scale PV installations has strong direct and also indirect, i.e., spillover effects on the adoption of rooftop PV installations. Finally, spillover effects from defined neighborhoods are found to become statistically insignificant with larger distances, promoting the use of such small-scale data.

Keywords: Solar PV adoption; Spatial econometrics; Adoption behavior; Energy transition

JEL-Classification: C31; Q28; Q55; R12

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# 1 Introduction

The presence of spatial patterns in the adoption of small-scale photovoltaic (PV) systems has received widespread recognition in the academic literature (e.g., Balta-Ozkan et al., 2015; Dharshing, 2017; Müller and Rode, 2013). This diffusion process depends on decisions made by a variety of actors, typically households, with their choices being shaped by a complex interplay of system characteristics, the built environment, economic factors, individual preferences, and the influence of peer behavior (Alipour et al., 2021). While different studies have attempted to capture a variety of these determinants, the use of macro-level datasets often leads to limitations in capturing the complex and ‘authentic’ spatial patterns that determine adoption dynamics at the small spatial scale (Alipour et al., 2021).

In this study, we therefore shift the focus to the use of small-scale raster data to identify spatial spillover effects underlying the adoption of rooftop PV installations. To shed light on the latent spatial dependence, we employ spatial econometric models that allow for a more accurate estimation of the comprehensive spatial relationships – and thus enable better predictions of future penetrations and the resulting impacts on the distribution grids. The inclusion of socioeconomic information at a small spatial scale further allows to control simultaneously for differences in neighborhoods.

We thus examine (1) the influence of neighborhood-specific factors associated with the socioeconomic status and the built environment, and (2) the impact of spatial interaction effects on the adoption of residential solar PV systems, both at a standardized 1 km<sup>2</sup> grid level. Spatial interaction effects comprise spatial endogenous effects resulting from the adoption of solar PV systems in adjacent neighborhoods as well as spatial spillover effects resulting from driving factors in these surrounding neighborhoods.

This paper focuses on PV systems with a capacity of up to 10 kWp, following the research of Balta-Ozkan et al. (2015) and Dharshing (2017). However, in contrast to prior studies we expand the analysis by incorporating the impact of larger PV systems on the adoption of these smaller ones into our spatial regression modelling. Moreover, we calculate sensitivities across various neighborhood sizes, ultimately highlighting spillover effects within different spatial contexts.

We employ data from Germany as a case study, where there has been a significant increase in usage of PV systems in recent years. At present, Germany has 2.6 million PV systems with a total installed capacity of 70.6 GW (Statistisches Bundesamt, 2023). However, further

expansion is required as the Renewable Energy Sources Act (EEG) 2023 sets an expansion target of 215 GW for PV by 2030, roughly tripling the installed capacity over the next eight years compared to the expansion status at the end of 2022 (UBA, 2023).

Therefore, our paper makes three major contributions to the extant literature. First, we examine drivers for the adoption of small-scale PV installations while also controlling for regional differences in adopter characteristics and settlement structure at a standardized and very local level. We thereby investigate whether spatial autoregressive effects persist if similarities in socioeconomic factors are controlled for – and thus point at actual neighborhood interactions. Second, we extend previous findings by controlling for the influence of large-scale systems on the adoption of small-scale residential PV. Third, we test the sensitivity of the results to different cutoff distances in the definition of neighborhoods to determine the radius at which the spillover effects disappear.

The study is organized as follows. Section 2 provides a brief literature review, focusing on relevant empirical studies. Section 3 discusses some theoretical considerations regarding direct and indirect effects of different drivers for the adoption of residential PV. Section 4 then outlines the methodological approach as well as the data and data processing together with descriptive statistics. Empirical results are presented in Section 5 and further discussed in Section 6. Finally, Section 7 concludes.

## **2 Literature review**

Analyzing the adoption of residential PV systems has gained much attention in recent years; however, modeling technology diffusion across households has a long tradition in economics since Bass (1969). Most research focuses on Germany (e.g., Arnold et al., 2022; Baginski and Weber, 2019; Müller and Rode, 2013; Rode and Müller, 2021, 2016), the United States (e.g. Bollinger and Gillingham, 2019; Graziano et al., 2019; Irwin, 2021; Kwan, 2012) and the United Kingdom (e.g. Alderete Peralta et al., 2022; Balta-Ozkan et al., 2015; Collier et al., 2023; Snape, 2016), but there are also studies investigating inter alia China (Zhao et al., 2017), Australia (Lan et al., 2020; Li et al., 2023; Zander, 2021), Switzerland (Baranzini et al., 2018; Thormeyer et al., 2020), Japan (Zhang et al., 2011), Sweden (Mundaca and Samahita, 2020; Palm, 2017, 2016; Palm and Lantz, 2020), and Belgium (Groote and Verboven, 2019). Further, there are various strands of literature in this field, of which research on regional spillovers and spatial dependencies in technology diffusion (e.g., Copiello and Grillenzoni, 2017; Curtius et al., 2018), as well as on the sociodemographic and economic characteristics of PV adopters

(e.g., Dharshing, 2017; Moerkerken et al., 2023; Zhang et al., 2023b) are most important to our study.

Prior research generally confirms that predictors of adoption behavior can be categorized as either individual, social, or informational (Alipour et al., 2020). Moreover, numerous studies indicate that geographic characteristics, which include inter alii sunshine hours (Lamp, 2023) and solar irradiation but also spatial spillovers – both within (Rode and Weber, 2016) and even between counties (Fadly and Fontes, 2019) – or peer effects (e.g. Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Steadman et al., 2023; Wolske et al., 2020) play crucial roles in explaining the diffusion of residential PV systems. We subsequently focus on a review of key quantitative studies. For a qualitative analysis resulting in a comprehensive review of further drivers and barriers to technology adoption, see Balcombe et al. (2013); for a theoretical framework examining psychological and social determinants of interest in residential PV systems, see Wolske et al. (2017).

Rode and Weber (2016) concentrate their research on spatial components and investigate whether localized imitation is a driver for technology adoption. For more than 500,000 household PV systems installed in Germany through 2009, they employ an epidemic diffusion model, dating back on Bass (1969) and Geroski (2000), to control for spatial and temporal heterogeneity. The authors find that imitative adoption behavior is highly localized, with its effects decreasing with increasing distance in a predefined radius of 0.5 km, 1 km, 4 km and 10 km, respectively. There is no influence found for a radius larger than 1 km. Irwin (2021), Kim and Gim (2021), and Kosugi et al. (2019) also show spillover effects to be largest within the 15 nearest neighbors, within a 0.5 km radius or within a 1 km radius, respectively.

Based on econometric analysis, Schaffer and Brun (2015) investigate small-scale PV adoption in Germany as well, with more than 820,000 observations registered between 1991 and 2012. The authors find different effects between counties, which they partly explain by varying solar irradiation. However, they state that neighborhood effects such as the house density, the homeownership rate and the purchasing power per capita have greater influence on adoption rates. Similar results were found in various studies (e.g., Balta-Ozkan et al., 2015; Kosugi et al., 2019; Kucher et al., 2021).

Rode and Müller (2021) further explore the micro-level variation of peer effects in household PV adoption. By using geocoded data for Germany up until 2010 and panel data to construct a discrete choice model, they find evidence supporting causal peer effects that are strongest within up to 200 m. Nevertheless, these effects diminish over time and are found to be larger in



regions with low economic activity – suggesting that regionally different promotion and support may be necessary. Moreover, Balta-Ozkan et al. (2021) examine effects of various factors on the spatial patterns of PV adoption at a local level in the UK while also considering peer effects. They employ a geographically weighted regression model to corroborate the presence of peer effects and report regional differences in the influential factors.

A comprehensive review of studies is provided by Alipour et al. (2021, 2020). They state that „limited quality sample size has been a major drawback for many researchers, leading to few well-structured models developed to date, and weakly supported conclusions on causal relationships“ (Alipour et al., 2021, p. 484). Additionally, the authors criticize that most studies only focus on the years when financial incentives were introduced, with the phase-out years rarely being considered.

In addition, the empirical studies in the current literature that emphasize the spatial dimension of residential solar adoption have a major limitation. The low spatial resolution of the data used limits the ability to capture spatial characteristics and measure spatial interaction effects for small-scale PV system adoption. Multiple studies considered areas ranging in size from 288 km<sup>2</sup> (Müller and Trutnevyte, 2020) to 1,809 km<sup>2</sup> (Balta-Ozkan et al., 2015). Studies that utilize high-resolution spatial data often limit their observation frame to individual cities without looking at influences of the surrounding areas (e.g., Kosugi et al., 2019) or only look at spatial effects without the inclusion of additional explanatory variables (Rode and Müller, 2021; Rode and Weber, 2016). To our knowledge, there is only one recent study that accounts for such small spatial scales while also controlling for additional explanatory variables: Zhang et al. (2023a) explore spatial effects for over 13,000 neighborhoods in the Netherlands, each with an average size of 2.59 km<sup>2</sup>.

Furthermore, it is often argued that observational learning through the visibility of solar panels is one of the main mechanisms behind the spatial interaction effects. However, studies often limit these visible effects to small-scale residential PV systems while not considering the visible effects of larger PV systems. Thus, spatial interaction effects may be underestimated (Zhang et al., 2023a).

We therefore add to the extant literature in different ways. First, we create a unique dataset by using socioeconomic data at a standardized 1 km<sup>2</sup> grid level combined with geocoded PV data on an individual level. By employing a Spatial Durbin Model (SDM), we are able to capture both spatial spillover as well as spatial autoregressive effects. Second, we include large installations in our analysis to account for visible effects of these PV systems. Third, we apply

different cutoff distances in the definition of neighborhoods to test the sensitivity of results regarding the spatial spillover effects. Finally, we draw on data from 2014 and 2020, and thus take two specific years with reduced financial incentives into account.

### 3 Drivers for PV adoption – theoretical considerations

The installation of a PV system on a building can be conceptualized as an individual discrete choice (cf. e.g., McFadden, 2001; Train, 2009) usually made by the building owner and potentially influenced by social interactions (cf. e.g., Brock and Durlauf, 2001). At the same time, the PV installation represents an investment which provides returns through feed-in compensations or through avoided costs for purchases from the electricity grid/retailer or both. The utility  $V_j$  of such a binary adoption choice  $\omega_j \in \{0,1\}$  may then be written in general terms as

$$V_j(\omega_j) = m_j(\pi_j(\omega_j, x_j)) + n_j(\omega_j, x_j, \omega_{-j}, x_{-j}) + \varepsilon_j. \quad (1)$$

The individual utility is thereby composed of a monetary part  $m_j$  which is a (monotonously increasing) function of the profit  $\pi_j(\omega_j, x_j)$ , depending in turn on the adoption decision  $\omega_j$  as well as on characteristics of both the building and its owner summarized in the vector  $x_j$ . Profit may be determined through a net present value calculation:

$$\pi_j(\omega_j, x_j) = -I_j + \sum_{t=1}^T \frac{1}{(1 + \delta_j)^t} O_{j,t} = -I_j + b(T, \delta_j) \bar{O}_j \quad (2)$$

with  $I_j$  the initial investment cost,  $\delta_j$  the discount rate and  $O_{j,t}$  the operational cash flows per year. These may be replaced by an appropriately weighted average  $\bar{O}_j$  multiplied by the present value factor  $b(T, \delta_j)$  which depends on the useful lifetime  $T$  and the discount rate  $\delta_j$ .

Besides the direct monetary benefits there may be other, often non-monetary advantages of PV adoption which are summarized in the term  $n_j$  and where we also hypothesize a dependence on individual characteristics  $x_j$ , on adoption decisions of other individuals  $\omega_{-j}$  (aggregated in a decision vector) and on the characteristics of these other individuals  $x_{-j}$ . Besides these (in principle) observable utility components there is also an unobservable stochastic component  $\varepsilon_j$ .

In detailed studies on adoption behavior, various, often rather detailed behavioral models have been used for investigation (cf. Alipour et al., 2020). However, when it comes to large data sets on PV adoption (as available for Germany), the level of detail regarding the individual adoption

decisions remains limited and information on the characteristics of the buildings and decision makers are only available at the neighborhood level. In this setting, the individual decisions may be aggregated to the neighborhood level by defining the PV adoption rate as a dependent variable, corresponding to the share of buildings with a small-scale PV installation on the roof. For explaining this adoption rate, the available information may then be classified according to the four categories indicated in Figure 1.

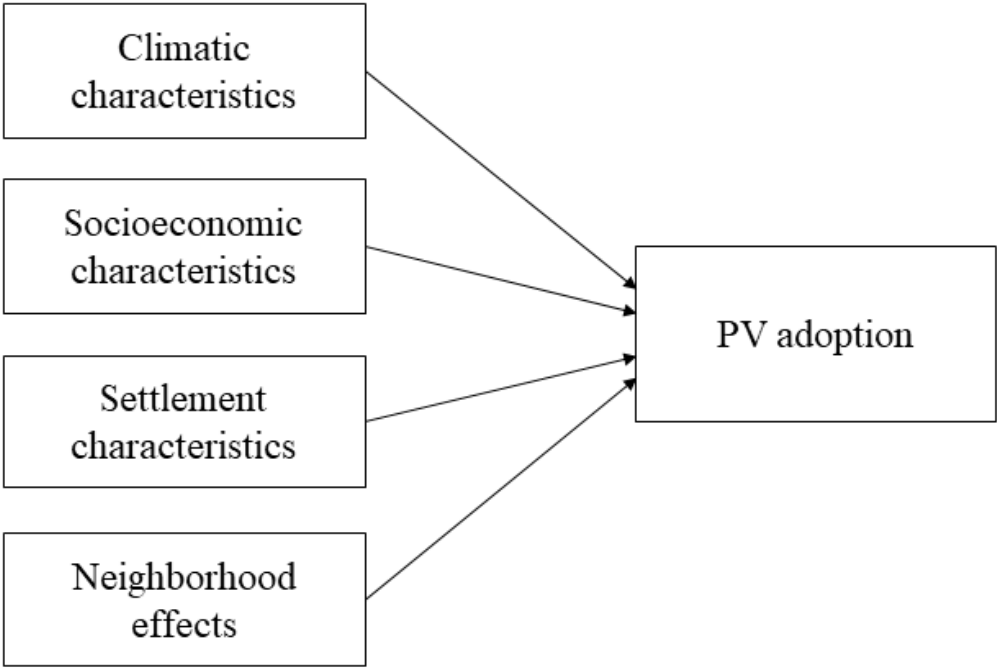


Figure 1 Drivers for PV adoption.  
 Source: Own illustration.

Each category includes various influencing factors that may affect both the monetary and the non-monetary utility components driving the adoption of residential PV installations. At the level of neighborhoods, we may then consider direct effects on adoption, which describe the impact of an influencing factor in a given (focal) neighborhood on the adoption of PV in the same neighborhood. But additionally indirect effects may arise, which encompass impacts of an influencing factor of a neighboring region on the PV adoption in the focal neighborhood. All factors considered in this study, including the expected direct and indirect effects, are summarized in Table 1.

In the category of *climatic characteristics*, the annual solar irradiation is a key physical driver for the profitability of PV systems, since it has direct effects on the electricity production and, consequently, the operational cash flows generated by a PV installation. Indirect effects of solar irradiation are yet implausible since the radiation in neighboring regions has no impact on the

profitability and also no transmission channel for indirect impacts on the adoption of PV systems seems likely.

Table 1 Expected direct and indirect effects of the drivers for PV adoption.

<b>Category</b>	<b>Influencing factor</b>	<b>Direct effects</b>	<b>Indirect effects, i.e., spillover effects</b>
Climatic characteristics	Solar irradiation	positive: the higher the solar irradiation, the higher the profitability of the system	no effects
Socioeconomic characteristics	Purchasing power per household	positive: with higher income it is easier to bear large investments	positive: network effects
	Unemployment rate (UER)	negative: high UER is associated with higher income risk	negative: spillover of income risk from neighborhoods
	Old-age-dependency ratio	negative: for a relatively older population long-term investments might not be profitable. Moreover, future expected incomes tend to be lower due to retirement	no effects
Settlement characteristics	Share of 1- and 2-family homes	positive: residential PV installations are common on individual houses and are not complicated by the landlord-tenant dilemma or by issues of co-propriety	positive: network effects
	Household density	negative: high household densities are related to a high share of multi-family buildings, which has direct negative impacts on the available roof size for PV installations	positive: network effects  negative: if seen as indicator for settlement structure, it has opposite effects of the share of 1- and 2-family homes
Neighborhood effects	PV adoption rate in surroundings	-	positive: effects due to visibility of systems and network effects
	No. of large-scale PV systems	positive: effects due to visibility of systems	positive: effects due to visibility of systems

Source: Own illustration.

Regarding *socioeconomic characteristics*, two key influencing factors are the purchasing power per household and the unemployment rate, both related to the wealthiness of a neighborhood.

High purchasing powers are correspondingly expected to have positive direct effects, as investments are less restricted by borrowing constraints (which would translate into higher discount rates and thus lower investment profitability). For the unemployment rate, a negative correlation with the (unobservable) wealthiness is likely, and moreover a higher unemployment rate is also an indicator of increased income risk – which in turn will induce a higher preference for liquidity and thus lower propensity to invest. Especially the latter transmission channel suggests that there may also be indirect effects of the same (negative) sign, as income risk is also dependent on unemployment rates beyond the immediate neighborhood.

Additionally also network effects (cf. Bollinger and Gillingham, 2012; Manski, 1993) may lead to indirect effects reinforcing the direct effects. Thereby two transmission channels are potentially relevant. First, social networks among adopters and potential adopters which lower the (non-monetary) costs of finding information and assessing adoption choices. Or put differently: in existing social networks, people can talk about (the advantages of) rooftop PV systems if someone starts to deal with the topic. Second, supplier-customer networks which not only channel information but are also enablers of adoption – as most homeowners will rely on craftsmen for the actual installation works – so their absence would increase the cost of adoption. Both types of networks tend to cover areas which extend beyond the immediate neighborhood yet fade out with larger distances. But especially social networks are only partly correlated with physical proximity and could also induce indirect effects over longer distances.

A further relevant socioeconomic factor is the age structure of the population. The old-age dependency ratio<sup>1</sup>, i.e., the share of the population aged 65 years and older in relation to the population aged 20 to 64, is used here to describe this socioeconomic characteristic of a neighborhood. Evidence regarding the effect of different age groups is rather mixed in the literature (cf. Alipour et al., 2020); however, we expect that a high old-age-dependency ratio has negative direct effects on the adoption of residential PV. The older the population, the higher the discounting of the (more distant) future given that it may exceed the individual lifespan. Correspondingly it becomes less profitable to make long-term investments such as installing PV systems. Also expected future incomes are lower due to retirement, inducing also more severe credit constraints. Given that these are impacts at the level of the individual profitability, we assume that there are no spillover effects of the old-age-dependency ratio from neighboring regions.

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<sup>1</sup> The old-age dependency ratio is easy to interpret and commonly applied in the literature (cf. Breidenbach et al., 2022). In a time series, this indicator maps the process of demographic aging of the population (VDSt, FachAG-Bevölkerung, Unterarbeitsgruppe Demografie, 2011).

Regarding the settlement structure, we retain two potential drivers for the adoption of small-scale PV. First, the share of one- and two-family homes is considered relevant as the installation of PV systems on individual houses is not complicated by the landlord-tenant dilemma or by issues of co-propriety. Moreover, positive network effects also tend to emerge based on this factor – if there are other areas with high shares of one- and two-family homes in the vicinity, this provides opportunities for information networks as well as supplier-customer networks as described above.

A second relevant factor regarding the settlement structure but linked also to socioeconomic characteristics is the household density, i.e., the number of households per 1 km<sup>2</sup>, which is related to the wealthiness of the population but also reflects the settlement structure in the specific grid cell<sup>2</sup>. When controlling for the settlement structure (cf. above), we expect the direct effect of household density still to be negative, as higher population densities are then an indication of rather confined dwelling space in larger multi-family buildings or smaller individual houses. This comes along with a more limited roof area available for PV installations. Regarding indirect effects, different transmission channels may be envisaged. On the one hand, positive network effects may be strengthened given the higher population density. On the other hand, the negative direct effect also implies that the probability for strong information and supply networks decreases inducing also a negative indirect impact.

The last category depicted in Figure 1 are *neighborhood effects*. Besides the spillover effects of influencing factors from the neighboring regions as discussed before, there are usually two channels of action discussed in the literature. One is the visibility of PV systems (cf. e.g., Rode and Müller, 2021). If people see a lot of PV systems in their own neighborhood and in the surrounding area, this could be a trigger for them to become involved in the issue. Another channel are the aforementioned network effects. The visibility argument provides a strong case to include spatial lags of the dependent variable into the specification, whereas the network effects could also be captured as spillovers from explanatory variables in neighboring cells.

A second relevant neighborhood effect is the total number of large-scale PV systems with a capacity of more than 10 kWp and up to 100 kWp. For these, the same arguments of visibility and network effects apply as for the small-scale units which are in the focus of the analysis. The existence of such larger PV system is an indication for not purely residential

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<sup>2</sup> This illustrates that settlement characteristics and socioeconomic characteristics of the population do not evolve independently one from another. The classification of the characteristics may therefore be considered to some extent as arbitrary, yet it is useful to distinguish more household and more building related characteristics.

neighborhoods, yet their impact may be similar if not more pronounced than for small-scale systems.

## 4 Methodological approach and data

Following inter alia Zhang et al. (2023a), Müller and Trutnevyte (2020), Kosugi et al. (2019) and Dharshing (2017), we use a spatial econometric approach to capture the impact of different socioeconomic and neighborhood characteristics, as well as spatial spillovers on the adoption of residential PV systems. We thereby distinguish between the use of a Spatial Autoregressive Model (SAR), Spatial Error Model (SEM) or Spatial Durbin Model (SDM). Model selection and specification are described in Chapters 4.1 and 4.2. Contrary to the previously mentioned studies, we use raster data that consist of 125,441 standardized 1 km<sup>2</sup> grid cells rather than pre-defined spatial units (e.g., counties, cities, postal code zones). This approach not only allows for a more flexible choice of neighboring units, but also for the investigation of highly localized effects.

### 4.1 Spatial model specification and selection

Two approaches are commonly used to select spatial econometric models: the specific-to-general approach and the general-to-specific approach (cf. Elhorst, 2010; Florax et al., 2003). We apply a mix of both approaches and first adopt the specific-to-general approach to determine whether the non-spatial model should be extended to a SAR or SEM. Later, we employ a general-to-specific approach to test whether the SDM should be simplified to either SAR or SEM. We perform a series of tests to identify the optimal spatial econometric models for our cross-sectional data. A description of variables included in the regression model is given in Section 3.

#### 4.1.1 Specific-to-general approach

The specific-to-general approach starts with a non-spatial linear regression model, estimated by ordinary least squares (OLS). It is assumed that the dependent variable in one spatial unit (i.e., grid cell)<sup>3</sup> manifests itself independently of its expression in neighboring spatial units (cf. Elhorst, 2010). The baseline equation takes the form:

$$Y = \alpha + \beta X + \varepsilon \tag{3}$$

---

<sup>3</sup> In the following we will only refer to grid cells even if the described models can be used with other spatial units too.

where  $Y$  is a  $N \times 1$  vector consisting of observations on the dependent variable – in our case, the adoption rate of PV systems up to 10 kWp – for each unit  $i$  in the data.  $X$  is a  $N \times K$  dimensional matrix of observations on  $K$  exogenous (explanatory) variables, i.e., the solar irradiation and different socioeconomic factors, for all  $i$  grid cells. The corresponding  $K \times 1$  vector of parameters is denoted by  $\beta$  while  $\alpha$  is the associated intercept parameter. Finally,  $\varepsilon$  is an  $N \times 1$  vector of error terms for the regression.

Spatial data often violate the standard assumptions of OLS models, which assume independency between observations. Using a Moran's I test (Moran, 1950), the assumption of no autocorrelation in the residuals can be tested. If this hypothesis is rejected, the OLS model can be extended to models incorporating spatial autocorrelation. Since Moran's I does not provide any guidance on whether to extend the OLS model to SEM or SAR, standard (Anselin, 1988) and robust (Anselin et al., 1996) Lagrange multiplier (LM) tests can be conducted.

In spatial autoregressive models, the value of the dependent variable in one grid cell is assumed to be influenced by the dependent variables of neighboring grid cells. The neighborhood structure is defined by the non-negative spatial matrix  $W$  of known constants displaying the spatial arrangement of the grid cells used in the dataset. The SAR model can be written as:

$$Y = \alpha + \rho WY + \beta X + \varepsilon \quad (4)$$

where  $\rho$  denotes the spatial autoregressive parameter of the dependent variable  $Y$  that measures the interdependence across grid cells. Interpretation in case of PV adoption is as follows: the PV adoption in grid cell  $i$  is dependent on different exogenous variables  $X$  in grid cell  $i$ , such as the solar irradiation, and also on spillover effects of the PV adoption in neighboring grid cells, as given by  $\rho WY$ .

The SEM specification, on the other hand, is dealing with the interactions between the residuals of the spatial units. Here, a spatial autoregressive specification is used to allow for spatial dependence in the model's disturbances. Thus, a certain disturbance in a single grid cell is expected to have an impact on the disturbances of neighboring grid cells according to a spatial weights matrix. The neighborhood matrix is the same as in the SAR model. The SEM is formulated as follows:

$$Y = \alpha + \beta X + u, \quad \text{with } u = \lambda Wu + \varepsilon \quad (5)$$

where  $Wu$  describes the impact of spatially correlated disturbances and  $\lambda$  is the corresponding spatial autocorrelation coefficient, whereas  $\varepsilon$  represents an independently and identically



distributed error term with zero mean and a constant variance  $\sigma^2$ . A statistically significant estimate for  $\lambda$  thus indicates that there is a spatial correlation in the disturbances of the PV adoption; however, it is not captured by the included exogenous variables.

Both, the SAR and SEM are estimated by maximum likelihood estimation (MLE)<sup>4</sup>. The two-step estimation procedure consists of a numerical optimization of the spatial error parameters first, and second, of a parameter estimation for  $\beta$  by generalized least squares (GLS).

#### **4.1.2 General-to-specific approach**

If the LM-test results reject the OLS in favor of SAR and SEM, the next step is to test if an SDM can be reduced to SAR and SEM.<sup>5</sup> For this purpose, an SDM is set up, which takes the following form:

$$Y = \alpha + \rho WY + \beta X + \theta WX + \varepsilon \quad (6)$$

where  $\rho$  has the same definition as in the SAR model, while  $\theta$  represents a  $K \times 1$  vector of coefficients of spatially lagged exogenous variables, i.e., it captures the influence of inter alia socioeconomic variables of grid cell  $j$  on the PV adoption in the focal grid cell  $i$ , and  $\beta$  remains a vector of parameters for the exogenous variables. The SDM model is also estimated by MLE.

The results of the SDM are utilized to conduct a Likelihood Ratio (LR) test to evaluate the two hypotheses:  $H_0: \theta = 0$  and  $H_0: \rho\beta + \theta = 0$ . The first hypothesis examines whether the SDM can be simplified to SAR, whereas the second hypothesis examines the possibility of simplifying to SEM. Based on test results, there are four possible outcomes (cf. Burridge, 1981): First, if both hypotheses are rejected based on the LR tests, then the use of the SDM is preferred for the data at hand. Second, if  $H_0: \theta = 0$  cannot be rejected through LR while the LM test results point towards SAR, then the SAR model should be used. Third, if  $H_0: \rho\beta + \theta = 0$  cannot be rejected via LR, while the LM test results point towards SEM, then a SEM is the most appropriate model for the data. Finally, if neither of these conditions is satisfied, a SDM should be used to account for both SAR and SEM arguments. Figure 2 illustrates the relationship among the various spatial econometric models examined in this study.

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<sup>4</sup> While MLE is the most commonly used method for estimation of SAR/SEM SDM, other methods like quasi-maximum likelihood, Bayesian Markov Chain Monte Carlo (MCMC), semiparametric models, and GMM could also be used as alternatives.

<sup>5</sup> If the LM-test does not reject the null hypothesis, a calculation of an OLS model including spatially lagged explanatory variables can be used to test if  $\theta = 0$ . If this is also rejected, OLS remains the most appropriate model, and it is not desirable to make further generalizations.

In the presence of a spatially lagged variable  $WY$  or/and  $WX$ , the point estimates should not be interpreted in the way they are in the usual linear model framework. In spatial regression models point estimates are used to calculate overall multiplier effects because they can potentially affect the entire sample. LeSage and Pace (2009) show that impact measures should be used that distinguish between direct effects and indirect effects. Direct effects are defined as a measure of the effect of changes in the independent variable  $X_i$  in the same grid cell  $i$  on the dependent variable  $Y_i$ , including feedback effects that arise from the change from  $X_i$  on  $Y_j$  in the system of spatially dependent regions. The indirect effects deal with the impact of changes in the independent variables of neighboring grid cells  $X_j$  on the dependent variable in grid cell  $i$  (i.e.,  $Y_i$ ) – which mainly describes the spillover effects (LeSage and Pace, 2009). In an OLS and SEM, the  $\beta$  coefficients correspond to the direct effects, and the indirect effects are zero (Elhorst, 2010).

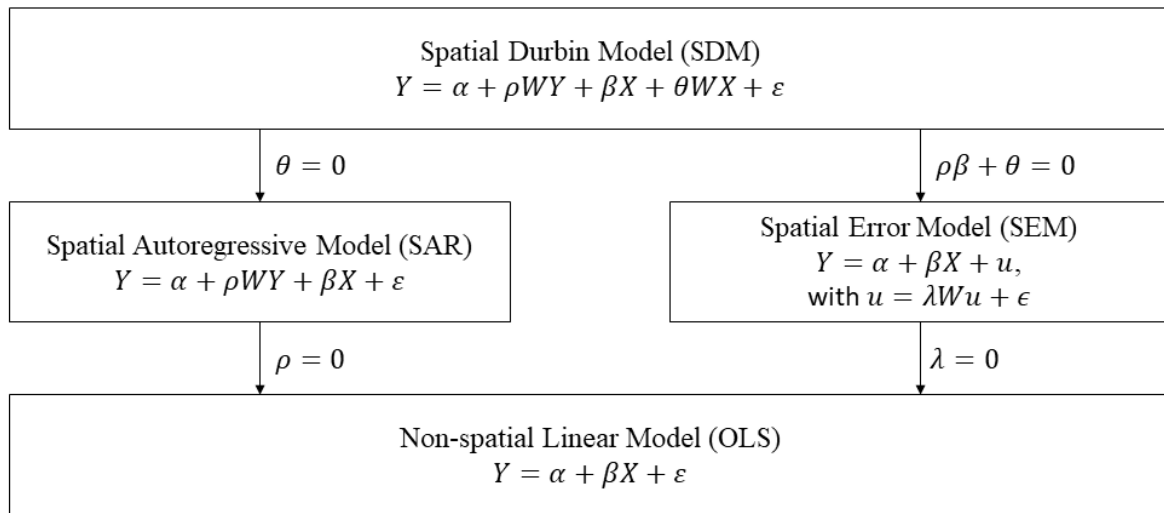


Figure 2 Comparison of the different spatial model specifications.  
 Source: Own illustration based on Elhorst (2010).

## 4.2 Spatial weights

$W$  is a  $N \times N$  non-negative, non-stochastic and symmetric spatial weights matrix, reflecting the spatial structure of the units in our sample. It is utilized on several occasions in this spatial econometric study. It is employed to compute the spatial lag, examine spatial autocorrelation, and importantly, compute the Jacobian determinant in the MLE. It generally takes the form:

$$W_{i,j} \begin{cases} > 0, & \text{if } i \text{ and } j \text{ are neighbors} \\ = 0, & \text{otherwise} \end{cases} \quad (7)$$

By convention, the diagonal elements of the weights matrix are set to zero, as units cannot be their own neighbors while all non-zero elements of the matrix reflect neighboring units. Further, the weights matrix is row-standardized such that the elements of each row sum up to one. This facilitates the interpretation of operations with the weights matrix as an averaging of neighboring values (Anselin and Bera, 1998).

Several methods exist to define the neighbors, e.g., based on distance (i.e., all spatial units within a specific radius are neighbors) or contiguity (i.e., all spatial units that either share a border or a single point are neighbors). We use a spatial weights matrix based on distance to define the neighborhood, i.e., all grid cells whose centers are within a certain radius are counted as neighbors. With an increasing radius, the number of (possible) neighbors thus increases. Figure 3 illustrates the number of (possible) neighbors within a 1 km and 2 km radius.

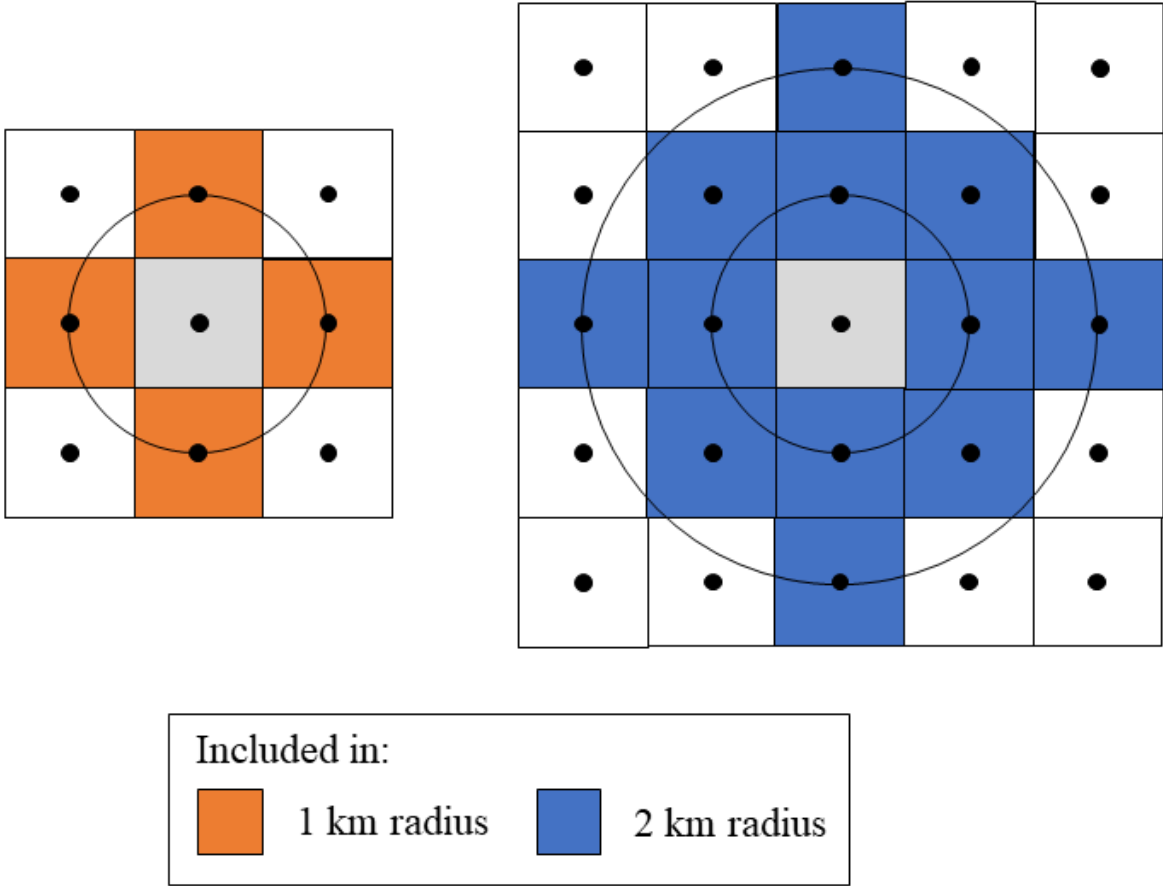


Figure 3 Neighbors within a 1 km and 2 km radius.  
 Source: Own illustration.

Higher order matrices, i.e., matrices using a larger cutoff distance (or a larger radius respectively), can be constructed analogously<sup>6</sup>. In this way, we can test the sensitivity of our

<sup>6</sup> LeSage (2014) shows that the concept of neighbors in spatial weights matrices may be extended to regions or grid cells that are not in direct vicinity.

results, especially with regard to the spillover effects. With larger distances and a higher number of neighbors, spillover effects are assumed to decrease. Since we apply a row standardization to unity, the same weight is assigned to each neighbor when estimating spillover effects. Thus, with an increasing number of neighbors, the value of each weight decreases<sup>7</sup>.

All benchmark analyses are performed using a radius of 1 km, which is the smallest possible radius that generates neighbors in our data. We then gradually expand the radius in 1 km steps up to a radius of 10 km. Additionally, a radius of 15 km is tested to account for even larger distances<sup>8</sup>.

### 4.3 Data

Our dataset combines information on PV systems with socioeconomic data on a small spatial scale. The PV data originates from the “**MarktStammdatenRegister (MaStR)**” and is obtained from the **BundesNetzAgentur (BNetzA, 2021)**. The data is georeferenced at an individual level. The socioeconomic data (RWI-GEO-GRID) is obtained from microm Micromarketingsysteme and Consult GmbH, a research firm specializing on regional analysis and is provided by the RWI – Leibniz-Institute for Economic Research (RWI and microm, 2022). Georeference is given at a 1 km<sup>2</sup> grid level. Finally, yearly information on solar irradiation per 1 km<sup>2</sup> grid cell are downloaded from the Open Data Server of the German Weather Service (DWD, 2023)

After assigning the individual PV systems to the 1 km<sup>2</sup> grid cells and removing outliers based on the 0.5 and 99.5 percentiles, the final dataset consists of 2×125,441 observations (i.e., grid cells<sup>9</sup>) for 2014 and 2020. Table 2 reports descriptive statistics for the year 2020, which is used for all benchmark estimations. Descriptive statistics for 2014 that are used for a robustness check, are shown in Table A 1.

The variable to be explained is the adoption rate of small-scale PV systems, given as the ratio of the number of PV systems with a capacity up to 10 kWp<sup>10</sup> to the number of houses. We normalize the number of PV systems to the number of houses to abstract from different

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<sup>7</sup> We additionally tested a weights matrix based on inverse-distance where the weight of each neighbor decreases with distance, i.e. spatial units that are farther away have a smaller weight and thus a smaller impact on the focal spatial unit. Results are available on request.

<sup>8</sup> The average commuting distance in Germany is about 16.9 km (BBSR, 2022), and the average radius of a NUTS3 region in Germany, which is often used as a spatial unit in other studies (e.g., Dharshing, 2017; Schaffer and Brun, 2015) is roughly 16.8 km. Our largest distance is therefore still somewhat smaller.

<sup>9</sup> PV systems were summed up at grid level.

<sup>10</sup> The PV systems under investigation were limited to a capacity of up to 10 kWp, which 1) corresponds to a common rooftop system for one- to two-family homes, 2) is used as a limit for specific regulations (cf. §48 Section 2, EEG (2017)) and 3) is also a commonly used threshold in the literature (cf. Balta-Ozkan et al., 2015; Dharshing, 2017). The lower bound is set to 0.1 kWp to remove outliers, such as small pocket systems.

settlement structures and to describe the degree of saturation regarding PV installations. The adoption share is (loosely) bounded from above by a maximum share of one, which corresponds to one PV system per building<sup>11</sup>. The PV adoption rate averages 0.09, i.e., 9 % of all houses have a small-scale PV system installed. The maximum of 1.86 shows that there are rare cases, in which there are more PV systems than houses, e.g., since several PV systems are installed on one roof. Nevertheless, only 38 grid cells out of 125,441 have a PV adoption rate above 100 %. The solar irradiation only shows small variations across grid cells and amounts, on average, to 1,171 W/m<sup>2</sup>. The minimum is about 1,040 W/m<sup>2</sup> whereas the maximum is 1,320 W/m<sup>2</sup>. Despite the small variation, clear regional differences can be identified. Solar irradiation is stronger in the southern and eastern parts of Germany (cf. Figure A 1).

Three factors are considered when describing the socioeconomic characteristics of the respective neighborhood. The purchasing power per household ranges from €22,500 to €72,400, with an average household income of €48,800. The average unemployment rate amounts to about 4 %<sup>12</sup>. Finally, the old-age dependency ratio represents the ratio of persons aged 65 years and older to 100 persons from 20 to 64 years. It ranges from 17 to 70, with an average of 39.9.

For the settlement structure, we mainly look at the share of one- and two-family homes. On average, each grid cell has 128 houses, of which about 70 % are one- or two-family homes. Contrary to solar irradiation, the number of houses as well as population and household densities, i.e., the number of inhabitants or households per 1 km<sup>2</sup>, show large ranges between minimum and maximum values, pointing at huge differences in settlement structures. Also, very high numbers of population densities occur (in contrast to official federal statistics), as only inhabited grid cells are included and grid cells with forest and water areas, for example, are excluded for calculations.

Finally, additionally to the small-scale PV installations, there are also on average 3.23 large-scale PV systems installed per grid cell, referring to systems between 10 and 100 kWp. The maximum amounts to 24 systems, the median is 2 systems. As large-scale installations require

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<sup>11</sup> An adoption rate of 100 % means that all houses have an installed PV system. However, in some rare cases, there may be more PV systems than houses, e.g., if installations have been put up on large garages or if more than one PV system has been installed on one roof.

<sup>12</sup> The unemployment rate (UER) is slightly lower than the one reported in official statistics, because we calculate the simple average over all grid cells and do not weight the UER with the number of inhabitants per grid. This “cell-based” averaging may also distort other averages compared to the numbers reported in official statistics.

more space compared to small-scale systems, they are often found in more rural regions but also in some densely populated areas such as Berlin<sup>13</sup> (cf. Figure A 2).

Table 2 Descriptive statistics for the year 2020. (n = 125,441)

Variable	Mean	Std. Dev.	Min	Max	Median
PV adoption rate, i.e. No. of PV $\leq$ 10 kWp/No. of houses	0.09	0.10	0.00	1.86	0.06
Solar irradiation, in W/m <sup>2</sup>	1,171.24	59.36	1,042.00	1,318.61	1,162.40
Purchasing power per household, in €	48,788.62	8,625.33	22,534.39	72,392.13	48,599.57
Unemployment rate, in %	4.07	2.19	0.00	20.15	3.67
Old-age dependency ratio	39.90	8.73	17.48	70.62	38.69
No. of houses	127.64	176.33	2.00	1,038.00	54.00
Share of one-, two-family homes, in %	69.68	20.68	2.04	100.00	73.22
Population density, inhabitants/km <sup>2</sup>	454.96	815.62	12.00	7,262.00	145.00
Household density, households/km <sup>2</sup>	224.10	414.67	10.00	3,928.00	69.00
No. of large-scale PV systems, > 10 kWp and $\leq$ 100 kWp	3.23	4.10	0.00	24.00	2.00

Notes: Descriptives for 2014 are reported in Table A 1 in the appendix. The old-age dependency ratio represents the ratio of persons of retirement age (here: 65 years and older) to 100 persons of working age (here: from 20 to 64 years). Values are based on inhabited 1 km<sup>2</sup> grid cells only.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

To have a closer look at the regional distribution of small-scale PV installations across Germany, Figure 4 illustrates this regional distribution for the year 2020. Grey spots represent grid cells without small-scale PV systems, whereas white spots denote areas with no population at all<sup>14</sup>. Grid cells with installed PV systems are indicated in yellow to red, with darker colors indicating a higher number of installations. Large regional differences in the distribution of small-scale PV installations can be observed. We find large clusters of grids with high PV adoption rates at the southern and south-eastern border of Germany in Bavaria and Baden-Wurttemberg. Another cluster is located in the north of the largest federal state in terms of population, North Rhine-Westphalia, at the border to Lower Saxony. In northern and especially eastern Germany, on the other hand, we find lower adoption rates, with the exception of the Berlin region, the northern part of Schleswig-Holstein and the southern part of Saxony.

<sup>13</sup> These may be larger installations on shopping malls, etc.

<sup>14</sup> These could either be water or forest areas, or the grid cell was either anonymized due to data security constraints (if a grid has less than 10 households, it will be removed from the analysis) or removed as an outlier.

## PV adoption rate per grid cell in 2020

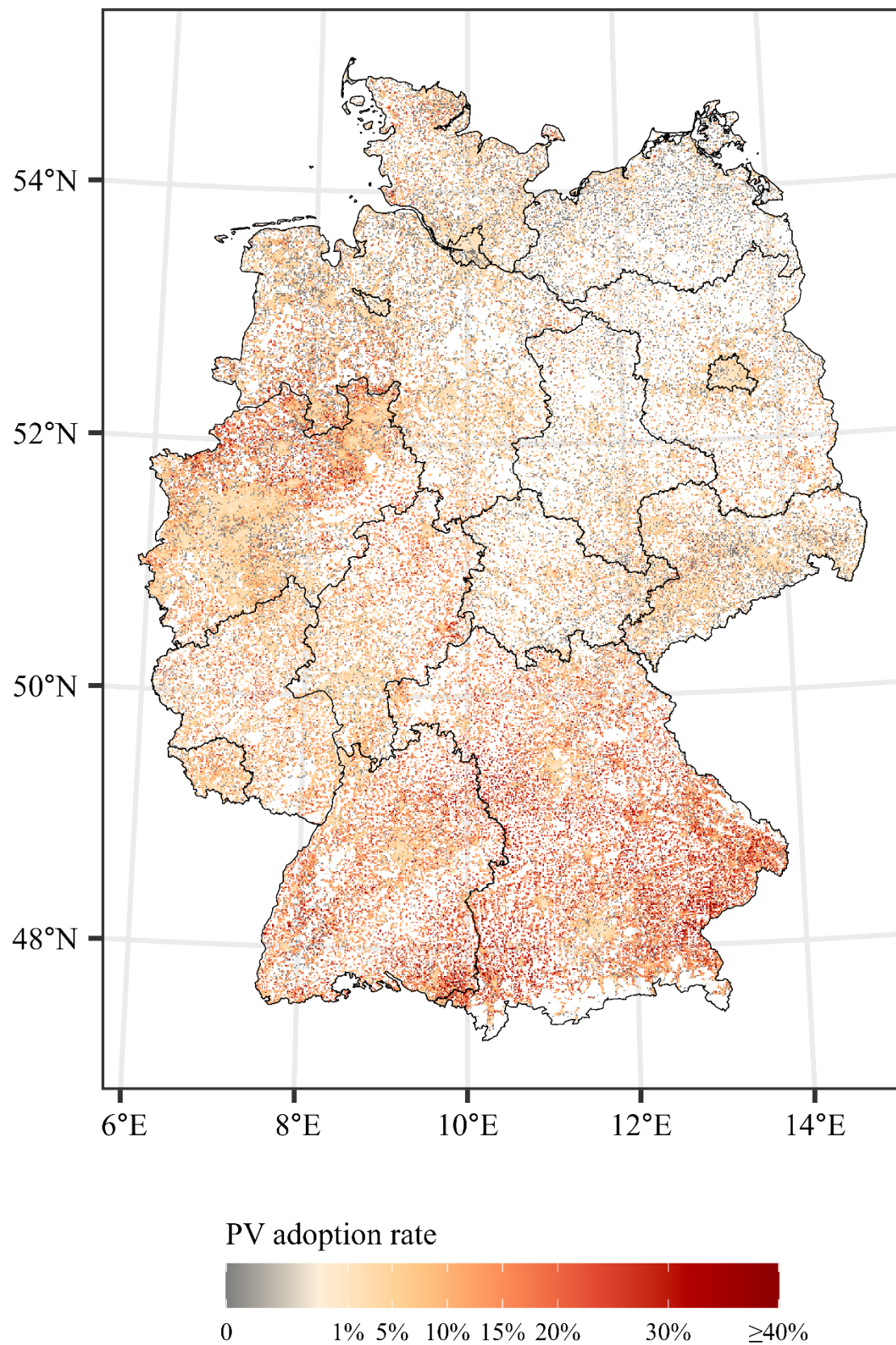


Figure 4 Regional distribution of small-scale PV adoption rates in Germany, 2020.

Source: Own illustration based on MaStR and RWI-GEO-GRID. Map data: @GeoBasis-DE/BKG 2021

## 5 Results

Regression results for the non-spatial OLS with data for 2020 are reported in Table 3. Results reveal that the main physical driver, the solar irradiation, has a positive and significant effect on PV adoption rates.

Table 3 Main regression results for the non-spatial OLS model.

Dependent Variable: <b>PV adoption rate</b>	<b>OLS</b>
Solar irradiation	0.0003 *** [4.41e-06]
Purchasing power (in €1,000)	0.0006 *** [3.35e-05]
Unemployment rate	-0.0044 *** [0.0001]
Old-age dependency ratio	-0.0010 *** [2.98e-05]
One-, two-family homes	0.0004 *** [1.40e-05]
Household density	-3.30e-05 *** [7.14e-08]
No. of large-scale PV	0.0039 *** [6.38e-05]
Constant	-0.3144 *** [0.0060]
Adj.-R <sup>2</sup>	0.1981
Observations	125,441

Notes: Standard errors in brackets. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.  
Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

Regarding the socioeconomic drivers, evidence is rather mixed. While the purchasing power per household shows positive effects, the old-age dependency ratio as well as the unemployment rate show negative effects on the adoption rate of small-scale PV systems. However, these effects are in line with the expected effects described in section 3. Also for the settlement and neighborhood characteristics, mixed effects are found. The share of one- and two-family homes as well as the number of large-scale PV systems between 10 and 100 kWp have positive impacts on the adoption of small-scale PV, whereas household density has a negative impact, in line with expectations. Nevertheless, the OLS explains only a small part of the variance, so that the relatively small R<sup>2</sup> already indicates a rather poor model fit.

For the model selection, we first tested for spatial correlation in the OLS by calculating Moran's I (Moran, 1950). Test results are presented in Table 4. The positive value points to spatial



dependence of the OLS residuals between neighboring grid cells. Following the specific-to-general approach, we then employed the LM and robust LM tests to evaluate the null hypothesis of no spatial dependence against alternatives of spatial error and spatial lag dependence, respectively.

All LM test results are statistically significant, thus rejecting the null hypotheses of no spatial dependence. Accordingly, the non-spatial OLS regression is inappropriate and may lead to biased estimates because the spatial forces driving photovoltaic expansion are not limited to the 1 km<sup>2</sup> grid cells but are likely to spill over into nearby neighborhoods. The OLS model is therefore rejected in favor of SAR and SEM.

Table 4 Tests for OLS extension.

<b>Tests for spatial dependence in the OLS regression:</b>	
Morans's I for residuals	54.8 ***
LM (error)	3,003.3 ***
robust LM (error)	1,770.5 ***
LM (lag)	4,102.8 ***
robust LM (lag)	2,870.0 ***

Notes: \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.

Source: Own calculations.

## 5.1 Spatial model specification

Spatial regression results for the SAR, SEM and SDM using a cutoff distance of 1 km are presented in Table 5. Compared to the OLS results, the signs of the coefficients do not change when incorporating spatial models; however, the magnitude of all  $\beta$ -estimates in the SAR and SDM (except of solar irradiation) decrease. In the SEM, however, the  $\beta$ -estimates are comparable to those in the non-spatial OLS. Also, the positive and significant spatial effects of  $\lambda$  and  $\rho$  in all models suggest the existence of spatial dependence between neighboring grid cells. The coefficient  $\rho$  is slightly larger in the SAR compared to the SDM; however, as the latter also controls for spatial spillovers of the exogenous variables, less unobserved autocorrelation is left to be captured by  $\rho$ .

According to the general-to-specific approach, we conducted two LR tests to determine whether the SDM can be simplified towards SAR or SEM. Both test statistics were positive and significant. Thus, it can be inferred that the null hypotheses have to be rejected, indicating that the SDM should not be restricted to either a SAR or a SEM. Thus, the SDM is the best model to fit our data and will therefore be used for the following interpretation and analyses.

Table 5 Spatial regression results using a cutoff distance of 1 km.

	SAR	SEM	SDM	
Dependent Variable: <b>PV adoption rate</b>	$\beta$	$\beta$	$\beta$	$\theta$
Solar irradiation	0.0003 *** [4.43e-06]	0.0004 *** [5.11e-06]	0.0003 *** [4.47e-06]	
Purchasing power (in €1,000)	0.0005 *** [3.36e-05]	0.0006 *** [3.70e-05]	0.0002 ** [6.11e-05]	0.0003 *** [6.75e-05]
Unemployment rate	-0.0036 *** [0.0001]	-0.0045 *** [0.0002]	-0.0011 *** [0.0003]	-0.0022 *** [0.0003]
Old-age dependency ratio	-0.0008 *** [2.89e-05]	-0.0010 *** [3.29e-05]	-0.0003 *** [5.65e-05]	-0.0004 *** [6.33e-05]
One-, two-family homes	0.0003 *** [1.38e-05]	0.0003 *** [1.43e-05]	0.0002 *** [1.51e-05]	0.0002 *** [1.95e-05]
Household density	-2.89e-05 *** [6.93e-07]	-3.14e-05 *** [7.40e-07]	-2.26e-05 *** [8.32e-07]	-9.19e-06 *** [1.11e-06]
No. of large-scale PV	0.0032 *** [6.27e-05]	0.0030 *** [6.49e-05]	0.0022 *** [6.66e-05]	0.0036 *** [8.14e-05]
Constant	-0.2619 *** [0.0061]	-0.3226 *** [0.0068]	-0.2502 *** [0.0064]	
$\lambda$		0.1584 *** [0.0028]		
$\rho$	0.1746 *** [0.0027]		0.1523 *** [0.0027]	
LR (error)			3,335.4 ***	
LR (lag)			2,359.9 ***	
Log-likelihood	131,655.5	131,167.7	132,835.4	
Observations	125,441	125,441	125,441	

Notes: Standard errors in brackets. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05. For SDM,  $\beta$ -estimates show coefficients for the independent variables;  $\theta$ -estimates show coefficients for the spatially lagged independent variables. Data for 2020 is used in all regressions.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

The positive and significant autoregressive parameter  $\rho$  in the SDM indicates that there is still a significant level of spatial autocorrelation, even when controlling for spatial spillovers of e.g., socioeconomic factors. This provides evidence of spatial endogenous effects at grid level on the adoption of small-scale PV systems. Hence there is more than network effects induced by socioeconomic or settlement factors – although the available data do not enable us to disentangle the impact of PV visibility from the network effects related to actually installed PV systems (notably supplier networks).

As the interpretation of point estimates may lead to erroneous conclusions (cf. section 4.1), Table 6 provides corresponding impact measures that are used for the interpretation of direct

and indirect effects. The indirect effect (and also the total effect, i.e., the sum of direct and indirect effects) of solar irradiation is excluded, as we suggest that there are no logical reasons to believe that solar irradiation from neighboring spatial units has any additional impact on the PV adoption rate in the focal unit.

Table 6 Impact measures of the SDM.

	<b>Direct</b>	<b>Indirect</b>	<b>Total</b>
Solar irradiation	0.0003 ***		
Purchasing power (in €1,000)	0.0002 ***	0.0004 ***	0.0006 ***
Unemployment rate	-0.0013 ***	-0.0026 ***	-0.0039 ***
Old-age dependency ratio	-0.0003 ***	-0.0005 ***	-0.0009 ***
One-, two-family homes	0.0003 ***	0.0002 ***	0.0005 ***
Household density	-2.35e-05 ***	-1.40e-05 ***	-3.75e-05 ***
No. of large-scale PV	0.0024 ***	0.0044 ***	0.0068 ***

Notes: \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.

Source: Own calculations.

As expected, solar irradiation has a positive direct effect on the PV adoption rate. If the solar irradiation increases by one unit, the PV adoption rate is likely to increase by 0.03 percentage points on average. The purchasing power per household also shows the expected outcomes. Increasing the average purchasing power per household by €1,000 is associated with a projected increase of 0.02 percentage points in the adoption rate of small-scale PV systems. Indirect effects, indicating the wealthiness of the surrounding neighborhood, are double in size.

Conversely, the unemployment rate shows expected negative coefficients. If the unemployment rate increases by one percentage point, the PV adoption rate is expected to decrease by 0.13 percentage points. Again, indirect impacts are larger than direct impacts, indicating that the overall unemployment rate in the surrounding area is more important than the unemployment rate in just the local grid cell – at least within a radius of 1 km.

Negative effects are also found for the old-age dependency ratio. A one-unit increase is indicative of a 0.03 percentage point decrease in the PV adoption rate. Contrary to our expectation, we also find significant indirect effects within a 1 km radius. By 2045, the old-age dependency ratio is expected to increase by about 11 points (Destatis, 2023). Other things remaining equal, this would imply a reduction in the PV adoption rate by a mere 0.33 percentage points.

Furthermore, direct and indirect effects of the share of one- and two-family homes on the PV adoption rate are positively correlated as expected: a one percentage-point increase in the share of one- and two-family homes in the focal neighborhood indicates an increase in the PV

adoption rate of on average 0.03 percentage points. A one percentage-point increase in the share of one- and two-family homes in the defined neighborhood is related to an additional increase in the PV adoption rate of 0.02 percentage points.

The household density serves as a proxy for a high degree of urbanization, which is associated with a larger number of multi-family buildings that rarely have PV installations in Germany. The direct and indirect effects are thus expected and also found to be opposite to the effects of the share of one- and two-family homes. Thereby, direct impacts are larger (negative) than indirect impacts.

Finally, a positive effect on the PV adoption rate can also be found for the number of large-scale PV systems. If the number of large-scale PV systems in the focal neighborhood increases by one unit, it is associated with a PV-adoption-rate increase of 0.0024, i.e., 0.24 percentage points. With an increase of 0.44 percentage points in the adoption rate, the indirect impact and thus the spillover effect of an increase in the number of large-scale PV systems in neighboring units is even larger than the direct effect.

## **5.2 Variations in neighborhood size**

To check the sensitivity of our results regarding the size of the defined neighborhood, we estimate the SDM using increasing cutoff distances of up to 15 km. Thereby, possible changes in the significance of direct and indirect effects might be detected. Further, the changing influence of endogenous spatial autoregressive effects will be examined. Direct effects and indirect effects are illustrated in Figure 5. Corresponding regression results are given in Table A 2 and Table A 3 in the appendix.

On the one hand, all direct effects, are statistically significant at least at the 5 % level, regardless of the cutoff distance used in the regression. On the other hand, indirect or spatial spillover effects of the share of purchasing power per household, unemployment rate, old-age dependency ratio as well as one- and two-family homes become insignificant<sup>15</sup> with increasing distances. The spillover effects of large PV systems and the household density, however, remain statistically significant at the 0.1 % level in all specifications. Looking at the log-likelihood as

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<sup>15</sup> As soon as the coefficients with the 95% Conf. Int. cross the zero line (cf. Figure 5), they become statistically insignificant at the 5 % level.

a goodness-of-fit measure, a radius of 8 km yields the best results for our data. With larger distances beyond this threshold, the log-likelihood starts decreasing again.

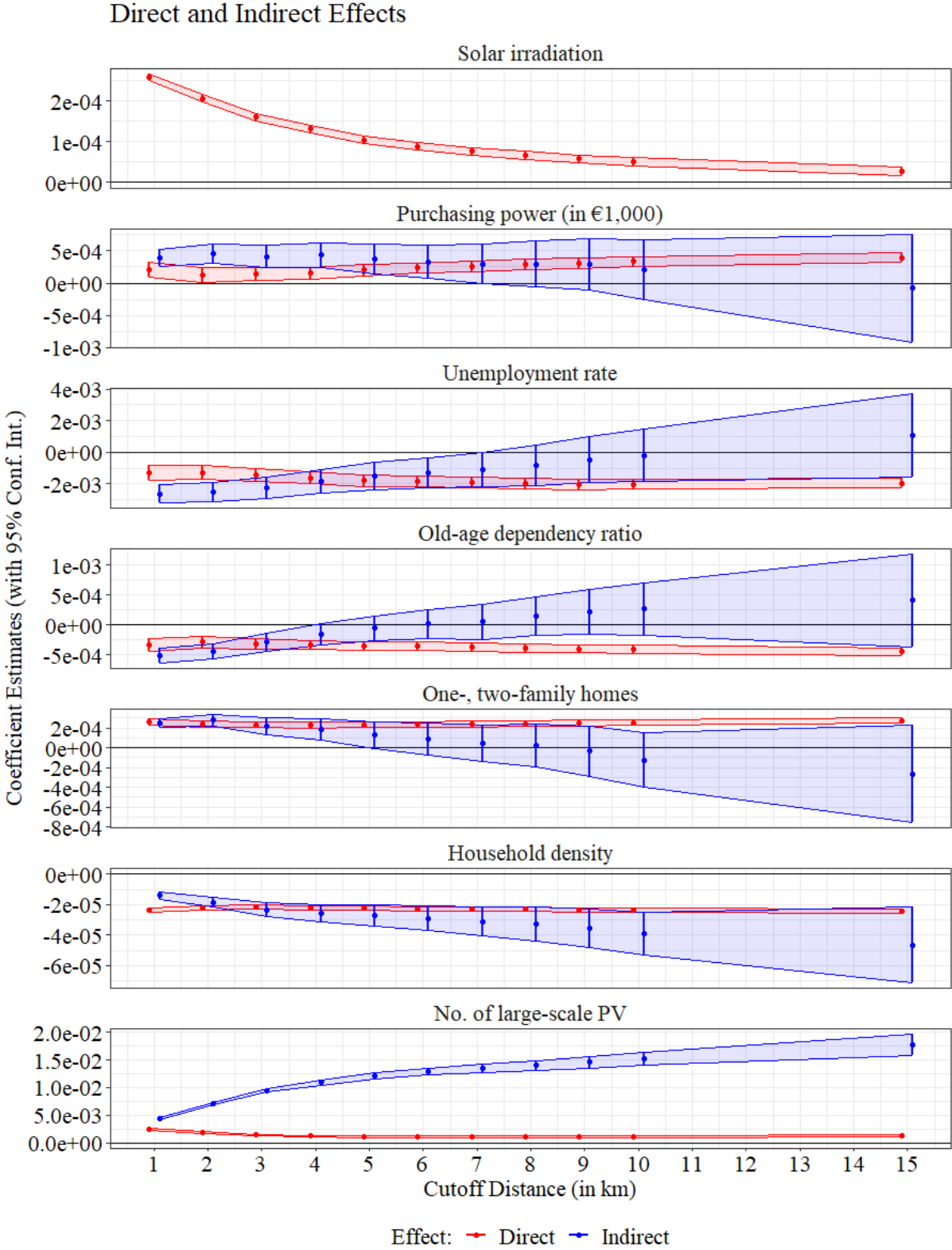


Figure 5 Direct and indirect effects of all exogenous variables for different cutoff distances.  
 Source: Own calculation and illustration based on MaStR, DWD and RWI-GEO-GRID.

With increasing cutoff distances, the positive direct effects of solar irradiation and the number of large-scale PV systems are decreasing. Contrary, the spillover effects of the number of large-scale systems are increasing with rising cutoff distances and this effect largely overcompensates the decrease in the direct effect. This suggests that the visibility (and possibly also the network effects) of (large) PV systems do not only impact the immediate neighborhood, but also affects adoption decisions in a wider area.

This finding corresponds to the results obtained for the autoregressive parameter  $\rho$ . Also, this parameter increases with distance (cf. Figure 6), indicating spatial spillovers of the adoption of small-scale PV systems in neighboring regions even over distances above 10 km and when controlling for socioeconomic and settlement factors.

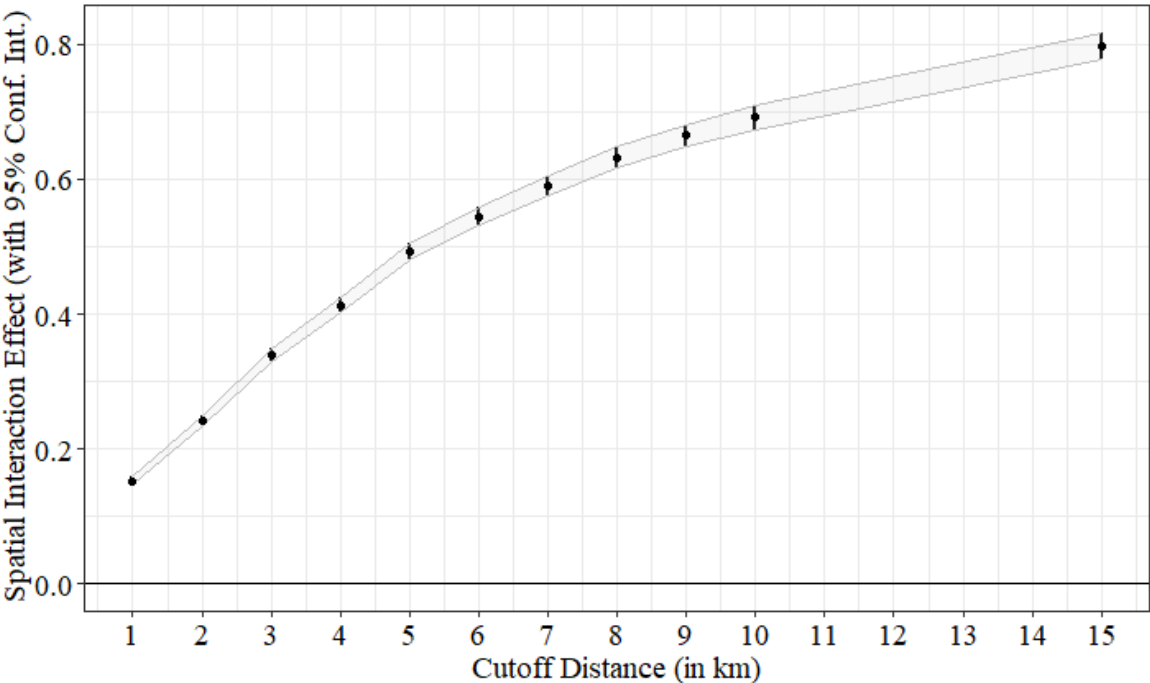


Figure 6 Spatial interaction effect for different cutoff distances.

Source: Own calculation and illustration based on MaStR, DWD and RWI-GEO-GRID.

For the socioeconomic factors themselves, i.e., purchasing power per household, unemployment rate and old-age dependency ratio, results are substantially different. The magnitude of direct effects tends to increase slightly with larger cutoff distances whereas the magnitude of spillover effects decreases. For both purchasing power and unemployment rate, the indirect effects become insignificant when the cutoff distance exceeds a radius of 6 km. In the case of the old-age dependency ratio, the spillovers already become statistically insignificant for distances of 4 km and more. As the best fit in terms of log-likelihood is obtained for a cutoff distance of 8 km, we tentatively conclude that spillovers for socioeconomic factors are rather irrelevant – and that their presence at smaller cutoff distances rather

constitutes an artefact which results from the omission of far-ranging indirect effects of (small and large) PV installations.

Regarding the settlement structure, similar patterns emerge for the share of one- and two-family homes. As for the socioeconomic factors, its indirect effect decreases at higher cutoff distances, becoming insignificant from a radius of 5 km onwards. For the household density, both direct and indirect effects remain significant across the different regression specifications, with the magnitude of indirect effects even increasing with higher cutoff distances. “Rurality”, which broadly corresponds to large areas with low household density, hence, seems to have a substantial positive effect – other things being equal – on the adoption of PV systems.

### **5.3 Robustness of results**

To test the robustness of our results, we additionally use data for 2014 and re-estimate the SDM for a cutoff distance of 1 km. Results for the SDM regression and corresponding impact measures are given in Table 7. The autoregressive parameter  $\rho$  is slightly lower compared to the results for 2020, yet remains positive and statistically significant, indicating endogenous spatial spillovers between neighboring grids. The minor decrease in the parameter value may be related to the fact that there were generally fewer PV installations in 2014 than in 2020 and spillover effects due to the visibility of other installations in neighboring regions have been correspondingly lower.

With the exception of purchasing power, old-age dependency ratio and the number of large-scale PV systems, all direct effects are slightly smaller in 2014 compared to 2020. The direct effects of purchasing power and large-scale PV systems on the adoption rate of small-scale installations, are on the contrary larger in the regression with data of 2014 – which suggests that PV adoption at that time was more driven by higher income classes and the presence of large “pilot” installations. For the spillover effects, rather similar patterns arise exempt for the unemployment rate: indirect effects are slightly smaller in 2014 compared to 2020. The indirect effect of purchasing power per household, even becomes statistically insignificant when using data of 2014. Overall, changes in effect sizes appear to be rather limited. Accordingly, the results are robust to changes in the year under consideration.

Table 7 SDM regression results and impact measures, using a cutoff distance of 1 km and data from 2014 .

Dependent Variable: <b>PV adoption rate</b>	SDM		Impact measures		
	$\beta$	$\theta$	Direct	Indirect	Total
Solar irradiation	0.0002 *** [4.81e-06]		0.0002 ***		
Purchasing power (in 1,000 €)	0.0003 *** [6.63e-05]	-0.0001 * [7.35e-05]	0.0003 ***	-0.0001	0.0002 ***
Unemployment rate	-0.0005 * [0.0002]	-0.0025 *** [0.0002]	-0.0006 **	-0.0029 ***	-0.0035 ***
Old-age dependency ratio	-0.0002 *** [5.77e-05]	-0.0001 * [6.52e-05]	-0.0003 ***	-0.0002 **	-0.0005 ***
One-, two-family homes	0.0001 *** [1.40e-05]	0.0001 *** [1.80e-05]	0.0002 ***	0.0001 ***	0.0003 ***
Household density	-2.00e-05 *** [7.86e-07]	-7.59e-06 *** [1.05e-06]	-2.07e-05 ***	-1.16e-05 ***	-3.23e-05 ***
No. of large-scale PV	0.0028 *** [6.99e-05]	0.0038 *** [8.51e-05]	0.0031 ***	0.0046 ***	0.0077 ***
Constant	-0.1613 *** [0.0063]				
$\rho$	0.1468 *** [0.0028]				
Log-likelihood	138,887.4				
Observations	125,441				

Notes: Standard errors in brackets. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05. For SDM,  $\beta$ -estimates show coefficients for the independent variables;  $\theta$ -estimates show coefficients for the spatially lagged independent variables.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

## 6 Discussion

Estimation results reveal that the adoption of residential solar PV systems is influenced by a combination of local factors, such as socioeconomic characteristics, settlement structure as well as features describing the physical environment. Moreover, there's an observable impact from spillover effects. Similar to numerous studies, we incorporate solar irradiation as an explanatory variable in the category of *climate characteristics*. Since solar irradiation varies geographically, areas with greater solar irradiation can generate more electricity from the same system size (and cost), leading to improved economic viability. This is found to have positive and significant effects on the adoption of residential PV installations. Our results are thus in line with Balta-Ozkan et al. (2015), Balta-Ozkan et al. (2021), Copiello and Grillenzoni (2017), Schaffer and Brun (2015) and Collier et al. (2023), among others.

Regarding the *socioeconomic characteristics* of the respective neighborhood, we find positive and statistically significant direct effects for purchasing power that were also reported inter alia



in Zhang et al. (2023a), Dharshing (2017) and Irwin (2021). This is in line with expectations, as higher-income households tend to have fewer financial constraints and a higher willingness to bear risk for new investments such as installing PV systems. These results are contrary to those of Balta-Ozkan et al. (2015), who found insignificant impacts of income on the diffusion of residential solar PV systems in the UK.

Besides positive direct effects, we additionally find statistically significant indirect impacts of purchasing power on PV saturation – at least when limiting neighborhood sizes to a radius of 6 km or less. These results are contrary to those of Zhang et al. (2023a), as they report insignificant indirect impacts drawing on data of about 13,000 neighborhoods in the Netherlands (and using a cutoff distance of 3.5 km). The significant indirect effects in our study may be explained by network effects that are not limited to the own neighborhood in a 1 km<sup>2</sup> grid and that are not captured by existing PV installations (cf. below). So these are probably information networks in the sense that there is more talk and discussion about the merits of sustainable technologies, which reduces uncertainties e.g., about possible payback periods (cf. Bollinger and Gillingham, 2012). Another explanation is the increased probability of a larger fraction of high-income residents in the area if the average income in the surrounding area is also higher. The effect thus reflects some spillover in the overall economic situation of the neighborhood.

The consistent (negative) effects of the unemployment rate further support this hypothesis. Elevated unemployment within a neighborhood often correlates with lower rates of homeownership and, consequently, reduced disposable income. Additionally, there's a direct connection with the number of welfare recipients, showing an inverse relationship with the percentage of the population that earns an income. These factors have also been explored in other studies (e.g., Baginski and Weber, 2019; Thormeyer et al., 2020; Zhang et al., 2023a), which discover negative impacts associated with the proportion of welfare recipients and positive impacts linked to an increasing prevalence of homeownership and income-earning individuals in the population. Consequently, these outcomes align with the negative effects we have identified concerning increasing unemployment rates.

Regarding effects of age on the adoption of residential PV installations, there is mixed evidence in the extant literature (cf. Alipour et al., 2020). Contrary to most studies that use shares of different age groups, we align with studies on the demographic transition and include the old-age dependency ratio in our analysis (cf. Section 3). This leads to negative and significant direct effects in all model specifications. As a result, PV adoption rates decrease when the ratio of

people aged 65 and over to people aged 20 to 64 increases, i.e., the population becomes proportionately older. A negative effect of the share of people aged 65 and older was also found in Bollinger and Gillingham (2012), Dharshing (2017) and Zhang et al. (2023a); however, all studies also report negative effects for younger age groups, leading to an inconclusive or non-linear effect of age on the adoption of residential solar PV.

A factor describing the *settlement structure* of the neighborhood is the share of one- and two-family homes. Some studies also use the share of detached houses or single-family houses only; however, effects are comparable as all of these factors describe the built environment in a neighborhood. Similar to Kucher et al. (2021), Müller and Rode (2013), Dharshing (2017), Balta-Ozkan et al. (2015) and Collier et al. (2023), among others, we find positive direct and indirect effects in all specifications; however, the spatial spillovers for this variable become insignificant with cutoff distances beyond 4 km.

The impact of household density, serving as a representation of urbanization, follows a similar pattern. In regions with elevated household density, the adoption of PV systems tends to be lower (e.g., Balta-Ozkan et al., 2015; Bollinger and Gillingham, 2012; Collier et al., 2023; Kucher et al., 2021; Kwan, 2012). This might be attributed to a greater prevalence of apartments, a particularly significant factor in urban settings – albeit this is in principle already controlled for ex negative by including the share of one- and two-family houses as explanatory variables. Hence it is rather attributable to smaller available rooftop spaces in high-density neighborhoods, which reduces the profitability of PV installations. This prevails also in the indirect effects indicating that household density in the surroundings does not induce strong positive network effects as hypothesized in Section 3.

Finally, *neighborhood effects* are captured inter alia by the impact of large-scale PV installations on the adoption of residential rooftop PV. To our knowledge, this has not received attention in the existing literature (cf. Zhang et al., 2023a). It is often argued that peer effects mainly work through the visibility of other PV installations (Bollinger and Gillingham, 2012; cf. Rode and Müller, 2021). The strong positive direct and indirect effects of large-scale PV plants that we find in all models supports this visibility argument. Concurrently, it implies that the inclusion of large solar installations is crucial, even when studying the distribution of smaller installations.

Neighborhood effects are also captured by the autoregressive parameter  $\rho$ . As the size of this coefficient is dependent on inter alia the weights matrix used and also the chosen cutoff distances, it is not directly comparable to other studies. With an increasing distance, we find

that the autoregressive parameter  $\rho$  also increases. The effect depicts spillovers of the adoption of small-scale PV systems in the surrounding neighborhood on the adoption rates in the focal neighborhood and thus is an indicator for the effect of visibility of these systems.

The increase in spatial autocorrelation underscores the enduring importance of PV system visibility beyond small neighborhoods and points to the conclusion that not only neighborhoods but also supply and information networks matter. This also underlines the increasing indirect effects of large-scale PV systems with increasing distances. Contrarily, indirect effects and thus spillover effects of almost all other variables become insignificant when neighborhood size is increased. This aligns with results from studies using coarser data, yet any estimate of spillovers related to visibility and network effects will be blurred if coarse data is used – as then there is a broad range of distances between individual units belonging to contiguous neighborhoods, e.g., in a range between less than 1 km up to 40 km, if two regions of 20 km diameter are next to each other.

## 7 Conclusion

Based on a Spatial Durbin Model and a novel dataset at a standardized 1 km<sup>2</sup> grid cell level, we investigate the adoption of residential solar PV systems in Germany for the year 2020. Thereby, we not only consider socioeconomic as well as geographic factors at a small spatial scale; we also examine spatial spillovers for different neighborhood sizes and investigate the effect of large-scale solar PV systems up to 100 kWp on the adoption of installations up to 10 kWp. Our results reveal that the number of large-scale PV systems has strong positive effects on the adoption of residential PV installations, indicating that an inclusion of such systems is crucial for estimating adoption effects. It further indicates that the installation of large systems in neighborhoods with low adoption rates may foster the installation of residential PV.

Additionally, the autoregressive parameter increases with increasing neighborhood sizes, pointing to relevant spatial effects e.g., due to the visibility of small-scale PV systems, even beyond the immediate neighborhoods. However, spillover effects of other explanatory factors become insignificant with larger distances. Given these differentiated findings, we strongly recommend the use of high-resolution spatial data to avoid the blurring of different types of spillover effects when using coarser data.

Nevertheless, there are several limitations to this study. First, system prices and subsidies are found to be important drivers of PV diffusion, both of which are not included in our study. This is, however, related to the use of cross-sectional data for a single year on which we base our

analysis. As spatial price variations are hardly observable, we have excluded these factors from the regression. Second, a minor drawback is the lack of information on the share of owner-occupied homes as this is also found to have significant influence on the adoption of residential PV systems (e.g., Zhang et al., 2023a). Nonetheless, as previous research consistently points to the same outcome, the inclusion of this factor would probably not have led to new findings.

Finally, as we employ cross-sectional data, unobserved time-invariant effects that occur during dynamic technological diffusion processes are not captured in our analysis. However, we leave this for future research, as our initial objective has been to examine the merits of small-scale raster data with combined adoption, socioeconomic and settlement variables to assess the impact of neighborhood effects on the penetration of residential solar PV installations when controlling for multiple other factors.

## Acknowledgements

Funding: The work of Lisa Sieger on the topic was supported by a grant of the Graduate School for Sustainable Energy Systems in Neighbourhoods [grant number 321.8.03.110 116441], funded by the Ministry of culture and Science of the state of North Rhine-Westphalia.

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## Appendix

Table A 1 Descriptive statistics for the year 2014. (n = 125,441)

Variable	Mean	Std. Dev.	Min	Max	Median
PV adoption rate, i.e. No. of PV $\leq$ 10 kWp/No. of houses	0.07	0.09	0.00	4.00	0.04
Solar irradiation, in W/m <sup>2</sup>	1,074.69	50.80	936.70	1,224.00	1,069.00
Purchasing power per household, in €	44,939.86	7,704.12	22,338.10	71,515.86	44,809.51
Unemployment rate, in %	4.73	3.01	0.00	20.00	4.11
Old-age dependency ratio	36.19	7.64	17.28	70.24	35.33
No. of houses	120.86	167.93	2.00	1,032.00	50.00
Share of one-, two-family homes, in %	67.44	21.08	1.91	100.00	70.77
Population density, inhabitants/km <sup>2</sup>	444.27	791.77	12.00	6,998.00	143.00
Household density, households/km <sup>2</sup>	221.48	411.75	10.00	3,873.00	67.00
No. of large-scale PV systems, > 10 kWp and $\leq$ 100 kWp	2.79	3.69	0.00	24.00	1.00

Notes: The old-age dependency ratio represents the ratio of persons of retirement age (here: 65 years and older) to 100 persons of working age (here: from 20 to 64 years). Values are based on inhabited 1 km<sup>2</sup> grid cells only.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

## Solar irradiation per grid cell in 2020

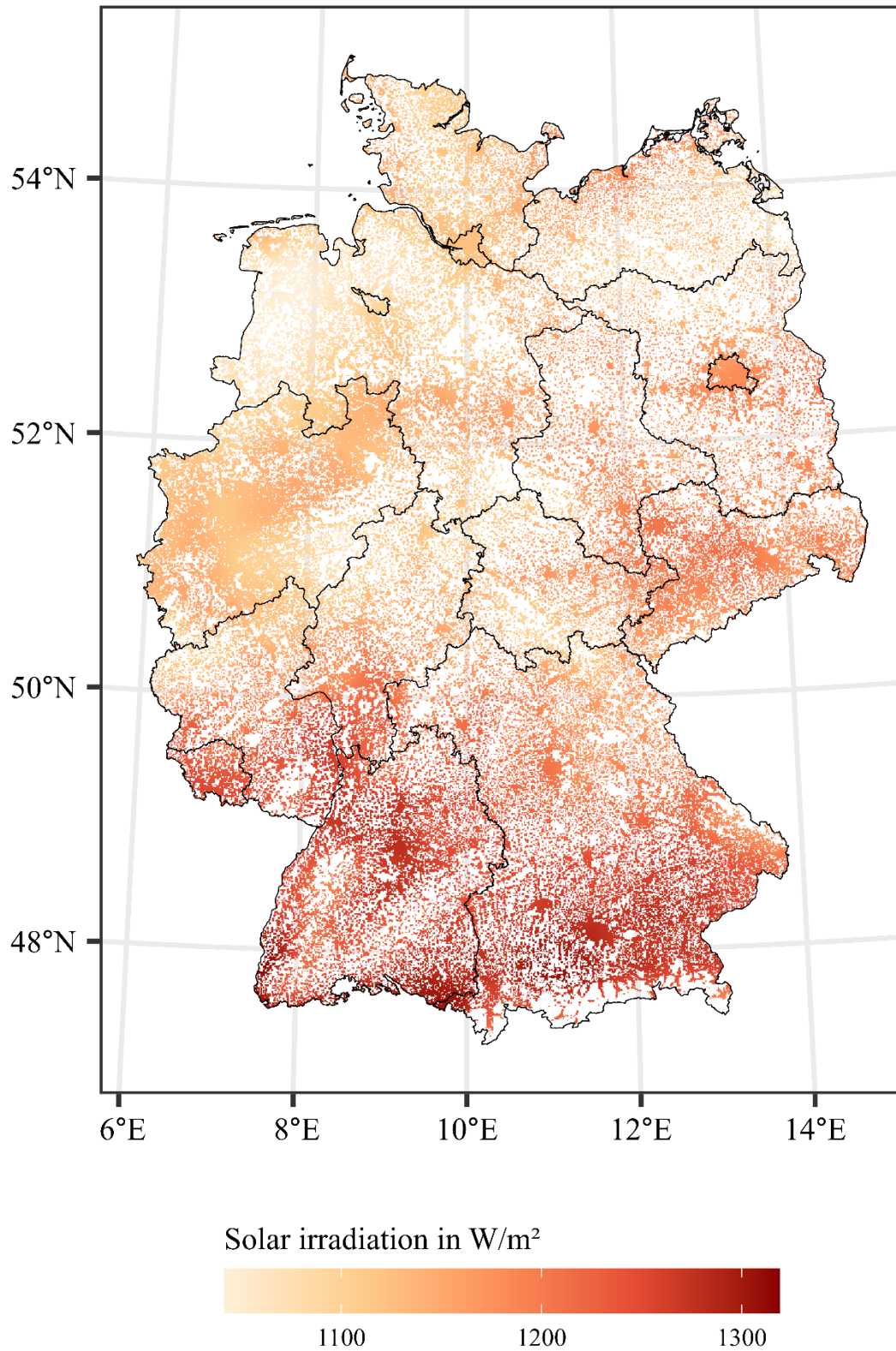


Figure A 1 Regional distribution of solar irradiation in 2020.

Source: Own illustration. Map data: @GeoBasis-DE/BKG 2021

## Number of large-scale PV systems per grid cell in 2020

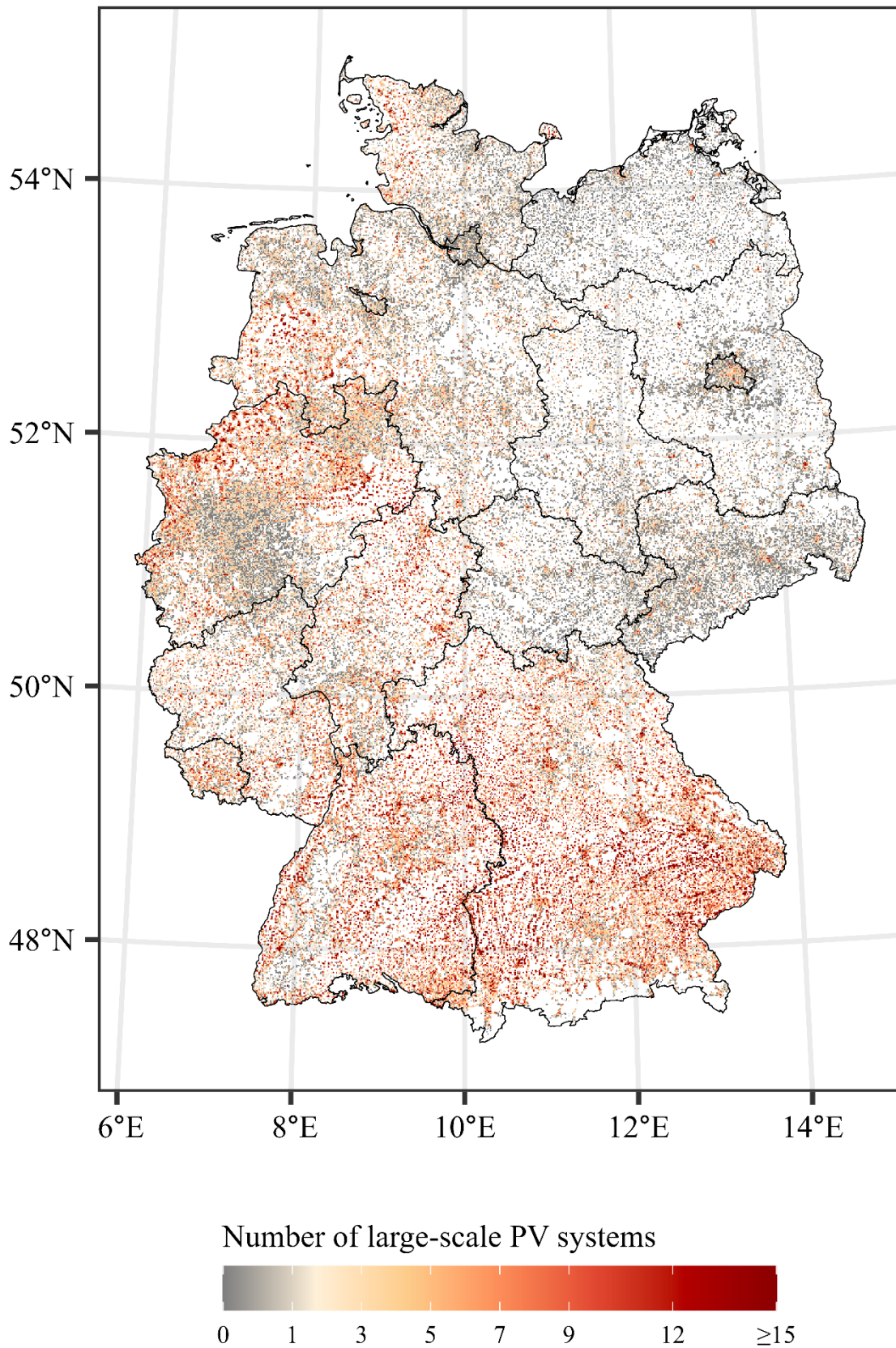


Figure A 2 Regional distribution of large-scale PV systems across Germany, 2020.

Source: Own illustration based on MaStR and RWI-GEO-GRID. Map data: @GeoBasis-DE/BKG 2021

Table A 2 SDM-regression results for cutoff distances of 2 km to 6 km.

Dependent Variable: <b>PV adoption rate</b>	<b>2 km</b>	<b>3 km</b>	<b>4 km</b>	<b>5 km</b>	<b>6 km</b>
<i><u><math>\beta</math>-estimates:</u></i>					
Solar irradiation	0.0002 *** [4.56e-06]	0.0002 *** [4.67e-06]	0.0001 *** [4.76e-06]	0.0001 *** [4.86e-06]	8.78e-05 *** [4.92e-06]
Purchasing power (in €1,000)	0.0001 [5.66e-05]	0.0001 ** [5.06e-05]	0.0001 ** [4.75e-05]	0.0002 *** [4.52e-05]	0.0002 *** [4.39e-05]
Unemployment rate	-0.0012 *** [0.0002]	-0.0014 *** [0.0002]	-0.0016 *** [0.0002]	-0.0018 *** [0.0002]	-0.0018 *** [0.0002]
Old-age dependency ratio	-0.0003 *** [4.96e-05]	-0.0003 *** [4.32e-05]	-0.0003 *** [4.02e-05]	-0.0004 *** [3.81e-05]	-0.0004 *** [3.70e-05]
One-, two-family homes	0.0002 *** [1.51e-05]	0.0002 *** [1.50e-05]	0.0002 *** [1.49e-05]	0.0002 *** [1.48e-05]	0.0002 *** [1.48e-05]
Household density	-2.14e-05 *** [8.13e-07]	-2.12e-05 *** [7.85e-07]	-2.14e-05 *** [7.72e-07]	-2.20e-05 *** [7.63e-07]	-2.24e-05 *** [7.58e-07]
No. of large-scale PV	0.0015 *** [6.72e-05]	0.0012 *** [6.75e-05]	0.0010 *** [6.77e-05]	0.0010 *** [6.78e-05]	0.0009 *** [6.79e-05]
Constant	-0.2038 *** [0.0068]	-0.1573 *** [0.0073]	-0.1315 *** [0.0077]	-0.1051 *** [0.0082]	-0.0891 *** [0.0085]
<i><u><math>\theta</math>-estimates:</u></i>					
Purchasing power (in €1,000)	0.0003 *** [6.93e-05]	0.0002 *** [6.88e-05]	0.0002 ** [6.96e-05]	9.43e-05 [7.17e-05]	2.57e-05 [7.37e-05]
Unemployment rate	-0.0017 *** [0.0003]	-0.0011 *** [0.0003]	-0.0005 [0.0003]	0.0001 [0.0003]	-0.0004 [0.0003]
Old-age dependency ratio	-0.0003 *** [6.22e-05]	-9.35e-05 [6.10e-05]	3.86e-05 [6.19e-05]	0.0001 * [6.44e-05]	-0.0002 ** [6.66e-05]
One-, two-family homes	0.0002 *** [2.50e-05]	7.37e-05 * [3.00e-05]	1.70e-05 [3.36e-05]	-4.77e-05 [3.70e-05]	-8.86e-05 * [3.92e-05]
Household density	-9.36e-06 *** [1.38e-06]	-8.66e-06 *** [1.59e-06]	-6.57e-06 *** [1.75e-06]	-3.17e-06 [1.92e-06]	-1.11e-06 [2.04e-06]
No. of large-scale PV	0.0052 *** [0.0001]	0.0061 *** [0.0001]	0.0061 *** [0.0002]	0.0058 *** [0.0002]	0.0054 *** [0.0002]
$\rho$	0.2420 *** [0.0038]	0.3386 *** [0.0048]	0.4123 *** [0.0056]	0.4930 *** [0.0065]	0.5448 *** [0.0071]
Log-likelihood	134,166.1	135,104.3	135,537.1	135,864.4	135,997.18
Observations	125,441	125,441	125,441	125,441	125,441

Notes: Standard errors in brackets. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.  $\beta$ -estimates show coefficients for the independent variables;  $\theta$ -estimates show coefficients for the spatially lagged independent variables. Data for 2020 is used in all regressions.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

Table A 3 SDM-regression results for cutoff distances of 7 km to 10 km and 15 km.

Dependent Variable: <b>PV adoption rate</b>	<b>7 km</b>	<b>8 km</b>	<b>9 km</b>	<b>10 km</b>	<b>15 km</b>
<i><u>β-estimates:</u></i>					
Solar irradiation	7.57e-05 *** [4.98e-06]	6.53e-05 *** [5.04e-06]	5.75e-05 *** [5.09e-06]	5.05e-05 *** [5.14e-06]	2.82e-05 *** [5.30e-06]
Purchasing power (in €1,000)	0.0003 *** [4.30e-05]	0.0003 *** [4.22e-05]	0.0003 *** [4.18e-05]	0.0003 *** [4.12e-05]	0.0004 *** [4.00e-05]
Unemployment rate	-0.0019 *** [0.0002]	-0.0020 *** [0.0002]	-0.0020 *** [0.0002]	-0.0020 *** [0.0002]	-0.0020 *** [0.0002]
Old-age dependency ratio	-0.0004 *** [3.62e-05]	-0.0004 *** [3.56e-05]	-0.0004 *** [3.51e-05]	-0.0004 *** [3.48e-05]	-0.0005 *** [3.37e-05]
One-, two-family homes	0.0002 *** [1.47e-05]	0.0002 *** [1.47e-05]	0.0002 *** [1.47e-05]	0.0003 *** [1.47e-05]	0.0003 *** [1.46e-05]
Household density	-2.26e-05 *** [7.53e-07]	-2.30e-05 *** [7.48e-07]	-2.32e-05 *** [7.45e-07]	-2.34e-05 *** [7.43e-07]	-2.46e-05 *** [7.33e-07]
No. of large-scale PV	0.0010 *** [6.78e-05]	0.0010 *** [6.78e-05]	0.0010 *** [6.78e-05]	0.0011 *** [6.78e-05]	0.0012 *** [6.74e-05]
Constant	-0.0762 *** [0.0088]	-0.0671 *** [0.0091]	-0.0596 *** [0.0094]	-0.0507 *** [0.0097]	-0.0268 * [0.0108]
<i><u>θ-estimates:</u></i>					
Purchasing power (in €1,000)	-2.98e-05 [7.57e-05]	-7.12e-05 [7.81e-05]	-0.0001 [8.06e-05]	-0.0002 * [8.32e-05]	-0.0003 *** [9.41e-05]
Unemployment rate	0.0007 * [0.0003]	0.0009 ** [0.0003]	0.0012 *** [0.0003]	0.0013 *** [0.0003]	0.0018 *** [0.0003]
Old-age dependency ratio	0.0002 *** [6.87e-05]	0.0003 *** [7.13e-05]	0.0003 *** [7.38e-05]	0.0004 *** [7.64e-05]	0.0004 *** [8.70e-05]
One-, two-family homes	-0.0001 ** [4.09e-05]	-0.0001 *** [4.27e-05]	-0.0002 *** [4.43e-05]	-0.0002 *** [4.57e-05]	-0.0003 **** [5.05e-05]
Household density	5.44e-07 [2.13e-06]	2.44e-06 [2.22e-06]	3.47e-06 [2.32e-06]	4.08e-06 [2.41e-06]	1.01e-05 *** [2.76e-06]
No. of large-scale PV	0.0050 *** [0.0002]	0.0046 *** [0.0002]	0.0042 *** [0.0002]	0.0040 *** [0.0002]	0.0026 *** [0.0003]
$\rho$	0.5900 *** [0.0076]	0.6321 *** [0.0081]	0.6646 *** [0.0085]	0.6913 *** [0.0089]	0.7977 *** [0.0102]
Log-likelihood	136,078.1	136,098.7	136,057.1	136,005.7	135,862.2
Observations	125,441	125,441	125,441	125,441	125,441

Notes: Standard errors in brackets. \*\*\* p < 0.001, \*\* p < 0.01, \* p < 0.05.  $\beta$ -estimates show coefficients for the independent variables;  $\theta$ -estimates show coefficients for the spatially lagged independent variables. Data for 2020 is used in all regressions.

Source: Own calculations based on MaStR, DWD and RWI-GEO-GRID.

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