Energy Economics 153 (2026) 109031

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

What drives disparities in the diffusion of residential PV and battery systems? A spatial econometric analysis in the context of dynamic regulatory arrangements

Gianmarco Aniello

Chair of Energy Systems and Energy Economics, Ruhr-Universität Bochum, Bochum, Germany
Institute of Climate and Energy Systems – Jülich Systems Analysis (ICE-2), Forschungszentrum Jülich GmbH, Jülich, Germany

ARTICLE INFO

JEL classification:
Q420
Q480
R150
R200

Keywords:
Residential PV diffusion
Residential battery storage diffusion
Regional energy transition
Spatial econometrics

ABSTRACT

Distributed PV plays an increasingly important role in the decarbonization of energy systems, yet its uneven patterns of diffusion may have implications for cost efficiency and distributional fairness. This paper investigates the drivers shaping the diffusion of small-scale, building-integrated PV systems (SBI-PV) and small-scale battery energy storage systems (S-BES) in Germany. A spatial econometric analysis was conducted by running consecutive cross-sectional regressions across 400 districts (i.e., NUTS-3,regions) spanning more than two decades, thereby assessing how the impact of drivers has been evolving under changing regulatory framework conditions. The study finds a highly relevant impact of endogenous interaction effects on SBI-PV diffusion, whereas interaction effects among error terms play a more important role in S-BES diffusion. The findings also show how several exogenous drivers can be connected either to the presence of single- and two-family homeowners (STFHO) and/or to socioeconomic and attitudinal factors (e.g., foreign population, age, income, education, political inclinations), which affect the capability and inclination to adopt such technologies. In contrast, drivers related to cost-efficient deployment patterns, such as spatial differences in PV generation potential and local power demand, appear to play a minor role. Finally, the paper discusses how regulatory changes may enhance the future deployment of SBI-PV and S-BES in terms of cost efficiency and distributional fairness.

1. Introduction and related work

1.1. Background

Solar photovoltaics (PV) is a key technology to advance the transition to a decarbonized energy sector: PV is expected to become globally the largest source of power generation in terms of installed capacity by 2027 (IEA, 2023b). Distributed PV, particularly rooftop installations on commercial and residential buildings, is also crucial, with a worldwide capacity increase anticipated to reach up to 170 GW per annum (IEA, 2023b). The German Government has assigned PV a major role in its decarbonization strategy since an early stage, i.e., with the first "EEG" (i.e., the Renewable Energy Sources Act). As of 2023, the German government aimed to increase the installed PV capacity from 67.3 GW at the end of 2022 to 215 GW by the end of 2030. This plan envisages an unprecedented acceleration in the deployment of additional PV capacity, with annual capacity additions of up to 22 GW (BMWK, 2023), that is, approximately three times the additional capacity installed in 2022. The deployment of PV in Germany has not been uniform over the years and has not shown a steady trend (see Fig. 1). These fluctuations have been influenced by market dynamics (e.g., technology costs), regulatory factors (e.g., feed-in tariffs and self-consumption regulation), and their interaction (e.g., retail electricity prices). Within the overall deployment of PV, the small-scale, building-integrated segment (SBI-PV[1]) has exhibited varying significance in terms of its share of total PV capacity. This study identifies several phases in the deployment of PV installations in Germany:

Proto-adopters (2000–2003): This phase began with the introduction of the first EEG in 2000. Until 1999, solar energy was compensated through a tariff linked to the final electricity price, while PV installed capacity remained below 50 MW. Under the EEG 2000 (Bund, 2000), PV electricity began receiving fixed Feed-In Tariffs (FiTs), guaranteed for a 20-year period, that were significantly higher than retail electricity prices at the time—DEM 0.99/kWh (equivalent to EUR 0.5062/kWh). These tariffs

E-mail address: gianmarco.aniello@ruhr-uni-bochum.de.

[1] The term SBI-PV is used in this paper to refer to building-integrated PV installations with a capacity from 1 kW to 30 kW. This upper threshold was chosen because it is applied to many regulatory aspects.

https://doi.org/10.1016/j.eneco.2025.109031
Received 2 October 2024; Received in revised form 26 September 2025; Accepted 2 November 2025
Available online 15 November 2025

were set to decline annually. However, technology costs were too high to support a substantial uptake in PV installation, with a LCOE of PV most likely above 50 ct/kWh,[2] suggesting that early PV adoption may have been driven by non-financial motivations. Between 2000 and 2003, approximately 380 MW of capacity was deployed, of which 84.2% consisted of SBI-PV installations.

Early adopters (2004–2008): This phase began with the amendment to the EEG at the end of 2003 and its new version in 2004. FiTs for PV electricity started to differ between stand-alone and building-integrated[3] installations and according to system size: as of 2004, FiTs for PV ranged 45.7–62.4 ct/kWh kW_p (Bund, 2004). Annual additional capacity grew by 5 times between 2003 and 2004, as installations increased both in number and size. A steady decrease in technology cost after 2005 (IEA, 2023b; Wirth, 2023), accompanied a steady growth in PV deployment until 2008. During 2004–2008 5.6 GW were deployed, of which 61.1% consisted of SBI-PV installations.

The "boom" (2009–2013): As of January 2009, following the EEG 2009, FiT for SBI-PV was at 43.01 ct/kWh. Although an automatic degression in FiTs had been embedded in the law, this was not sufficient to compensate the accelerating decrease in the cost of PV systems: e.g., by 2013 the final cost of rooftop installation had plummeted by approximately 70% compared to 2006 (Wirth, 2023). The annual deployment of PV capacity increased by eight times between 2008 and 2011, peaking at almost 8 GW. Afterwards, the continuous downwards adjustment to FiTs and the slowdown of the fall in modules' cost, caused a cooling down of the "PV boom". In 2012, a shift occurred for SBI-PV adopters: as self-consumption became more profitable than feed-in, adoption started being pushed by a "residual producer" rather than a "full producer" paradigm (Ossenbrink, 2017). In other words, new SBI-PV adopters became prosumers. Consequently, average installation sizes started decreasing (see Fig. 1). By the end of 2013, FiTs for SBI-PV systems had dropped under 14 ct/kWh and only approximately 3 GW of capacity were added. During 2009–2013 approximately 29.9 GW were deployed, of which 32.8% consisted of SBI-PV installations.

The "slump" (2014–2017): During this period additional annual capacity additions dropped below 2 GW. SBI-PV appeared to be particularly affected, given a decrease both in the number of installations and in their average size. As a matter of fact, PV prosumers were incentivized to optimize system-size based on self-consumption potential. On the one hand, FiTs was too low compared to the LCOE of PV; on the other hand, PV profitability relied on savings on increasingly expensive electricity bills, especially in terms of regulated tariff components.[4] Moreover, adoptions of battery energy storage (BES) systems started gaining momentum, pushed by the increase in and uncertainty about future retail electricity prices, as well as by direct subsidies in the form of federal grants (Figgener et al., 2018). During 2014–2017 approximately 6.3 GW were deployed, of which 28.1% consisted of SBI-PV installations.

Steady growth and prosumage surge (2018–currently): Since 2018 PV deployment has been gaining a new momentum, initially driven mostly by utility-scale installations. Only in 2020 SBI-PV accounted again for more than 30% of additional PV capacity, and grew to above 50% in 2023 (see Fig. 1).[5] This new trend has been increasingly supported by co-adoption of BES, which has become predominant among residential PV adopters since 2019–2020 (Figgener et al., 2021): in 2023 approximately 555,000 small-scale[6] BES (hereinafter S-BES) and 750,000 SBI-PV systems were installed. Such figures not only set a historic record for both technologies, but also imply that more S-BES capacity was installed in 2023 than over the previous 10 years. Such a surge in "prosumage"[7] may be attributed to an array of drivers. On the one hand, monetary drivers such as the steady decline in BES costs, the promotion schemes both at the national and subnational level[8] and the increasing retail power prices. On the other hand, non-monetary drivers may have also played a role: e.g., the desire to contribute to the energy transition, the interest in the technology, or the aspiration to become (partially) independent of electricity utilities in order to hedge against future electricity prices and counteract potential power outages (Figgener et al., 2018). The energy crisis, which affected many European countries during 2021–2023, seems to have accelerated such a "prosumage rush". Finally, new legislation passed over the period 2020–2022 has increasingly boosted the profitability of SBI-PV, while simplifying tax-related paperwork.[9] During 2018–2023 approximately 40.2 GW were deployed, of which 39.2% consisted of SBI-PV installations.

This paper investigates the patterns of diffusion of SBI-PV and S-BES systems, which, in the German case, can be mostly attributed to residential prosumers.[10] At the end of 2023, this SBI-PV segment amounted to approximately 31.1 GW, i.e., 37.7% of the total PV installed capacity in Germany, whereas S-BES amounted to approximately 9.8 GWh, i.e., 82.8% of the total BES capacity. The case of Germany is of particular interest. On the one hand, the rapid uptake of PV has often been regarded as a role model; on the other hand, its promotion through FiTs has been strongly criticized for its high costs, economic inefficiency in reducing carbon emissions, and regressive distributional effects (see, e.g., Frondel et al., 2014; Andor et al., 2015; Grösche and Schröder, 2014; Winter and Schlesewsky, 2019; Böhringer et al., 2017; Többen, 2017). Strong criticism of the inequity and inefficiency of subsidizing SBI-PV has also emerged beyond the German context

[2] First estimations of LCOE for PV for Germany are available for 2010, with values above 30 ct/kWh. By then, PV costs had already nearly halved in comparison to 2006 levels (Wirth, 2023), while PV modules' prices were rather stable between 2000 and 2006 (IEA, 2023a).

[3] And even according to the type of building-integration: during 2004–2008 rooftop installation were compensated 5 ct/kWh less that non-rooftop but building-integrated (e.g., façade-integrated).

[4] Most notably, volumetric network charges and EEG surcharge. Regarding the latter, only self-consumption from systems under 10 kW_p were fully exempted (Bund, 2014), thereby creating a further incentive for installing systems below this threshold.

[5] For a detailed breakdown of the deployment of PV see Kost (2024).

[6] A threshold of 30 kWh of storage capacity was chosen.

[7] Namely, the self-production, self-consumption and self-storage of electricity.

[8] Purchase of BES systems was subsidized by the Federal Government through the KfW (a state-owned bank) between 2013 and 2018 (Figgener et al., 2018). After 2018, the federal grants' scheme was discontinued, yet KfW has since then supported BES (and PV) adoption through promotional loan programs (KfW, 2022). Moreover, a number of subnational subsidy programs were started by federal states and municipalities (Energie-Experten, 2022).

[9] The EEG 2021 increased the threshold for the exemption of the EEG surcharge to systems up to 30 kW_p (Bund, 2020), removing an incentive for installing smaller SBI-PV. In 2022, for the first time after 2004, FiTS were increased (e.g., from 8.2 ct/kWh to 8.6 ct/kWh for installations up 10 kW_p. Moreover, special FiTs for "full-injection" PV installations were introduced (e.g., 13 ct/kWh for installations up 10 kW_p) (Bund, 2023). Finally, the tax law of 2022 abolished VAT (value-added tax) on the purchase and installation of small PV systems (up to 30 kW_p) (including on coupled BES systems), and abolished income tax on the revenue deriving from small PV systems (Bund, 2022).

[10] The German registry containing all grid-connected PV and BES systems (i.e., *Marktstammdatenregister* BNetzA, 2023) does not allow to assign each installation to the residential or commercial segment.

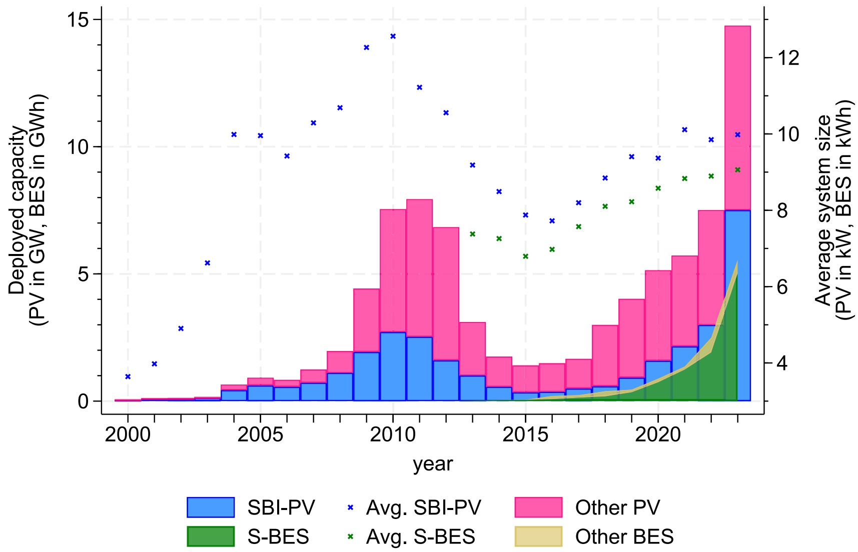

Fig. 1. Annual deployment of PV and BES capacity over the period 2000–2023.
Source: Own elaboration based on data from BNetzA (2023).

(see, e.g., Borenstein, 2022). After the considerable reduction in FiTs, the emergence of self-consumption-based profitability and prosumaging has also become a source of major concern (Kubli, 2018). Bill savings derived from self-consumption may be considered a cross-subsidy financed by standard "non-prosuming" electricity consumers, as long as they are based on the avoidance of the regulated volumetric (i.e., kWh-based) charges, which are levied to finance the infrastructure of the power system and the energy transition. Although residential BES may help integrate RES (renewable energy sources) into the power grid, system-oriented operation is crucial; in fact, self-sufficiency-focused prosumage may even cause additional costs for the system (Schill et al., 2017). In this regard, a body of literature has found that a non-system-friendly behavior of residential prosumers may even cause system-level costs to rise (e.g., Green and Staffell, 2017; Jägemann et al., 2013; Say et al., 2020), both in the case of Germany and in other countries. In the German context, few studies have investigated the degree of cross-subsidization from prosumers to standard consumers due to avoidance of levies, network charges, and taxes (e.g., Jägemann et al., 2013; Fett et al., 2019). Several studies have also considered alternative price signals and tariff structures for residential prosumers, with the objective of improving the cost reflectivity of energy tariffs and aligning the perspective of households and systems (e.g. Klein et al., 2019; Günther et al., 2021; Thomsen and Weber, 2021; Aniello and Bertsch, 2023; Eicke et al., 2024; Godron et al., 2024). In the case of Denmark, Gunkel et al. (2023) investigated the inequitable impact of tax exemption for self-consumption and proposed a uniform but lower tax on electricity.

In addition to distributional effects stemming from promotion schemes and cross-subsidies, the very diffusion of low-carbon technologies in general and residential PV in particular has also been associated with different kinds of inequality and spatially uneven patterns of diffusion. These divergences may arise from socioeconomic adoption drivers (e.g., income, dwelling ownership, education), peer effects (influence and imitation among adopters), built environment characteristics, renewable energy generation and self-consumption potential, as well as the interaction of these factors (see Balta-Ozkan et al., 2015 and Sovacool et al., 2022 for a comprehensive review).

1.2. Literature on PV diffusion

A large body of literature has aimed to assess socioeconomic and regional disparities related to PV diffusion across many countries (Konzen et al., 2024). This evidence indicates that significant disparities in the uptake of residential PV are linked to socioeconomic factors, including "low income and wealth, difficulties in accessing financing, housing-related structural aspects, lack of information, language barriers, lower rates of home ownership, challenges in benefiting from subsidies in the form of tax credits" the concentration of installers in affluent areas (Konzen et al., 2024). In the German context, heterogeneous volumetric network charges were also found to play a role in regional disparities of PV diffusion (Arnold et al., 2022), as the avoidance of such charges boosts PV profitability.

Part of this literature has investigated the uneven deployment of SBI-PV by focusing on the assessment of peer effects among adopters. Peer effects and their mechanisms were investigated at the household level using survey data, for instance, in relation to the relevance of active (e.g., direct influence and support) vs. passive (e.g., seeing PV installations) peer effects, e.g., Mundaca and Samahita (2020), Palm (2017) in the case of Sweden and Scheller et al. (2022) in the case of Germany.

In another set of studies, peer effects have been evaluated by considering the geographic proximity of PV adoptions, in that PV installations or PV capacity were usually aggregated in spatial units and then analyzed by means of econometric methods. Such studies have been conducted at the urban, regional, or national level, and across many countries: USA (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Graziano et al., 2019; Irwin, 2021; Kucher et al., 2021), UK (Balta-Ozkan et al., 2015, 2021; Stewart, 2022), Australia (Lan et al., 2021), Japan (Kosugi et al., 2019), France (Olivier and Del Lo, 2022), Italy (Pronti and Zoboli, 2024), Switzerland (Müller and Trutnevyte, 2020), Netherlands (Zhang et al., 2023) and Germany (Müller and Rode, 2013; Rode and Weber, 2016; Schaffer and Brun, 2015; Dharshing, 2017; Baginski and Weber, 2019; Stein et al., 2023). Although all these studies deal with the spatial dimension of PV diffusion, only a subset of them (i.e., Graziano et al., 2019; Kucher et al., 2021; Balta-Ozkan et al., 2015; Lan et al., 2021; Kosugi et al., 2019; Olivier and Del Lo, 2022; Pronti and Zoboli, 2024; Zhang et al., 2023; Schaffer and Brun, 2015; Dharshing, 2017; Stein et al., 2023) employed so-called spatial econometrics. Spatial econometric methods assess the impact of exogenous variables (in this case, e.g., solar radiation, average income, demographic factors) on a dependent variable (in this case, PV deployment) at an aggregated level of a spatial unit, while being able to control for spatial interdependence due to endogenous interaction effects (i.e., peer effects), exogenous interaction effects among exogenous variables, as well as interaction effects among the error terms (cf. Section 2.2).

Similarly to this paper, three studies (i.e.,Schaffer and Brun, 2015; Dharshing, 2017; Baginski and Weber, 2019) conducted a spatial econometric analysis at the level of NUTS-3 regions[11] for the case of Germany. In their cross-sectional analysis, Schaffer and Brun (2015) found that, in addition to solar radiation, socioeconomic and built environment characteristics (house density, home ownership, income) had significant impacts. Dharshing (2017) conducted a panel analysis, in which time-varying PV profitability — following time-varying FiTs and technology cost — was also considered. Dharshing found that (i) PV profitability, education, and income had positive impacts; (ii) unemployment, young age, and new construction had a negative impact; and (iii) the share of single-family homes and elderly people were mostly non-significant. Both studies (Schaffer and Brun, 2015; Dharshing, 2017) found no clear impact deriving from environmental attitudes measured as the share of Green Party voters, whereas spatial spillover effects were found. Baginski and Weber (2019) included in their analysis estimates of district-level energy demand and a dummy variable for former East Germany (i.e., GDR[12]) districts, finding a positive impact of the first and no significant impact of the latter. Moreover, in contrast to Schaffer and Brun (2015), Dharshing (2017), Stein et al. (2023), they considered within the same model spatial endogenous effects and spatial autocorrelation among error terms: they concluded that endogenous spillover effects are secondary in comparison to spatial autocorrelation due to spatially clustered unobserved characteristics (e.g., concentration of PV installers). Also in the German context, Stein et al. (2023) made use of 1 km^2 raster data on socioeconomic and settlement characteristics in combination with geocoded PV data, and analyzed both endogenous and exogenous interaction effects. They found that exogenous spillover effects become non-significant as neighbors beyond a distance of a few km were taken into account, concluding that such effects could be ruled out once endogenous effects of farther PV installations were considered in the model. They also found that larger PV installations (up to 100 kW_p) had positive effects on small-scale installations (up to 10 kW_p).

1.3. Contributions and scope

This study builds upon existing literature, updating the assessment to the most recent developments and substantially expanding the scope of analysis of the spatio-temporal patterns of SBI-PV and S-BES diffusion in Germany. To the best of the author's knowledge, this is the first study to perform an additional analysis of S-BES diffusion. Given that Germany has been regarded as a role model — or at least an early mover — for the energy transition in general, and for SBI-PV and S-BES in particular, the findings of this study are highly relevant in the context of other countries.

This study builds on prior research by integrating endogenous interaction effects and spatial autocorrelation within the same model specification. Moreover, it considers a large set of variables — all publicly available — that have been found to be relevant for PV diffusion, both in Germany and in other countries' contexts. Additionally, it updates the assessment to 2023, reflecting recent developments related to the energy crisis and newly implemented regulatory frameworks.

Building on previous studies, this paper examines 18 exogenous drivers related to solar radiation, the built environment, socioeconomic and demographic characteristics, political inclinations, and the diffusion of sector-coupling technologies. The inclusion of variables such as livestock units (as a proxy for farm-related buildings); the ratio between district residents and workers (as a proxy for non-residential buildings and non-residential electricity demand); underage population and gender-based differences in employment rate (as proxies for families and stay-at-home adults, respectively, namely households with a higher self-consumption potential); foreign population; the share of AfD Party voters (as a proxy for anti-establishment sentiment); the uptake of heat pumps and electric cars; are mostly a novelty in this strand of literature, especially in the case of Germany. By running 20 cross-sectional regressions over a 24-year period, this study aims to assess how the impacts of the drivers of SBI-PV and S-BES diffusion have evolved over time in response to shifts in underlying market forces and, more importantly, regulatory arrangements. The investigation of the dynamics of diffusion drivers constitutes another crucial contribution to the literature.

The final set of contributions relates to policy implications and the general scope of this study. In many studies analyzing the drivers of PV diffusion, the assessment of peer effects is a key objective. In this study, spatial dependence is important from a methodological standpoint but secondary from a policy perspective. Endogenous interaction effects only exacerbate inequities associated with SBI-PV diffusion, which stem from exogenous factors (e.g., differences in income, see in this regard Stewart, 2022). In the German context, the spatial diffusion of SBI-PV and S-BES has been greatly uneven (cf. Figs. 2 and 3). The main objective of this study is to assess the extent to which such divergent spatial patterns of diffusion reflect cost-efficient patterns of deployment, rather than the uneven impacts of regulatory and socioeconomic aspects unrelated to cost efficiency. A substantial part of the literature has focused exclusively on PV diffusion among homeowners living in detached houses, largely disregarding the rest

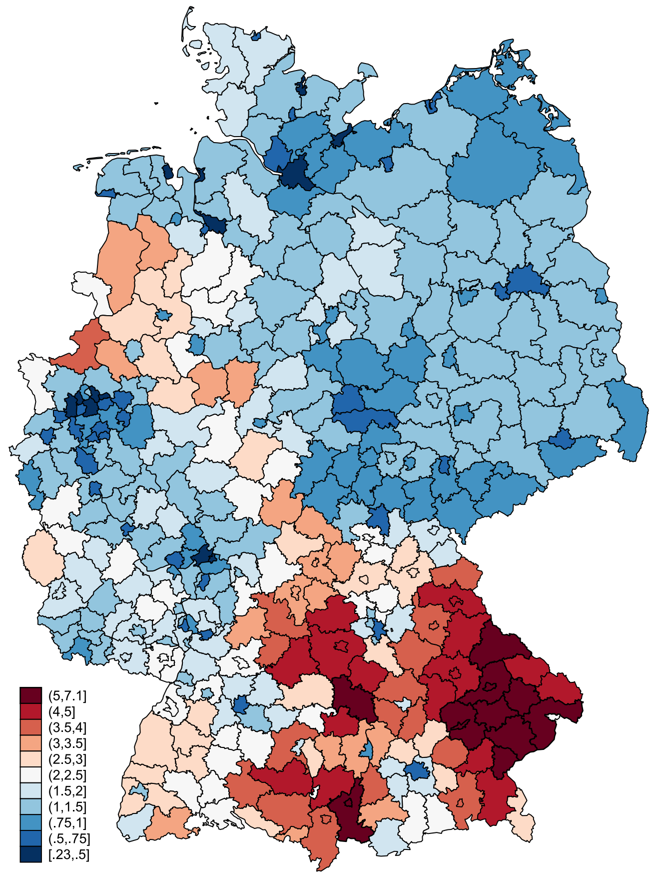

Fig. 2. Deployed capacity of SBI-PV systems commissioned in the period 2000–2023, in kW per residential building (i.e., *PV_cap*, cf. Section 2.1). *Source:* Own elaboration based on data from BNetzA (2023)

[11] The nomenclature of territorial units for statistics (*Nomenclature des Unités territoriales statistiques* – NUTS) is a geographical system, according to which the territory of the European Union is divided into hierarchical levels. This classification enables cross-border statistical comparisons at various regional levels within the EU. NUTS-3 regions are the smallest geographical units and in Germany are generally districts known as *Kreise* or as *kreisfreie Städte* (Destatis, 2025).

[12] German Democratic Republic.

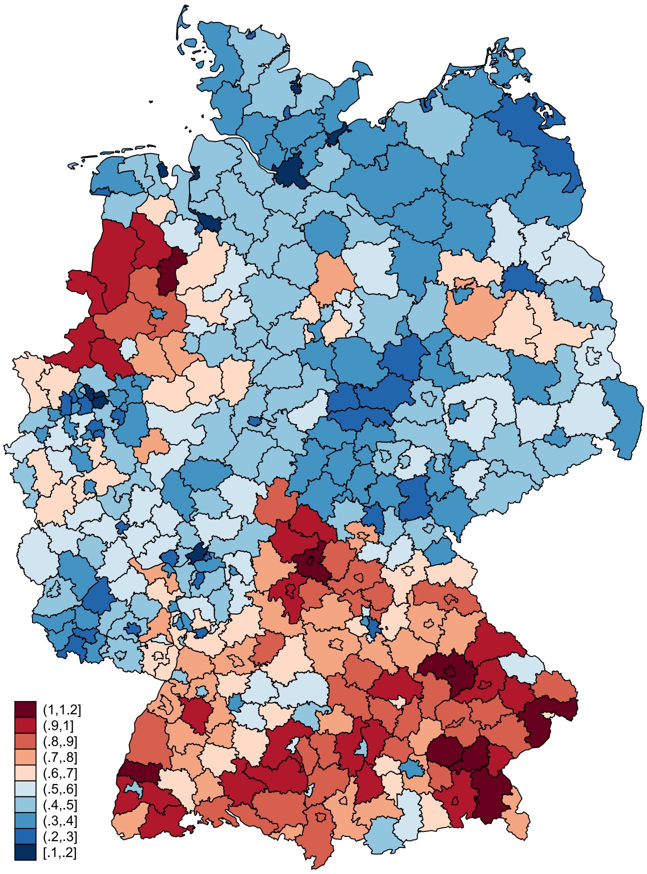

Fig. 3. Deployed capacity of S-BES systems commissioned in the period 2000–2023, in kWh per residential building (i.e., *BES_cap*, cf. Section 2.1).
Source: Own elaboration based on data from BNetzA (2023)

of the population. Homeownership rates and the share of single-family buildings are, at most, only one of the drivers considered in many analyses of PV diffusion. In contrast, this paper highlights and examines the divide between households residing in owner-occupied single- and two-family homes — hereinafter referred to as STFHO (single- and two-family homeowners) — and households residing in multifamily buildings and/or renting. STFHO can adopt, own, and operate SBI-PV and S-BES, benefiting from a regulatory framework that promotes self-consumption as defined by law. The latter group — namely tenants and dwellers of multifamily buildings — faces significant barriers to becoming PV prosumers.[13] Consumption of electricity from PV operated by third parties (e.g., landlords) does not legally qualify as self-consumption, even when generation and consumption occur within the same building, because the producer and consumer must be the same natural or juridical person (Bund, 2014). This divide not only reflects an inequitable but also an inefficient outcome of regulatory arrangements: installations on multifamily buildings may, in fact, be far more cost-efficient (cf. Section 4). The focus on the divide between STFHO and non-STFHO households is particularly relevant in the German context, where the homeownership rate is among the lowest in the OECD (OECD, 2023), especially in the lower income quintiles (OECD, 2022). Even among STFHO, as shown in the literature, many barriers to PV adoption are not related to cost efficiency. Therefore, this paper seeks to link diffusion drivers with market forces and regulatory arrangements, thus identifying the degree of market distortion that results in suboptimal outcomes in terms of both cost efficiency and distributional fairness.

The remainder of this paper proceeds as follows. Section 2 describes in detail the data and methods. In Section 3, the results are presented. Section 4 discusses the findings from a policy perspective. Section 5 concludes.

2. Data and methods

2.1. Data

Data on SBI-PV and S-BES installations were sourced from the *Marktstammdatenregister* (BNetzA, 2023), an open-access register maintained by the *Bundesnetzagentur*, the federal authority for networks. For this analysis, the dataset was restricted to building-integrated[14] PV systems ranging from 1 kW_p to 30 kW_p, and BES systems with capacities between 1 kWh and 30 kWh. The dataset was restricted to installations commissioned during the periods 2000–2023 for SBI-PV and 2013–2023 for S-BES. Only installations operational as of April 2024 were included. The final dataset comprises 3,084,348 SBI-PV installations and 1,104,676 S-BES systems. These data have spatial granularity at the municipality and ZIP code levels, and temporal granularity corresponding to the commissioning date. However, PV and BES data were aggregated to the district level (NUTS-3 regions) and annual values to align with the resolution of most explanatory variables, predominantly administrative data available at the NUTS-3 level. However, temporal availability varies across time series, with some starting in 2000 and others in later years. Additionally, certain variables were collected exclusively during the 2011 census, while others were intermittently available (e.g., federal election results). Though PV and BES data were available until 2023, administrative data cease in 2022 or even 2021. To estimate a model over the entire period 2000–2023, missing observations were filled using the previous year's values, linear interpolation, or by including the variables in the model once the time series began. All time series ending before 2023 were filled with 2022 values. During the analysis period, the number of NUTS-3 regions decreased from 440 in 2000 to 400 in 2021. Data were aggregated to align with current administrative boundaries. Table 1 summarizes the variables and provides descriptive statistics prior to standardization.

The dependent variables, namely SBI-PV and S-BES diffusion, are expressed as annual capacity additions, weighted according to the stock of residential buildings in the corresponding NUTS-3 region. The 18 independent variables can be grouped into five categories: (i) PV output potential; (ii) built environment variables; (iii) socioeconomic and demographic variables; (iv) politics-related variables; and (v) variables reflecting the uptake of sector-coupling technologies. Most of these variables or similar ones were used in the literature, both in the German context and in the case of other countries (cf. Section 1.2). Other variables represent a novel contribution of this study, at least within the German context (i.e., ***ratio_res2wor***, ***livestock***, ***pop_for***, ***pop_minor***, ***gdiff_emp***, ***afd_pol***). ***ratio_res2wor*** and ***livestock*** are variables to control for PV installations beyond residential systems. Most of the other variables are related to the profitability of PV and BES from the perspective of adopting households, as economic factors are likely the main drivers of PV adoption among German households (Jacksohn et al., 2019). However, some variables are also (in part) related to behavioral aspects, which can also affect the decision to adopt PV and BES. Following the classification outlined in the literature on behavioral aspects in the context of energy systems (Huckebrink and Bertsch, 2021), a loose distinction can be made between external/socio-demographic

[13] One exception is the adoption of "plug-in or balcony PV"–extremely small PV system (usually under 1 kW_p) that can be installed on balconies and directly connected to power outlets. In 2023, approximately 273,000 plug-in PV systems with an average size of 0.79 kW were deployed (BNetzA, 2023). This growing segment might reflect the aspiration of non-STFHO households to become prosumers.

[14] I.e., *Bauliche Anlagen* as specified in the *Marktstammdatenregister*.

Table 1
Description and summary statistics of variables.

Variable	Description	Obs.	Mean	Std. dev.	Min	Max
rbuild_2011	residential buildings stock in 2011	9,600	45,809	31,448	6,933	312,090
PV_cap	add. SBI-PV (kW per 1,000 *rbuild_2011*)	9,600	74.411	111.58	0	1,007.3
BES_cap	add. S-BES (kWh per 1,000 *rbuild_2011*)	4,400	48.681	84.381	0	571.73
glob_rad	avg. annual global radiation (kWh/m^2)	9,600	1,093.4	55.6	992.8	1,207.1
nrbuild	new buildings per 1,000 *rbuild_2011*	9,590	6.6137	3.5942	0	35.696
rbuild_sdf	share of one- and two-family rbuild.	9,600	0.8542	0.0985	0.4955	0.9717
rbuild_dens	rbuild. density (rbuild. per km^2)	9,600	4.0505	1.2822	1.1758	7.7467
ratio_res2wor	residents-to-workers ratio	6,400	1.1074	0.30341	0.32714	2.4887
livestock	livestock units per 1,000 *rbuild_2011*	9,600	711.52	831.05	0.81354	6518.4
fGDR	former GDR dummy	9,600	0.1875	0.39033	0	1
low_edu	share of adults with low education	9,600	0.1559	0.0511	0.0374	0.3039
income	per capita income (EUR)	9,600	23,462	5,807.5	10,735	51,635
pop_tot	pop. per 1,000 *rbuild_2011*	9,600	4,397.5	1,410.4	2,621	12,033
pop_over75	share of pop. over 75 years of age	9,600	0.0988	0.0206	0.0491	0.1814
pop_for	share of foreign pop.	9,600	0.0861	0.0525	0.0061	0.3897
pop_minor	share of underage pop.	9,600	0.1698	0.0215	0.1013	0.2595
gdiff_emp	gender gap in employment rate	6,400	0.126	0.0666	0.0001	0.3728
green_pol	share of Green Party voters	9,600	0.0891	0.043	0.0206	0.3596
afd_pol	share of AfD Party voters	9,600	0.074	0.0479	0.0223	0.3546
nrbuild_hp	share of *nrbuild* with a heat pump	3,200	0.3885	0.1775	0	0.9
ecars	share of electric cars	3,200	0.0077	0.0082	0	0.0354

Abbreviations: additional (add.), population (pop.), average (avg.), residential buildings (rbuild.).

factors (e.g., ***pop_over75***, ***low_edu***, ***income***) and internal/attitudinal factors (e.g., ***fGDR*** and politics-related variables). Many of the variables are also related to the prevalence of STFHO: namely, a very decisive factor determining the uptake of residential PV prosumers. Finally, the impact of many variables may unfold through multiple channels: the same variable can be simultaneously connected to the STFHO demographic, the capability or inclination to invest, attitudes towards these technologies, attitudes towards adoption-related hassle, and investment profitability. Therefore, Section 4 carefully examines the complexities of such channels of impact while considering system-level implications in terms of cost efficiency and distributional effects. For a detailed description of each variable, its sources, its construction, and its expected effects on SBI-PV and S-BES diffusion, see Appendix A.

2.2. Econometric modeling

To empirically study the impact of explanatory (independent) variables on a response (dependent) variable, linear regression analysis is commonly employed. The ordinary least squares (OLS) model is the most basic estimation method for linear regressions. Spatial data, however, frequently exhibit spatial dependencies, meaning that observations in one location (i.e., spatial unit) are influenced by those in other locations. Paul Elhorst (2014) identifies three types of interaction effects underlying these patterns of spatial dependence:

- Endogenous interaction effects among dependent variables, which occur when the dependent variable of spatial unit A affects the dependent variable in the neighboring spatial unit B, and vice versa. Such effects propagate to the neighbors of neighbors, therefore are global, in that all spatial units affect one another. In the literature on diffusion of residential PV, they are commonly referred to as peer effects, arising from social interactions through which nearby adopters influence and imitate each other.
- Exogenous interaction effects, which occur when independent variables in spatial unit A affect the dependent variable in the neighboring spatial unit B, and viceversa. Such effects are local, in that the spillover is limited to the set of neighboring spatial units. The theory does not appear to provide a reason for considering such a kind of exogenous spillover from independent variables in the case of SBI-PV and S-BES diffusion.[15]
- Interaction effects among error terms, which occur when the error terms are spatially autocorrelated. This could be due to unobserved shocks that follow a spatial pattern, or could happen as a result of missing explanatory variables that are spatially autocorrelated. In the case under study, such determinants might be, for instance, retail electricity prices (following geographical variability of network charges), the presence of competitive suppliers, or the existence of subnational subsidy programs.

In order to take into account such spatial interactions, a spatial lag of the dependent variable of nearby regions and spatially autocorrelated error terms are included in a spatial autoregressive model with autoregressive errors (i.e., the SARAR model). Eq. (1) depicts the SARAR model specification considered as the basis for the analysis in this work.

$$\mathbf{Y}_t = \lambda_t \mathbf{W}\mathbf{Y}_t + \mathbf{X}_t \boldsymbol{\beta}_t + \mathbf{u}_t \tag{1}$$

$$\mathbf{u}_t = \rho_t \mathbf{M}\mathbf{u}_t + \epsilon_t \tag{2}$$

In Eq. (1) $\mathbf{Y}_t$ are the $N \times 1$ N (with N being the number of spatial units) vectors of observations of the dependent variable. $\mathbf{X}_t$ is an $N \times K$ matrix representing the observations of the K dependent variables (plus the constant), whereas $\boldsymbol{\beta}_t$ is the $K \times 1$ vector of the corresponding unknown scalar parameters. In Eqs. (1) and (2), $\mathbf{W}$ and $\mathbf{M}$ are $N \times N$, time-invariant spatial-weighting matrices. $\mathbf{W}\mathbf{Y}_t$ and $\mathbf{M}\mathbf{u}_t$ are $N \times 1$ vectors representing the spatial lag of the dependent variable and the spatial lag of the residuals $\mathbf{u}_t$, respectively. λ_t are the time-varying scalar parameters of $\mathbf{W}\mathbf{Y}_t$, namely the spatial autoregressive coefficients. ρ_t are the time-varying scalar parameters of $\mathbf{M}\mathbf{u}_t$, namely the spatial autocorrelation coefficients. Finally, ϵ_t is an $N \times 1$ vector representing innovations, namely the uncorrelated error terms, which are generally assumed to be i.i.d. This last assumption is, however, partially relaxed as $\epsilon_{t,i}$ are assumed to be independent but not necessarily identically distributed, thereby allowing for heteroskedasticity. In order to estimate the SARAR model, the generalized spatial two-stage least-squares (GS2SLS) adjusted for heteroskedastic disturbances, described by Kelejian and Prucha (2010), was implemented by means of *Stata 18*. In contrast to a maximum likelihood (ML) estimator, this GS2SLS allows for consistent estimates even in the case of non-identically distributed independent disturbances $\epsilon_{t,i}$ (Drukker et al., 2013b). A further aspect of the model specification is the spatial weighting matrices $\mathbf{W}$ and $\mathbf{M}$, which define the interdependence between spatial units. Frequently used weighting matrices in spatial econometrics are queen-contiguity matrices and inverse-distance matrices (Drukker et al., 2013a). Beyond

[15] However, in the SARAR2 model (cf. Eq. (3)), spatial lags of past residual are included in the model and therefore can be considered as exogenous spillover effects.

the default weighting matrices, this study considered more complex specifications of $\mathbf{W}$ and $\mathbf{M}$. In addition to distance and contiguity, population size was incorporated into $\mathbf{W}$ to model endogenous interaction effects, under the assumption that peer effects scale with the number of people interacting. Population-based weighting was applied only to endogenous interactions, as autocorrelation in the error terms was assumed to depend on spatially correlated unobserved characteristics rather than population size.[16] The specific matrices are described below:

- **W** : **W_cdt50_pop_row**, a combination of an inverse-distance matrix and a queen-contiguity matrix. The matrix has non-zero values for contiguous and additional non-contiguous neighbors, in that also non-contiguous spatial units within a radius of 50 km are considered to be neighbors. The weights were firstly based on the inverse of distance with a truncation at 50 km (i.e., the weights of spatial units that are more distant than 50 km are set to 0). Secondly, weighting was implemented in terms of population size. This was based on the assumption that social interactions are dependent on relative population sizes.[17] Finally, the matrix was row-normalized, i.e., the sum of each row was made equal to 1, which means that the number of neighbors does not affect the magnitude of spatial spillovers.
- **M** : **W_cdt50_row** This matrix is based on the same extended queen-contiguity matrix **W_cdt50_pop_row**. However, population-based weights were not applied.

The regression model (cf. Eqs. (1) and (2)) was run separately for each period t: an initial "proto/early-adopters" period 2000–2004, and then for each single year until 2023, thereby allowing for the estimation of period-specific regression coefficients. Such a cross-sectional rather than panel regression analysis was carried out for several reasons: (1) several explanatory variables were available only for one or a few years, vary little over time and/or are time-invariant (e.g., long-term average solar radiation), making it difficult to achieve high "within" explanatory power; (2) the use of a fixed-effects model would cause the omission of important time-invariant variables (e.g., solar radiation); (3) time-varying, national-level regulatory and market frameworks (PV costs, power prices, FiT, and other regulatory aspects) are difficult to fully quantify, so part of their impact would be captured by year dummies; (4) year-specific, cross-sectional models allow for assessing how the impact of explanatory variables changes over time in response to the evolving regulatory and market framework, without requiring explicit quantification given their spatial invariance. However, running cross-sectional regressions for each year separately overlooks major information on past patterns of technology diffusion that may influence subsequent technology adoption. To address this, a second model specification was introduced, in which the estimated uncorrelated component of residuals (hereinafter "uncorrelated residuals") — i.e., $\hat{\epsilon}_t$ from (2) — was included as an explanatory variable in the model specification for subsequent years. In particular, the uncorrelated residuals of the period 2000–2004 (i.e., $\hat{\epsilon}_{04}$) were used in all subsequent regressions to control for unobserved characteristics affecting technology adoption and/or early-adoption inclinations. Such characteristics might also be permanent, i.e., fixed effects. From 2006 onward, the estimated uncorrelated residuals of previous-year regressions $\hat{\eta}_{t-1}$ (see Eq. (4)) were also added to the set of explanatory variables to measure how temporal lags of disturbances affect levels of deployment. Moreover, these disturbances may spill over to neighboring spatial units, which is why the spatial lags of such past uncorrelated residuals were also added to the model. This enhanced version of the SARAR model is referred to as "SARAR2" and is described by Eqs. (3) and (4).

$$Y_t = \lambda_t \mathbf{W} \mathbf{Y}_t + \mathbf{X}_t \beta_t + \hat{\mathbf{E}}_t \delta_t + \theta_t \mathbf{W} \hat{\mathbf{E}}_t + \mathbf{u}_t \tag{3}$$

$$\mathbf{u}_t = \rho_t \mathbf{M} \mathbf{u}_t + \boldsymbol{\eta}_t \tag{4}$$

In Eq. (3), $\hat{\mathbf{E}}_t$ is the $N \times 2$ matrix containing the estimated spatially uncorrelated residuals from previous regressions $\hat{\epsilon}_{04,i}$ (from SARAR) and $\hat{\eta}_{t-1,i}$ (from SARAR2), whereas $\boldsymbol{\delta}_t$ is the 2×1 vector of its unknown scalar parameters. $\mathbf{W}\hat{\mathbf{E}}_t$ is the $N \times 2$ matrix containing the spatial lags of $\hat{\mathbf{E}}_t$, whereas θ_t is the 2×1 vector of its unknown parameters. $\boldsymbol{\eta}_t$ in Eq. (4) is the $N \times 1$ vector of uncorrelated residuals. The remaining components of Eqs. (3) and (4) are identical to those in Eqs. (1) and (2).

3. Results

3.1. PV diffusion

This section presents the main estimation results of the regression models. To ensure comparability across years and assess the relative impact of variables, all variables (except the dummy variable *fGDR* and the estimated uncorrelated residuals of previous-period regressions) were standardized. Table 6 in Appendix B reports the OLS estimation results for the 20 periods. However, Moran's I test statistics detected spatial autocorrelation among the OLS residuals (cf. Table 6). This indicates that OLS estimates overlook spatial dependencies and that the estimated coefficients may be inconsistent. Therefore, the SARAR model was estimated, where both endogenous interaction effects and spatial interaction among error terms were considered. Subsequently, using the estimated uncorrelated residuals of previous-period regressions, the SARAR2 was estimated (cf. Section 2.2).

Table 2 reports the SARAR results for the period 2000–2004 and the SARAR2 results for the 19 years between 2005 and 2023. In addition, a heatmap of the time-varying coefficients from the same regressions is shown in Fig. 4. From 2005 onward, the regressions include the estimated uncorrelated residuals $\hat{\epsilon}_{04}$ of the SARAR (i.e., first column in the table) for the period 2000–2004. Additional previous-year residuals $\hat{\eta}_{t-1}$ appear from 2006 onward. Consequently, the SARAR2 model produces more accurate estimates and achieves far higher pseudo-R^2[18] scores than the SARAR model (cf. Table 7). $\hat{\epsilon}_{04}$ residuals appeared to have a strong effect on the SBI-PV diffusion in the following years. Between 2005 and 2020, the coefficient ranged from approximately 0.3 to 0.7 standard deviation units (SD).For example, a residual of 1 SD in *PV_cap* during 2000–2004 was associated with a 0.722 SD increase in *PV_cap* in 2005 and a 0.310 SD increase in 2020. This effect may reflect early-adopter tendencies in the local population and/or persistent, unobserved, spatially heterogeneous characteristics affecting PV diffusion. The effect waned over time and, while the coefficient became non-significant by 2023, the average total effect — including both direct and indirect effects (cf. Section 3.3) — was already non-significant by 2021. As $\hat{\epsilon}_{04}$ was positively correlated with past PV installations, one might suspect that the declining coefficient could be due to the saturation of PV deployment potential: i.e., the saturation effect due to a decrease in available free rooftops for new PV installations. However, this "saturation effect" can be dismissed: in 2023, past cumulative PV installations and new installations were still positively correlated, although a plateauing of this positive relationship can be observed in districts with more than 3 kW of PV capacity per residential building (cf. Fig. 6 in Appendix B).

[16] Appendix C presents the results stemming from alternative spatial weighting matrices and additional robustness checks.

[17] For instance, let us assume that A is a district of 100,000 inhabitants, whereas B is a district of 500,000 inhabitants. Before normalization and inverse-distance weighting and without population-based weighting, all the weights of interaction effects are equal to 1. With population-based weighting, the weight of the spillover of A on B will be 0.2, whereas the weight of the spillover of B on A will be 5.

[18] See Appendix C for a discussion on the model's performance and out-of-sample validation.

Table 2
Estimation results of SARAR2 model for *PV_cap* 2000–2023.

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
$\hat{\epsilon}_{04}$		0.722[a]	0.500[a]	0.635[a]	0.607[a]	0.625[a]	0.580[a]	0.454[a]	0.465[a]	0.405[a]
$\hat{\eta}_{t-1}$			0.840[a]	0.566[a]	0.775[a]	0.473[a]	0.748[a]	0.790[a]	0.837[a]	0.917[a]
glob_rad	0.320[a]	0.272[a]	0.232[a]	0.271[a]	0.280[a]	0.268[a]	0.280[a]	0.309[a]	0.313[a]	0.361[a]
nrbuild	−0.112[a]	−0.073[a]	−0.016	−0.056[a]	−0.070[a]	−0.043[b]	−0.060[a]	−0.074[a]	−0.030[c]	−0.029
rbuild_sdf	−0.147	0.033	0.110[b]	0.058	−0.044	0.037	0.025	0.07	0.100[b]	0.028
rbuild_dens	−0.133[a]	−0.131[a]	−0.101[a]	−0.142[a]	−0.142[a]	−0.124[a]	−0.172[a]	−0.221[a]	−0.249[a]	−0.274[a]
ratio_res2wor					0.055[b]	0.045[c]	0.031[c]	0.038[c]	0.071[a]	0.115[a]
livestock	0.141[b]	0.079[a]	0.068[b]	0.056[c]	0.080[a]	0.185[a]	0.219[a]	0.183[a]	0.148[a]	0.068[c]
fGDR	−0.657[a]	−0.189	−0.087	−0.350[c]	−0.303[a]	−0.589[a]	−0.652[a]	−0.828[a]	−0.848[a]	−0.700[a]
low_edu	−0.108	0.059	−0.01	−0.048	−0.036	−0.041	−0.012	−0.024	−0.031	−0.049
income	0.027	−0.036	−0.013	−0.025	0.069	−0.033	0.032	0.067	0.037	0.14
income2	−0.065	−0.001	−0.048	−0.032	−0.107	0.003	−0.047	−0.096	−0.1	−0.184[c]
pop_tot	0.088	0.229[a]	0.182[a]	0.185[a]	0.102[b]	0.222[a]	0.215[a]	0.221[a]	0.195[a]	0.101[c]
pop_over75	−0.088[c]	−0.072[a]	−0.045	−0.110[a]	−0.115[a]	−0.066[a]	−0.082[a]	−0.099[a]	−0.076[a]	−0.119[a]
pop_for	−0.250[a]	−0.310[a]	−0.189[a]	−0.208[a]	−0.214[a]	−0.250[a]	−0.270[a]	−0.272[a]	−0.239[a]	−0.256[a]
pop_minor	0.306[a]	0.361[a]	0.375[a]	0.314[a]	0.210[a]	0.145[a]	0.185[a]	0.193[a]	0.171[a]	0.151[a]
gdiff_emp					0.073[a]	0.111[a]	0.082[a]	0.028	0.036[c]	0.073[a]
green_pol	0.025	−0.014	−0.038	−0.104[b]	−0.068[b]	−0.090[a]	−0.130[a]	−0.183[a]	−0.163[a]	−0.135[a]
afd_pol										−0.037
nrbuild_hp										
ecars										
_cons	0.149[a]	0.078[b]	0.063[c]	0.107[b]	0.100[a]	0.152[a]	0.168[a]	0.199[a]	0.207[a]	0.169[a]
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$		−0.141	−0.092	0.037	0.022	−0.194[c]	−0.175[a]	−0.028	−0.026	0.023
$\hat{\eta}_{t-1}$			−0.106	0.303[c]	0.251[c]	0.053	0.235[a]	0.338	0.419[a]	0.522[a]
λ	0.535[a]	0.618[a]	0.633[a]	0.608[a]	0.628[a]	0.569[a]	0.506[a]	0.436[a]	0.416[a]	0.369[a]
M: Wcdt50_row										
ρ	−0.013	−0.196	−0.091	−0.037	−0.18	0.209	0.139	0.290[b]	0.195[b]	0.249[b]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.663	0.867	0.877	0.825	0.906	0.857	0.956	0.901	0.926	0.875

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{04}$	0.432[a]	0.281[a]	0.305[a]	0.355[a]	0.394[a]	0.314[a]	0.310[a]	0.211[a]	0.088[b]	0.033
$\hat{\eta}_{t-1}$	0.719[a]	0.726[a]	0.557[a]	0.590[a]	0.582[a]	0.748[a]	0.751[a]	0.782[a]	0.904[a]	0.703[a]
glob_rad	0.415[a]	0.413[a]	0.354[a]	0.314[a]	0.344[a]	0.312[a]	0.301[a]	0.247[a]	0.187[a]	0.152[a]
nrbuild	−0.031	−0.031	0.024	0.04	0.017	0.059[a]	0.022	0.031	0.086[a]	0.093[a]
rbuild_sdf	−0.035	−0.064	−0.147[b]	−0.121[c]	−0.142[a]	−0.062	−0.076	0.029	0.121[b]	0.159[a]
rbuild_dens	−0.273[a]	−0.241[a]	−0.183[a]	−0.170[a]	−0.178[a]	−0.170[a]	−0.151[a]	−0.151[a]	−0.105[a]	−0.031
ratio_res2wor	0.116[a]	0.109[a]	0.091[a]	0.028	0.060[b]	0.065[a]	0.049[b]	0.057[b]	0.037	0.076[a]
livestock	0.037	−0.013	0.019	0.094[a]	0.117[a]	0.122[a]	0.104[a]	0.070[a]	0.022	0.121[a]
fGDR	−0.513[a]	−0.594[a]	−0.388[a]	−0.608[a]	−0.702[a]	−0.505[a]	−0.540[a]	−0.415[a]	−0.242[c]	0.155
low_edu	−0.122[b]	−0.240[a]	−0.142[a]	−0.126[a]	−0.167[a]	−0.115[a]	−0.131[a]	−0.174[a]	−0.191[a]	−0.148[a]
income	0.157	0.198	0.275	0.319[b]	0.207	0.034	0.257[c]	0.031	0.236	0.458[a]
income2	−0.173	−0.206	−0.24	−0.293[b]	−0.221[b]	−0.076	−0.259[b]	−0.059	−0.244	−0.412[a]
pop_tot	0.046	−0.078	−0.121[b]	−0.049	−0.041	0.025	0.015	0.051	0.049	0.047
pop_over75	−0.091[a]	−0.133[a]	−0.087[b]	−0.124[a]	−0.126[a]	−0.088[a]	−0.125[a]	−0.123[a]	−0.065[b]	−0.008
pop_for	−0.228[a]	−0.148[b]	−0.187[a]	−0.230[a]	−0.267[a]	−0.303[a]	−0.341[a]	−0.333[a]	−0.311[a]	−0.283[a]
pop_minor	0.203[a]	0.168[a]	0.158[a]	0.136[a]	0.150[a]	0.169[a]	0.182[a]	0.179[a]	0.242[a]	0.229[a]
gdiff_emp	0.073[b]	0.039	0.058[b]	0.052[c]	0.049[c]	0.081[a]	0.045[c]	0.102[a]	0.077[b]	0.093[a]
green_pol	−0.117[a]	−0.131[a]	−0.056	−0.075[c]	−0.083[b]	−0.047	−0.165[a]	−0.201[a]	−0.178[a]	−0.115[a]
afd_pol	−0.111[a]	−0.114[a]	−0.073[c]	−0.016	−0.048	−0.110[a]	−0.150[a]	−0.210[a]	−0.237[a]	−0.332[a]
nrbuild_hp			0.107[a]	0.155[a]	0.091[a]	0.112[a]	0.079[a]	0.066[a]	0.071[a]	0.079[a]
ecars			0.014	0.011	0.027	0.026	0.072[b]	0.177[a]	0.157[a]	0.091[a]
_cons	0.144[a]	0.146[a]	0.110[a]	0.140[a]	0.164[a]	0.131[a]	0.136[a]	0.117[a]	0.089[b]	0.018
Wcdt50_pop_row										
$\hat{\epsilon}_{04}$	0.004	0.014	−0.107	−0.042	−0.107	−0.005	−0.122	−0.187[b]	−0.127	−0.073
$\hat{\eta}_{t-1}$	0.539[a]	0.547[a]	0.415[a]	−0.182	0.244	0.450[a]	0.134	0.786[a]	0.473[a]	1.007[a]
λ	0.393[a]	0.406[a]	0.457[a]	0.439[a]	0.469[a]	0.478[a]	0.480[a]	0.455[a]	0.459[a]	0.479[a]
Wcdt50_row										
ρ	0.116	−0.026	−0.103	−0.212[c]	−0.102	−0.067	0.220[b]	0.341[a]	0.406[a]	0.161[b]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.892	0.821	0.842	0.864	0.883	0.891	0.896	0.875	0.86	0.866

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1.

Previous-year residuals $\hat{\eta}_{t-1}$ from the SARAR2 were part of the specification from 2006 onward and appeared to have an even stronger effect, with an average coefficient of 0.723 over the whole period. This impact could be attributed to previous-period adoptions, namely peer effects within the same spatial units, by which adopters in a given year t influence adoption in the following year $t+1$. Interestingly, the lowest coefficient value (0.473) was achieved in 2009, the year in which PV systems started to become increasingly financially attractive; this may indicate a possible change in the motivations for PV adoption, between early adopters, who were potentially more interested in the technology itself rather than in its profitability, and late adopters, who may have been driven mainly by financial gains.

The spatial lags of *PV_cap* had a highly significant impact, especially during the first years of the analysis, with autoregressive coefficients λ averaging 0.622 over the period 2005–2008. Afterwards, λ coefficients declined, indicating a lesser role of peer effects once technology

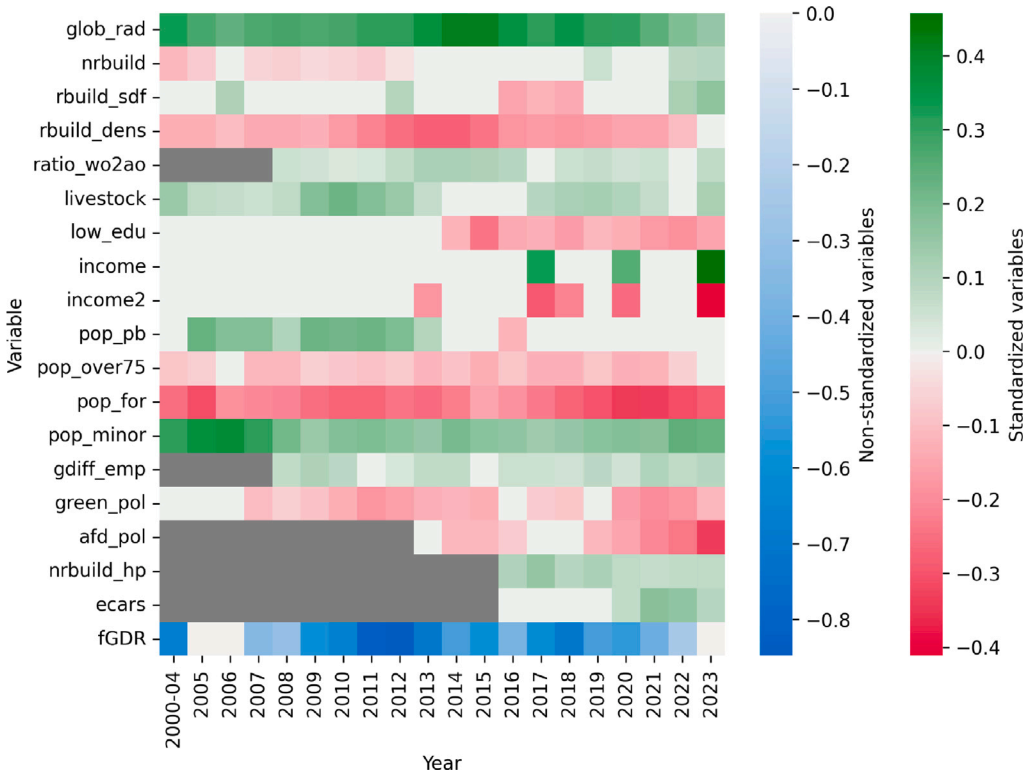

Fig. 4. Heatmap of coefficients for exogenous variables estimated from SARAR2 regressions (based on Table 2; non-significant coefficients set to 0).

became more widespread. Between 2011 and 2023, λ values were fairly consistent, fluctuating around an average of 0.441.

Compared to autoregressive spatial effects, the evidence for spatial autocorrelation among errors is much weaker[19]: ρ coefficients were positive and significant in the periods 2011–2013 and 2020–2023. This finding could be due to local shortages or abundances of installers during high PV growth phases, or, in the later period, to the increasing relevance of local electricity prices and the diffusion of local promotion schemes for residential prosumers, such as subsidies for purchasing BES systems.

Regarding the coefficients of the independent variables, the first variable is ***glob_rad***, which reflects the potential PV output. As a climate-related variable, this variable is highly spatially correlated, which is why the standard OLS model systematically overestimated the impact of this variable (cf. Table 6 in Appendix B). In the SARAR2, ***glob_rad*** had an average coefficient of 0.296 and was highly statistically significant throughout the analysis period. A slight trend over time can be noticed: in the first years, the coefficient was below 0.3; from 2011, it fluctuated around values consistently above 0.3, whereas from 2020, a steady decline occurred, reaching a value of 0.152 for 2023. A potential explanation for this trend is that adopters were less motivated by generation potential during the early-adoption phase, whereas in later years PV output potential became crucial for profitability, especially following the sharp drop in FiTs. Finally, during 2020–2023, PV output potential may have played an increasing marginal role in the new PV boom, most likely as a result of self-consumption-driven adoption, widespread BES coupling and, most importantly, the energy crisis. Following the energy crisis, an increasing number of households may have rushed to become prosumers with the aim of reaching (partial) energy self-sufficiency, irrespective of a relatively low generation potential.

The next set of variables reflects the built environment. ***rbuild_new***, namely the new residential buildings finished in each given year, did not appear to play a major role, with coefficients non-significant for many years and magnitudes below 0.1 SD. Interestingly, new buildings had a negative and significant impact intermittently until 2011, whereas the impact was highly significant again in 2019 and 2022–2023, and its sign turned positive. This could be the result of a paradigm shift in terms of the perceived attractiveness and/or suitability of SBI-PV for new buildings, but it could also stem from changes in the building code, which pushed for renewable energy technologies in new constructions.

rbuild_sdf reflects the prevalence of single- and two-family homes. While this variable positively correlates with PV deployment, controlling for other built-environment-related and socioeconomic variables rendered it non-significant—or even negative and significant over several years. This may be due to other variables (e.g., ***rbuild_density*** and ***pop_tot***) already capturing the presence of STFHO. Regarding the negative coefficients in 2016–2018, the low absolute numbers of SBI-PV adoptions meant that, ceteris paribus, more urbanized areas — with a lower share of single- and two-family homes — could exhibit relatively higher PV deployment during this slump phase, as well as an earlier uptake of prosumage. However, once PV regained momentum, this negative effect disappeared, and during the most recent PV boom (2022–2023) the coefficient turned positive and significant (e.g., 0.159 in 2023).

rbuild_density, namely the density of residential buildings, had a negative and significant impact across all the years except 2023, as a high density of buildings might result in fewer suitable rooftops for PV in terms of generation potential. Between 2005 and 2022, the coefficient had an average value of −0.177, with an identifiable inverted U-shaped trend where the highest (absolute) values were reached around 2013–2014: the reasons for such a trend could be similar to those already mentioned for ***glob_rad*** and ***rbuild_sdf***. Until 2012,

[19] In the SARAR model however, autocorrelation coefficients were consistently significant from 2011 onward. This implies that accounting for uncorrelated residuals of regressions of previous periods captured, in part, spatially correlated unobserved characteristics and/or shocks, which would otherwise enter the spatially correlated error term.

this variable grew in importance, probably due to widespread feed-in-oriented adoption, whereas in the period 2012–2014, the decline in FiTs may have concentrated the deployment of PV installations in less densely urbanized areas with the most suitable roofs and/or more STFHO. The decline in absolute values after 2015 may be attributed to the further decrease in the importance of output potential (for feed-in) and to the uptake of prosumage, primarily in more urbanized areas. Finally, the energy crisis over the period 2021–2023 may have accelerated PV installations on suboptimal roofs.

ratio_res2wor, namely the ratio between residents and employees in a given region, aims to reflect the extent to which the building stock (and also the power demand) is residential rather than commercial. The coefficient was positive and significant for most of the years, with a sharp increase from 2012 to 2013: this implies that as FiTs fell, they became more predominant in more residential-oriented districts. The effect appeared to wane in more recent years.

livestock aims to reflect the presence of buildings in the farming sector, which could be used for SBI-PV installations: this coefficient was positive and significant for the years in which considerable profitability was achieved thanks to generous FiTs (2009–2011), with an average value of 0.196. Afterwards, when self-consumption became a decisive factor for PV profitability, the coefficient declined and became non-significant, suggesting a drop in the share of small-scale PV installations in farm-related buildings. After 2017 the impact of ***livestock*** rose again up to 0.122 in 2019, indicating a comeback of profitable (larger[20]) PV installations in farm-related buildings. The effect waned again in the period 2020–2022, yet reappeared in 2023, possibly as a result of the newly introduced “full-injection” FiTs.

The next set of variables is related to socioeconomic and demographic aspects. The coefficients of ***fGDR*** showed that having been part of the GDR negatively affected the diffusion of SBI-PV. This effect was highly significant over the period 2008–2021 and with substantial magnitudes of up to −0.85 SD, especially during the boom years 2010–2013. Over the last few years, such a negative effect appeared to wane and, in 2023, became non-significant. ***low_edu***, namely a variable reflecting the share of the adult population with a low level of education, had a negative and significant effect during the period 2014–2023, with an average coefficient of 0.156. ***income*** and ***income2*** were non-significant in most years, likely because other variables captured the relevant socioeconomic factors. The exception was 2023, when ***income*** was significant with a relatively high coefficient (0.458).

One possible explanation could be that the increase in living costs, the energy crisis, and the subsequent rush to become prosumers may have caused shortages and price spikes in the PV market, resulting in PV deployment being relatively more concentrated in more affluent districts. For the same year, ***income2*** was negative and significant, indicating a non-linear, U-shaped relation, according to which the positive impact of income on PV deployment diminishes as per capita income increases.[21]

pop_tot reflects the number of people living in the district; therefore, it aims to mirror residential power demand. Its coefficient was positive and highly significant only between 2005 and 2012, with an average value of 0.194. This finding highlights a paradox: as long as SBI-PV adoption was based on the revenue from feed-in, deployment occurred in districts with more people per residential building (i.e., more multifamily buildings). Conversely, as self-consumption became relevant, SBI-PV deployment tended to move to districts with a lower district-level self-consumption potential (i.e., lower residential demand).

pop_over75 had generally a negative and significant impact, with magnitudes of up to approximately 0.13 SD. The effect declined and disappeared over the period 2022–2023. ***pop_for***, i.e., the share of the foreign population, was found to have a highly significant negative impact on SBI-PV diffusion, with consistently negative coefficients throughout the entire period. The coefficients were relatively large, with an average value of −0.255. The effect was weakest during the low-deployment period of 2015–2016.

pop_minor, i.e. the share of the underage population, had a positive and significant effect over the whole period. The average coefficient was 0.206, indicating the rather important role of families with underage children.

gdiff_emp was available only from 2008 onward. This variable, reflecting gender disparities in employment rates, exhibited a moderate positive (up to approximately 0.1 SD) and significant coefficient only during the initial and final years of the analysis period. Gender differences in the employment rate aim to reflect households with a stay-at-home adult, which, ceteris paribus, could have a higher self-consumption potential due to higher residential demand during PV generation. However, the positive and significant coefficients before 2012, i.e., before the shift to a self-consumption paradigm, suggest that reasons other than self-consumption potential could explain the significant effect of this variable: e.g., the presence of STFHO consisting of married couples (both with and without minor children). The following set of variables is related to political inclinations. ***green_pol***, the share of votes for the Green Party, was non-significant in the early-adopter phase; however, a negative and significant effect emerged post-2006, intensifying as SBI-PV deployment increased. The coefficient peaked in 2011 at −0.183, subsequently declining, but rose again in recent years, reaching another peak of 0.201 in 2020. The reasons for this, unexpected, negative impact might be linked to the demographic characteristics of green voters (cf. Section 4). In contrast, ***afd_pol***, the share of votes for the AFD party, had an even stronger and increasingly negative coefficient in recent years, reaching −0.332 in 2023.

The final set of variables reflects the diffusion of sector-coupling technologies. The financial performance of such technologies benefits from cheap, self-generated PV electricity. At the same time, the higher self-consumption potential of such technologies makes PV investment more profitable. ***nrbuild_hp***, namely the share of new buildings with a heat pump, had a positive and significant effect, with an average value of 0.116 over the period 2016–2019. Subsequently, when both PV and heat pump adoption accelerated, the diffusion of heat pumps appeared to have a lesser role in the diffusion of SBI-PV, with an average coefficient of 0.072 during the period 2020–2022. The coefficient of ***ecars***, in contrast, was positive and significant only from 2020 onward, with an average value of 0.135 over the period 2020–2022.[22]

3.2. BES diffusion

Table 3 reports the results of the SARAR model for the period 2013–2014 and of the SARAR2 model over the 9 years in the period 2015–2023. In addition, a heatmap of the time-varying coefficients from the same regressions is shown in Fig. 5. The regressions included the estimated uncorrelated residuals $\hat{\epsilon}_{\mathbf{14}}$ of the SARAR regression (first column in the table) for the period 2013–2014. Such residuals appeared to have a significant positive impact on the diffusion of BES systems in the following years, with a coefficient declining from 0.398 (in 2015) to approximately 0.09 (in the period 2021–2023). As in the case of SBI-PV diffusion, this effect could be attributed to early-adopter inclination and/or persistent, unobserved characteristics affecting S-BES diffusion.

[20] By extending the sample to building-integrated installations up to 100 kW_p the coefficient of ***livestock*** reaches 0.254 (cf. Table 12 in Appendix C).

[21] For 2023, the turning point in which the impact of income becomes negative was at approximately EUR 69,000, i.e., well above the maximum value of the variable ***income*** before standardization cf. Table 1.

[22] The lack of observations on sector-coupling technologies for 2023 is particularly critical for these variables (given their high temporal variability), which is why the estimated coefficients for 2023 should not be considered very robust.

Table 3
Estimation results of SARAR2 model for *BES_cap* 2013–2023.

Variable	2013–14	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{14}$		0.398[a]	0.226[a]	0.209[a]	0.177[a]	0.164[a]	0.134[a]	0.089[a]	0.083[a]	0.091[a]
$\hat{\eta}_{t-1}$			0.324[a]	0.282[a]	0.496[a]	0.474[a]	0.472[a]	0.641[a]	0.718[a]	0.611[a]
PV_cap	0.466[a]	0.587[a]	0.505[a]	0.641[a]	0.699[a]	0.630[a]	0.752[a]	0.836[a]	0.915[a]	1.063[a]
glob_rad	−0.093	−0.106[c]	0.057	0.018	0.033	0.103[b]	0.103[a]	0.008	0.005	−0.038
nrbuild	0.097[b]	0.002	−0.053	0.012	0.046	0.043	−0.015	−0.008	0.044[b]	0.016
rbuild_sdf	−0.271[a]	−0.104	−0.016	−0.121	0.005	0.003	−0.006	0.054	−0.01	−0.017
rbuild_dens	−0.043	−0.068	−0.077[c]	−0.043	−0.013	−0.031	0.002	0.040[c]	0.050[b]	0.075[a]
ratio_res2wor	0.096[c]	0.06	−0.011	0.070[b]	0.036	0.072[a]	0.049[b]	0.035[b]	0.019	0.017
livestock	−0.006	0.067	0.067[c]	−0.028	−0.051[c]	−0.084[a]	−0.094[a]	−0.008	−0.039[c]	−0.055[a]
fGDR	0.046	−0.548[b]	−0.902[a]	−0.399[b]	−0.380[b]	0.138	0.106	0.071	0.211[b]	0.512[a]
low_edu	0.002	−0.093	−0.201[a]	−0.130[b]	−0.083	−0.021	−0.03	−0.04	−0.011	0.008
income	0.186	−0.094	−0.022	0.017	0.243	0.459[a]	0.205	0.274[a]	0.504[a]	0.458[a]
income2	−0.138	0.114	−0.024	0.013	−0.205	−0.422[a]	−0.147	−0.176[b]	−0.392[a]	−0.368[a]
pop_tot	−0.196[b]	−0.062	0.061	−0.014	0.03	−0.029	−0.013	0.036	−0.037	−0.057[c]
pop_over75	−0.01	−0.052	−0.088[c]	−0.04	−0.023	0.080[b]	0.037	0.049[b]	0.027	0.071[a]
pop_for	−0.086	0.03	−0.108	−0.152[a]	−0.09	−0.07	−0.086[b]	−0.051	−0.01	0.095[a]
pop_minor	0.125[b]	0.053	0.089[c]	0.075[b]	0.081[b]	0.150[a]	0.139[a]	0.068[a]	0.048[b]	0.048[b]
gdiff_emp	0.004	−0.058	−0.080[b]	−0.061[b]	−0.081[b]	−0.041	−0.071[a]	0.001	−0.017	−0.049[b]
green_pol	0.093	0.02	−0.117[b]	−0.037	−0.046	0.036	0.015	−0.003	0.037	0.046
afd_pol	0.116[b]	0.128[b]	0.064	0.046	0.080[c]	0.01	−0.014	0.01	0.046	0.016
nrbuild_hp			0.033	0.011	−0.013	−0.005	−0.029	−0.025	−0.007	0
ecars			0.071[c]	0.117[a]	0.089[a]	0.123[a]	0.060[b]	0.043[c]	−0.036	−0.007
_cons	0.022	0.119[b]	0.180[a]	0.084[b]	0.075[b]	−0.015	−0.016	−0.003	−0.041	−0.097[a]
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$		0.09	0.310[a]	−0.045	0.185[b]	0.184[a]	0.111	0.155[a]	0.121[b]	0.150[b]
$\hat{\eta}_{t-1}$			0.219	0.193[c]	0.098	0.218[c]	0.290[b]	0.428[a]	0.528[a]	0.469[a]
λ	0.576[a]	0.314[a]	0.260[a]	0.195[a]	0.117	0.216[a]	0.170[a]	0.112[a]	0.018	−0.005
M: Wcdt50_row										
ρ	−0.103	−0.048	0.033	0.062	0.14	0.153	0.366[a]	0.353[a]	0.431[a]	0.500[a]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.547	0.678	0.77	0.821	0.867	0.881	0.922	0.946	0.948	0.944

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1.

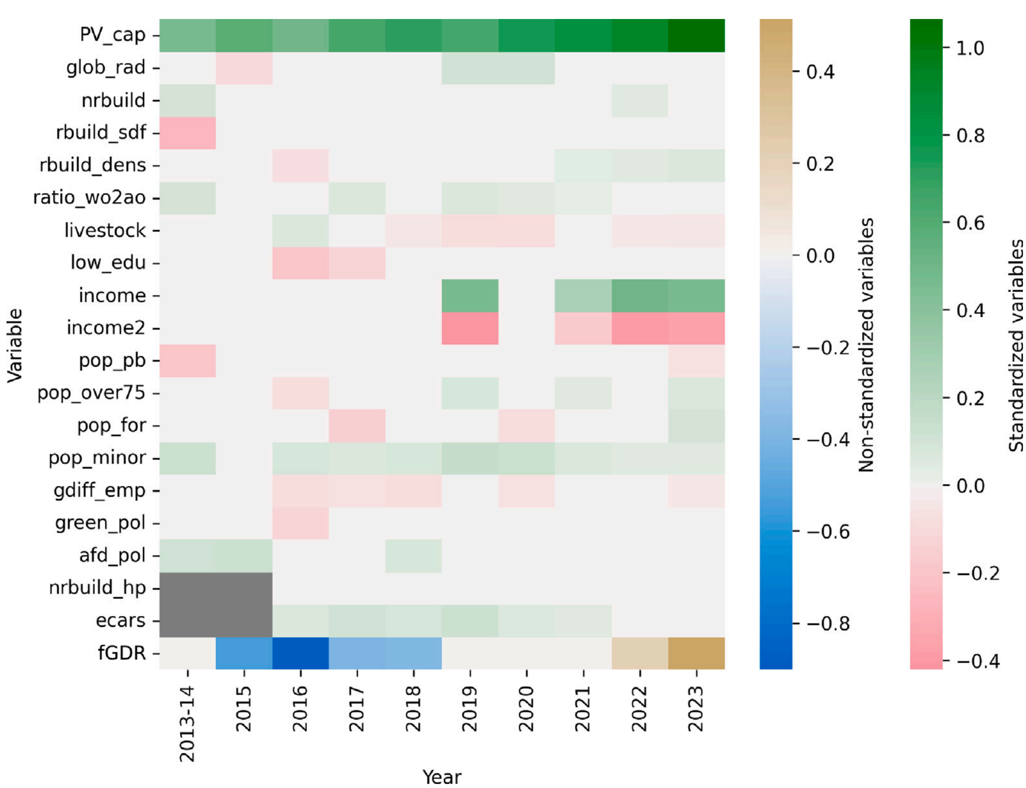

Fig. 5. Heatmap of regression coefficients for exogenous variables (based on Table 3; non-significant coefficients set to 0).

Previous-year estimated uncorrelated residuals $\hat{\eta}_{t-1}$ from the SARAR2 model are part of the specification from 2016 onward. $\hat{\eta}_{t-1}$ had a rather high coefficient, which tended to grow over time, reaching a value of 0.718 in 2022. Similar to SBI-PV diffusion, such an impact could result from temporal peer effects within the same spatial units, whereby adopters in a given year influence adoption in the subsequent year.

The autoregressive coefficients λ, which measure spillover effects from nearby adoptions, are significant for several years. However, in contrast to SBI-PV diffusion, their magnitude was much weaker and tended to wane over time: coefficients above 0.25 were observed only for the period 2015–2016, whereas the effect in 2022–2023 was not significant.

Regarding spatial correlation between error terms, the autocorrelation coefficient ρ was non-significant for the period 2015–2019. From 2020, ρ was positive and significant with magnitudes between 0.366 and 0.500. Interestingly, autocorrelation became significant as nationwide grant schemes for BES purchase were discontinued and regional-level promotion schemes emerged. The first and most important independent explanatory variable driving the diffusion of BES systems is ***PV_cap***, since S-BES are mostly coupled to new SBI-PV installations. This variable had a very strong and significant effect for all the years, and its coefficient grew from 0.505 (in 2016) to 1.063 (in 2023). The remaining independent variables are the same as in the SBI-PV diffusion model; therefore, their impact must be considered as conditional on the simultaneous deployment of PV capacity: i.e., their coefficients reflect the effect of each given variable in addition to the indirect effect that the same variable channels through SBI-PV diffusion.

A number of these variables (***glob_rad***,***rbuild_new***, ***rbuild_sdf***, ***pop_tot***) had little (and mostly non-significant) effect on S-BES diffusion when this is conditional on the deployment of PV capacity. In contrast to PV, ***rbuild_density*** had a small (up to 0.075 SD) but significant and positive effect on BES in 2022 and 2023, possibly indicating a higher BES deployment in more urbanized areas. ***ratio_res2wor*** had a few positive and significant coefficients (up to 0.072 in 2019), confirming that S-BES diffusion (similarly to SBI-PV) tends to occur in more residential regions. ***livestock*** had a negative impact with a few significant coefficients of up to 0.094; this may confirm that BES uptake occurs in more urbanized areas rather than in rural ones. Overall, after controlling for the deployed capacity of SBI-PV, there is general evidence that variables reflecting a more urban and residential (rather than rural and commercial) built environment had a mild positive impact.

Regarding socioeconomic and demographic aspects, ***fGDR*** had a significant and negative effect during the first period 2015–2018 (with an average coefficient of −0.557). This effect turned non-significant after 2018 and even became positive and significant over the most recent years, reaching a value of 0.512 in 2023. Such a recent positive impact may indicate a catch-up effect occurring in former GDR districts, by which BES deployment might also occur through the retrofit of existing SBI-PV installations. ***low_edu*** had a negative and significant impact only in the period 2016–2017. ***income*** and ***income2*** played a more relevant role in S-BES diffusion than SBI-PV diffusion: the coefficients of ***income*** were positive and significant for 2019 and over the period 2021–2023, with values of up to approximately 0.5 SD. ***pop_tot*** was mostly non-significant, whereas ***pop_over75*** and ***pop_for*** had a few unexpectedly positive and significant coefficients (especially for 2023).***pop_minor*** had a positive and significant impact, which peaks in 2019 (0.150) and declined Afterwards (0.048 in 2023). Families with children may have been more inclined to adopt BES (e.g., due to their higher self-consumption potential); yet, as BES became largely predominant during the energy crisis, the impact of this demographic appeared to have lessened. ***gdiff_emp*** had negative and significant coefficients over the period 2016–2018, for 2020, and for 2023, yet magnitudes are rather low with values of up to 0.081. This result is in moderate contrast to the positive impact of the same variable on SBI-PV diffusion, suggesting potentially different self-consumption patterns: in regions where gender differences in employment are narrower, daytime home occupancy may be lower, thereby incentivizing BES adoption. Regarding the variables on political inclinations, both ***green_pol*** and ***afd_pol*** had hardly any significant impact. Interestingly, in contrast to the SBI-PV diffusion model, the only highly significant coefficient of ***afd_pol*** was positive, which might (rather weakly) indicate that aspiration towards "energy autarky" may be correlated with a general distrust of institutions and subsequent voting for anti-establishment parties.

Regarding variables on sector-coupling technologies, the coefficient of ***nrbuild_hp*** was never significant, whereas ***ecars*** had several positive and significant coefficients with a value of up to 0.123, which declined after a peak in 2019. However, such significant effects might reflect a general correlation in the (early) diffusion of "green technologies" rather than a direct causal link between electric mobility and residential BES.

3.3. Average direct, indirect and total effects

The β coefficients presented in Tables 2 and 3 do not reflect the average impacts of the exogenous variables: the "true" impacts are determined by the recursive interaction of endogenous effects. For instance, an increase in ***glob_rad*** in spatial unit A has a positive impact on ***PV_cap*** in spatial unit A, which in turn produces a spillover into neighboring spatial units and propagates into their respective neighbors. This increase in SBI-PV diffusion in neighboring spatial units due to the very same initial increase in ***glob_rad*** spills over back to the same spatial unit A, which in turn produces a further spillover into its neighbors, and so on. The impact of ***glob_rad*** observed in spatial unit A on the same spatial unit is a so-called direct effect, whereas the impact deriving from *glob_rad* observed in the other spatial units (both neighboring and not) on spatial unit A is a so-called indirect effect. Table 4 provides an overview of average direct, indirect, and total effects of exogenous variables for three selected years, namely 2010, 2016, and 2022. In the case of **X** variables (i.e., exogenous variables excluding residuals from previous periods), direct effects had a slightly larger magnitude than the coefficients of Table 2. Following substantial endogenous spillover effects, significant indirect effects accounted for almost half of the total effects in 2010 and were still above 40% of total effects in 2016 and 2022.

Turning to the effects of past residuals, the indirect effect of $\hat{\epsilon}_{04}$ accounted for only approximately 28% of the total effect in 2010, whereas the indirect effects were non-significant in 2016 and 2022. In other words, the positive indirect effect deriving from early-adoption inclinations in other spatial units appears to wane much earlier than the direct effect. On the contrary, the indirect effects of $\hat{\eta}_{t-1}$ account for 60%–65% of the total effects in the three selected years: the indirect effects of temporal lags of disturbances in other spatial units had a larger aggregated impact than the disturbances within the same spatial unit, also because spatial lags of $\hat{\eta}_{t-1}$ had positive and significant effects on the dependent variable of neighboring spatial units (cf. Table 2).

Table 5 provides an overview of average direct, indirect, and total effects of exogenous variables on BES deployment for three selected years. In the case of **X** variables, direct effects also had a slightly larger magnitude than the coefficients of Table 3. Indirect effects, however, accounted for less than 30% of total effects in 2016 and 2019, whereas they were not significant in 2022. This is due to much smaller or even non-significant endogenous spillover effects in the case of S-BES diffusion compared to PV diffusion. Indirect effects of $\hat{\epsilon}_{14}$ were, however, substantial, accounting for more than 60% of total effects over the three selected years. Indirect effects of $\hat{\eta}_{t-1}$ accounted for 54% of total effects and declined over time to 43% of total effects.

In summary, indirect effects were highly relevant to exacerbating direct impacts, especially in the case of SBI-PV diffusion and in the case of temporal lags of disturbances $\hat{\eta}_{t-1}$. For the latter, the total impact

Table 4
Average direct, indirect and total impacts on *PV_cap* (selected years).

Variable	2010			2016			2022		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
$\hat{\epsilon}_{04}$	.592^a	.229^b	.821^a	.308^a	.056	.364^b	.08^b	−.154	−.074
$\hat{\eta}_{t-1}$	.81^a	1.183^a	1.993^a	.614^a	1.174^a	1.788^a	.981^a	1.562^a	2.543^a
glob_rad	.294^a	.273^a	.567^a	.368^a	.283^a	.651^a	.195^a	.151^a	.346^a
nrbuild	−.063^a	−.058^a	−.121^a	.025	.019	.044	.09^a	.07^a	.159^a
rbuild_sdf	.026	.025	.051	−.153^b	−.118^b	−.271^b	.126^b	.098^b	.223^b
rbuild_dens	−.181^a	−.168^a	−.349^a	−.19^a	−.147^a	−.337^a	−.109^a	−.085^a	−.194^a
ratio_res2wor	.033^c	.03^c	.063^c	.094^a	.073^b	.167^b	.039	.03	.069
livestock	.23^a	.214^a	.444^a	.019	.015	.034	.023	.018	.041
fGDR	−.685^a	−.636^a	−1.321^a	−.403^a	−.311^a	−.713^a	−.251^c	−.195^c	−.446^c
low_edu	−.013	−.012	−.025	−.148^a	−.114^a	−.262^a	−.198^a	−.154^a	−.352^a
income	.033	.031	.064	.286	.22	.506	.245	.19	.436
income2	−.05	−.046	−.096	−.25	−.193	−.442	−.254	−.197	−.451
pop_tot	.226^a	.21^a	.436^a	−.126^b	−.097^c	−.223^b	.051	.04	.09
pop_over75	−.086^a	−.08^a	−.165^a	−.09^b	−.07^c	−.16^b	−.067^b	−.052^b	−.12^b
pop_for	−.283^a	−.263^a	−.546^a	−.195^a	−.15^a	−.345^a	−.324^a	−.251^a	−.575^a
pop_minor	.194^a	.181^a	.375^a	.165^a	.127^a	.291^a	.252^a	.196^a	.448^a
gdiff_emp	.086^a	.08^a	.165^a	.06^b	.046^b	.106^b	.08^b	.062^b	.141^b
green_pol	−.136^a	−.127^a	−.263^a	−.058	−.045	−.103	−.185^a	−.144^a	−.329^a
afd_pol				−.076^c	−.058^c	−.134^c	−.247^a	−.191^a	−.438^a
nrbuild_hp				.112^a	.086^a	.198^a	.074^a	.057^b	.131^a
ecars				.015	.011	.026	.164^a	.127^a	.291^a

^{a} denotes a p-value < 0.01, ^{b} denotes a p-value < 0.05, ^{c} denotes a p-value < 0.1.

Table 5
Average direct, indirect and total impacts on *BES_cap* (selected years).

Variable	2016			2019			2022		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
$\hat{\epsilon}_{14}$	.241^a	.482^a	.723^a	.171^a	.272^a	.444^a	.083^a	.125^b	.208^a
$\hat{\eta}_{t-1}$	.336^a	.396^c	.733^a	.485^a	.398^b	.883^a	.719^a	.549^a	1.268^a
PV_cap	.511^a	.172^a	.682^a	.635^a	.169^a	.805^a	.915^a	.016	.931^a
glob_rad	.058	.02	.078	.104	.028^b	.132^b	.005	.	.005
nrbuild	−.053	−.018	−.071	.043	.012	.055	.044^b	.001	.045^b
rbuild_sdf	−.016	−.005	−.021	.003	.001	.004	−.01	.	−.01
rbuild_dens	−.078^c	−.026	−.104^c	−.032	−.008	−.04	.05^b	.001	.051^b
ratio_res2wor	−.011	−.004	−.015	.073^a	.019^b	.092^a	.019	.	.019
livestock	.068^c	.023	.091^c	−.085^a	−.023^b	−.107^a	−.039^c	−.001	−.04^c
fGDR	−.912^a	−.307^a	−1.219^a	.139	.037	.176	.211^b	.004	.215^c
low_edu	−.203^a	−.068^b	−.271^a	−.021	−.006	−.026	−.011	.	−.011
income	−.022	−.007	−.029	.462^a	.123^a	.585^a	.504^a	.009	.513^a
income2	−.024	−.008	−.033	−.425^a	−.113^a	−.538^a	−.392^a	−.007	−.399^a
pop_tot	.061	.021	.082	−.029	−.008	−.037	−.037	−.001	−.038
pop_over75	−.089^c	−.03	−.119^c	.081^b	.022^b	.103^b	.027	.	.027
pop_for	−.109	−.037	−.146	−.07	−.019	−.089	−.01	.	−.01
pop_minor	.09^c	.03	.12^c	.152^a	.04^a	.192^a	.048^b	.001	.049^b
gdiff_emp	−.081^b	−.027	−.108^c	−.041	−.011	−.052	−.017	.	−.017
green_pol	−.118^b	−.04^c	−.157^b	.036	.01	.045	.037	.001	.038
afd_pol	.065	.022	.087	.01	.003	.013	.046	.001	.047
nrbuild_hp	.033	.011	.045	−.005	−.001	−.007	−.007	.	−.008
ecars	.072^c	.024	.096	.124^a	.033	.157	−.036	−.001	−.036

^{a} denotes a p-value < 0.01, ^{b} denotes a p-value < 0.05, ^{c} denotes a p-value < 0.1.

of such past shocks was often more than two times larger than the β coefficients reported in Tables 2 and 3, as spatial spillover effects occur both through spatial lags of the same $\hat{\eta}_{t-1}$ variable and through the endogenous interaction effects of the dependent variable.

4. Discussion

This analysis has demonstrated how a wide range of drivers has shaped the geographically uneven diffusion of SBI-PV and S-BES in Germany and how the influence of each driver has evolved over the past two decades. From a policy perspective, understanding these diffusion drivers is important for several reasons:

1. To assess whether these impact channels produce negative system-level effects in terms of cost efficiency and distributional fairness.
2. To identify how the regulatory framework influences these channels and how policy interventions could promote cost-efficient technology deployment and operation.
3. To use ex-post insights to predict future adoption patterns, enabling a more informed, effective, and efficient transition to a low-carbon energy system.

The following two subsections address the first two points, while the third point is reserved for future research.

4.1. Interpretation of exogenous drivers and implications for cost efficiency and distributional fairness

In the SARAR2 model, the inclusion of uncorrelated residuals from past regressions is methodologically important, as these residuals help control for unobservable, confounding factors that could otherwise reduce the accuracy of other estimated coefficients. Similarly, taking into account spatial dependence allows for a correct assessment of the role of exogenous variables. Social interaction effects could be seen as enhancers of exogenous drivers of diffusion, which may exacerbate inequalities (see Stewart, 2022) rather than being primary factors causing uneven and/or suboptimal outcomes. On the contrary, each of the exogenous variables deserves a separate and careful interpretation, as these are prime drivers of diverging patterns of technology diffusion.

Regarding the effect of solar irradiation (***glob_rad***), which is consistently positive and significant, PV operator and system perspectives are aligned: on the one hand, PV output potential increases household-level profitability; on the other hand, from a system perspective, it is more cost-efficient to deploy more PV capacity in regions with higher solar irradiation. The decreasing value of its coefficient over the last few years deserves further attention, as PV installations may have been deployed in less optimal locations in the aftermath of the energy crisis.

The impact of new buildings (***rbuild_new***) has reversed over the years. The negative effect in the earlier years (in line with the findings of Dharshing, 2017) can be considered sub-optimal: possibly due to SBI-PV being perceived as aesthetically unappealing for new buildings and/or a lack of expertise among constructors in integrating PV into building designs. While a non-significant effect would appear consistent with cost-efficient deployment, the positive impact in later years could still reflect efficiency-related considerations—such as lower installation costs for PV on new buildings compared to existing ones, or the intentional planning of new buildings for optimal PV integration.

The deployment of SBI-PV has relied on the adoption — and often personal investment — by STFHO (i.e., single- and two-family homeowners). The available data, however, do not provide detailed information on the building type for each PV system, nor make it possible to determine the number of STFHO in each NUTS-3 region. Despite these limitations, many variables in this analysis are linked to the STFHO demographic, underscoring the central role of this group in the significant effects observed.

First and foremost, the share[23] of single-family and two-family homes (***rbuild_sdf***) is strictly connected to the STFHO demographic.[24] Although controlling for many other built environment and socioeconomic variables makes the impact of ***rbuild_sdf*** non-significant (and even negative and significant) over many years, this variable had a positive and significant effect during the new boom 2022–2023. Therefore, as of 2023, the STFHO demographic appears to be now more than ever pivotal in the deployment of residential PV. The importance of STFHO is also (partly[25]) embedded in the significant effects of ***pop_minor*** and ***gdiff_emp***, as these variables are connected to the prevalence of families with underage children and cohabiting couples, which are greatly over-represented among STFHO (Destatis, 2019).[26] Finally, even the unexpectedly negative impact of green voters (***green_pol***) can most likely be attributed to the demographic characteristics of this constituency. In fact, the Green Party performs particularly well in urban centers and university cities, as well as among young people and among unemployed people (Decker, 2023): that is, in areas and among population segments with fewer STFHO. The density of residential buildings (***rbuild_dens***) is strictly connected to the degree of urbanization and to the share of single- and two-family homes, which is why its exclusion would result in the estimation of higher positive impacts of ***rbuild_sdf***. However, this variable is included in the final specification to control for the fact that building concentration may result in fewer roofs suitable for cost-efficient PV installations (e.g. due to shadowing or contiguous buildings with smaller roof areas). The erosion of this effect during the years of the energy crisis (2021–2023) can imply, marginally, a decrease in the cost efficiency of SBI-PV deployment as a result of a rush to prosumage.

The inclusion of ***ratio_res2wor*** and ***livestock*** is used to control for the stock of non-residential buildings and non-residential energy demand. ***livestock*** serves as a control for SBI-PV installations on farm-related buildings and has, in fact, a positive impact, especially during periods of high FiTs. The ratio between residents and people working in a given district (***ratio_res2wor***) is more relevant from a policy perspective: this variable should ideally have a negative impact on SBI-PV diffusion, as a smaller ratio tends to imply more commercial buildings and, more importantly, higher electricity demand from non-residential consumers. Therefore, evidence of a moderate positive impact of ***ratio_res2wor*** may indicate suboptimal deployment of SBI-PV.

The impact channel of socioeconomic variables operates through two main channels. First, less educated, foreign (e.g., see Friedrich, 2008), poorer households (e.g., see Destatis, 2019) are presumably less likely to belong to the STFHO demographic. In this regard, regional disparities in PV deployment may build upon substantial, preexisting regional disparities in homeownership, which are themselves shaped by socioeconomic and demographic factors as well as heterogeneous regional housing markets (Lerbs and Oberst, 2012). Second, households with a lower socioeconomic status, less integrated into society, or limited trust in institutions may face additional barriers that restrict the uptake of PV self-generation even within the STFHO demographic. Such marginalized segments of the population may have less knowledge and time to learn about the technology, promotion schemes, and administrative procedures; may have less access to capital and loans; may lack personal connections to suppliers and/or other PV adopters; may be risk-averse to investment; and may be wary of PV adoption (cf. Konzen et al., 2024). The elderly population may be subjected to all the previous hurdles, while at the same time, given their age, may not consider PV adoption as a viable long-term investment. The negative impacts ***fGDR***, ***low_edu***, ***pop_for***, and ***pop_over75*** tend to confirm the presence of such barriers. The effect of ***fGDR*** has declined in recent years and has even become positive in the case of S-BES diffusion, thereby indicating a possible East–West convergence. On the contrary, uneven impacts across other socioeconomic divides seem to be widening. The effect of ***income*** was very relevant in 2023 for SBI-PV diffusion and has been very important for S-BES diffusion overall. Similarly, the negative effects of the foreign population (***pop_for***) and AfD voters (***afd_pol***) were at their highest in 2023.

Such findings on the STFHO demographic and socioeconomic characteristics not only highlight the socially uneven patterns of residential SBI-PV diffusion but also point to a major source of cost inefficiency for the power system. Compared to single- and two-family homes, multifamily buildings often have larger roof areas, allowing for the installation of larger and thus more cost-efficient PV systems. More importantly, due to their higher number of inhabitants, multifamily buildings typically offer greater potential for self-consumption.

The evolution of the effect of the number of persons per residential building (***pop_tot***) revealed a paradox: the coefficient was positive and significant until 2012 but became non-significant thereafter—precisely when FiTs dropped below retail power prices and self-consumption became central to the profitability of SBI-PV. This is paradoxical because, under a self-consumption-driven regime, buildings with more residents — and therefore higher electricity demand — should be more attractive for PV adoption due to their greater potential for on-site use of generated electricity. This paradox likely stems from the fact that, prior to 2012, full-injection SBI-PV systems were installed on all

[23] (Adjusted share, cf. 2.1).

[24] The data on ownership status of dwellings is available only for the year 2011. The homeownership rate has a correlation of 93% with ***rbuild_sdf*** for the year 2011. According to a 2018 survey (Destatis, 2019), of the estimated 17.4 million households living in single-family and two-family homes, approximately 4.3 million were renting, while 13.4 million households were homeowners. With regard to multifamily buildings, there were 18.6 million renters and only 3.5 million homeowners.

[25] Another factor affecting the impact of these variables is the higher self-consumption potential of families with children (e.g., in comparison to people living alone).

[26] In Germany in 2018, according to own calculations based on Destatis (2019), 48.5% of families with underage children (*Paare mit Kindern*) and 43.8% of cohabiting couples (*Paare ohne Kinder*) were STFHO. Of the remaining households (i.e., mostly people living alone), only 24% were STFHO.

types of buildings, including multifamily buildings with a high number of residents. Following the shift to the "residual producer" paradigm in 2012 (cf. Ossenbrink, 2017), SBI-PV began to be optimized for the self-consumption potential of STFHO, resulting in smaller installations increasingly coupled with BES systems.

4.2. Policy recommendations

Germany's past and current regulatory framework has resulted in suboptimal SBI-PV deployment, favoring prosumage among STFHO while marginalizing multifamily and tenant-occupied buildings. This imbalance creates both cost inefficiencies and distributional inequities in the residential energy transition. To address these issues, three complementary strategic directions for policy intervention are proposed to better align the deployment and operation of SBI-PV and S-BES with the objectives of cost efficiency and distributional fairness.

Introduce dynamic, cost-reflective energy tariffs that are carbon- and grid-oriented

Current energy tariffs for residential consumers — and prosumers — in Germany are very far from being an efficient set of price signals, which, according to Pérez-Arriaga et al. (2017), should be: highly granular (in space and time); technology-neutral; symmetric in terms of electricity withdrawal and injection; and include dynamic, capacity-based charges reflecting real-time grid congestion. This is not only relevant for future deployment, but also for the operation of existing technologies (especially S-BES), which, as widely discussed in the literature (e.g., Schill et al., 2017), is also crucial for an effective, cost-efficient, and fair energy transition.

Due to the current regulatory framework, the self-consumption maximization strategy of prosumers does not result in significant savings for the system, but rather in an unfair redistribution of system-related costs from prosumers to standard consumers (Eicke et al., 2024). A regulatory reform towards carbon-oriented and grid-oriented, cost-reflective tariffs — see Aniello and Bertsch (2023) for a proposal in this direction — would help create a more just distribution of the costs and benefits of the energy transition, in that both prosumers and standard electricity consumers would be able to benefit from cheaper, low-carbon electricity (at times of high RES generation) and pay peak-coincident capacity charges independent of self-consumption volumes. Moreover, such a regulatory shift would bring about additional system-level benefits (and bring down costs for all consumers), in that prosumers would be incentivized to operate the existing BES capacity to avoid grid congestion, to charge during times of abundant RES generation, and to discharge during times of RES scarcity. While further research is needed to quantify the full socioeconomic implications of such a regulatory shift, a system-oriented operation of residential batteries, EVs, and heat pumps could save the German energy system EUR 4.8 billion annually by 2035 (Godron et al., 2024).

While the regulatory framework strongly favors self-consumption by STFHO, the recently introduced "full-injection" FiTs reward PV operators who inject electricity exclusively into the grid rather than self-consuming it. This provides a simplified business case for PV integration in all types of buildings, including multifamily units.

This scheme adds to a patchwork of incentives — in the form of subsidies, charges, taxes, levies, and tax breaks — that extends beyond energy tariffs, resulting in a complex and somewhat inconsistent regulatory landscape.

Although necessary, a shift towards carbon- and grid-oriented dynamic energy tariffs alone may be insufficient to establish a level playing field, enabling broader deployment of residential PV and BES beyond the STFHO sub-segment.

Harmonize regulatory and tax frameworks governing within-building PV self-consumption, irrespective of system size, building type, or ownership structure

The suboptimal deployment of SBI-PV is the direct result of a regulatory framework that systematically promotes self-consumption for STFHO, while lacking the same kind of incentives for other residential segments. The EEG defines self-consumption as the consumption of PV electricity, which occurs on-site to meet the demand from the very same operator of the PV system. In other words, the electricity generated by a SBI-PV system and consumed within the same building has a different legal status depending on whether the PV operator and the electricity consumer are the same natural or juridical person. Such a legal definition of self-consumption has implications for levies on electricity, VAT (value-added tax) and the taxation of income from PV. The abolition of the EEG surcharge in 2022 has definitely been a step towards a level playing field, as only small-scale prosumers used to be exempt from such a levy before its abolition. Since 2017, a special regulatory framework has actively promoted the deployment of PV energy in multifamily and/or tenant-occupied buildings: namely the *Mieterstrom* model. The *Mieterstrom* promotion scheme exempts on-site (i.e., within-building) consumption of PV electricity from network charges and other levies. It also sets a kWh subsidy for the PV operator (BNetzA, 2024), which is paid in addition to the electricity rate charged to the tenants. However, PV uptake within the *Mieterstrom* framework appears to be largely underwhelming: out of approximately 750,000 new SBI-PV installations in 2023, only approximately 2,200 (0.29%) were registered in the *Mieterstrom* program (according to the *Marktstammdatenregister* BNetzA, 2023).[27] While there are alternatives to the *Mieterstrom* model for the promotion of PV deployment on multifamily buildings (EnBW, 2024), the findings of this study tend to confirm the large anecdotal evidence that SBI-PV has been — and is now more than ever — mostly deployed on owner-occupied single-family (and two-family) homes.

Aside from the exemption of electricity charges and surcharges on self-consumed electricity, fiscal aspects have also been rather relevant for SBI-PV profitability in the past years (Aniello et al., 2021; Dietrich and Weber, 2018). Therefore, the impact of the recent tax reforms (see Bund, 2022) should also be discussed. Such new tax breaks seem to deepen the profitability gap between SBI-PV for STFHO and SBI-PV for multifamily buildings. For instance, a full VAT exemption applies to self-consumption as defined by the law, exempting mostly STFHO prosumers (and not, e.g., customers in a *Mieterstrom* model). Regarding the exemption from income tax, the new law sets limits on the maximum size of PV installations, which vary according to the type of building. More importantly, the exemption is granted for up to a maximum of 100 kW of installed capacity per taxpayer.

Therefore, it must be stated in clear terms that as long as "within-building" self-consumption is regulated differently for STFHO prosumers, PV on multi-family buildings will lag behind. German policymakers have decided that (i) massive deployment of SBI-PV is necessary for a successful energy transition; and that (ii) on-site, within-building self-consumption must be maximized. Consequently, as noted by Aniello et al. (2024), regulatory arrangements should be at least consistent with these objectives. The regulatory framework for building-integrated PV ought to be made homogeneous within the building sector: the type of building, its ownership status, the ownership status of PV and BES systems, the size of PV installations, and the number of dwellings within the building should be irrelevant for the regulated components of electricity tariffs, for tax purposes, and for any associated bureaucratic hassle. For instance, the VAT on within-building self-consumed electricity should be either levied on any final consumer or canceled altogether. Ideally, a reduced, revenue-neutral, uniform

[27] Raising the sample's threshold to building-integrated installations up to 100 kW_p increases the *Mieterstrom* segment to 0.33% of the total.

VAT rate on all electricity would even be fair to inhabitants of buildings without PV (as proposed for the Danish case Gunkel et al., 2023). Such a reform harmonizing self-consumption regulation would make larger installations on buildings with higher self-consumption potential relatively more profitable than smaller PV installations on single-family homes or PV installations based on a "full-injection" model.

Develop regulatory and legal frameworks enabling viable business models for third-party-owned SBI-PV and S-BES installations

With the right regulatory and legal framework, new business models could emerge in which companies invest in, install, and operate SBI-PV and S-BES systems in the most economically advantageous locations—both in terms of power generation potential and within-building self-consumption. Such third-party-owned[28] installations would eliminate the investment risk and administrative burden for building owners, who could instead benefit from, for example, low-cost electricity, long-term lease payments, or a free rooftop retrofit.

More importantly, low-cost electricity could be sold to homeowners or tenants through long-term PPA contracts and even coupled with smart energy services, thereby incentivizing and optimizing self-consumption within buildings.

Furthermore, because such PV systems would be installed and operated by specialized companies, additional efficiency gains could be realized through economies of scale, market leverage, and technical expertise, thereby further reducing the cost of distributed PV generation (Aniello and Bertsch, 2023).

Substantial differences in business models for distributed PV can be observed across different regulatory contexts, with third-party ownership being historically common in the U.S. market, in contrast to the context of European countries (Burger and Luke, 2017). In Southern California, third-party ownership has been shown to broaden residential PV adoption among younger, less affluent, and less educated demographics (Drury et al., 2012).

4.3. Limitations and outlook for further research

This study has several limitations. Firstly, many variables affecting regional variability in SBI-PV profitability were missing from the analysis (e.g., subnational subsidies, network charges, heating systems in existing buildings, competitiveness of local PV installers). This study aims to mitigate the impact of such shortcomings by controlling for spatial autocorrelation and temporally lagged residuals. Secondly, data on SBI-PV and S-BES systems provide no exhaustive information on the type of buildings nor on the "self-generation business model" of such installations, which is why this study takes into account the potential for non-residential PV deployment by using proxy variables. Thirdly, as noted by Zhang et al. (2023), the low level of spatial resolution is not ideal for assessing spatial interaction effects, whereas the impact of exogenous drivers may be underestimated due to the level of aggregation (e.g., average income can conceal significant inequalities).

A higher level of spatial resolution, or alternative methodological approaches using adopter-level survey data or geolocated building-level data, could more effectively disentangle causal relationships arising from peer effects and spatial dependencies associated with unobserved spatially clustered characteristics. Similarly, granular household-level data would allow a more rigorous assessment of the relationship between exogenous drivers (e.g., income) and technology adoption.

Moreover, the selection of spatial weighting matrices is somewhat discretionary, which is why the robustness to alternative spatial weighting strategies was considered in this study. Nonetheless, spatial effects could follow spatially diverse patterns, which cannot be captured by a spatial weighting matrix that is based solely on contiguity and air distance. Other factors arguably play a role in shaping both autocorrelation and interaction effects (e.g., topography, roads, location of settlements within spatial units, higher-level administrative borders (e.g., state borders)).

Overall, the study identified broad impacts of exogenous drivers, while (imperfectly) controlling for spatial dependencies. In this regard, the robustness checks and out-of-sample estimations (cf. Appendix C) support the validity of this study's main results.

Further research is necessary to explore specific policy interventions in greater detail, as this paper only provides an overview due to its limited scope. Additionally, although this study focuses on Germany, it is relevant to examine how the findings translate to other national contexts—for instance, in countries characterized by higher homeownership rates, greater prevalence of single-family housing, or differing self-consumption regulations. A cross-country analysis of how regulatory frameworks shape — and potentially distort — the diffusion of SBI-PV and S-BES would thus represent a highly relevant avenue for future research.

Future research could also build on this study's findings — or combine its methodological approach with highly granular data on building stock, available rooftops, and residential energy demand — to estimate the potential and future deployment of PV and BES in the residential sector. The impact of regulation-related drivers could also be isolated to evaluate alternative regulatory scenarios of spatial diffusion. Finally, these scenarios should be examined within the context of broader energy tariff reforms and using an energy system model to assess the potential for more cost-efficient deployment and operation key residential energy technologies, including PV, BES, heating systems, and electric vehicles.

5. Conclusions

This study investigated how a large set of drivers has been shaping an uneven diffusion of small-scale, building-integrated PV (SBI-PV) and small-scale BES systems (S-BES) in Germany. The analysis spanned more than two decades and examined how the impact of drivers has been evolving in connection to a dynamic regulatory framework.

In the case of SBI-PV, many statistically significant exogenous drivers can be linked to the presence of single- and two-family homeowners (STFHO) and to socioeconomic or attitudinal factors (e.g., foreign population, age, income, education, political inclinations), which shape the capability and willingness to adopt this technology. By contrast, drivers associated with cost-efficient deployment patterns played only a minor role. For instance, global radiation was the sole driver strongly linked to cost efficiency, showing a consistently positive and statistically significant impact over the years, yet its magnitude was comparable to that of the foreign population share alone. Variables reflecting residential and non-residential local power demand, also related to cost efficiency, had only marginal, and at times even negative, effects on SBI-PV deployment.

The additional deployed capacity of SBI-PV was unsurprisingly found to be the main driver of S-BES diffusion, while income also appeared to have a substantial positive effect.

In addition to the observed exogenous drivers, endogenous interaction effects and interaction effects among error terms were found: the former were particularly important in the case of SBI-PV diffusion, while the latter played a more decisive role in the case of S-BES diffusion. Endogenous interaction effects (i.e., peer effects) exacerbated the impact of the observed exogenous drivers of diffusion. Spatially correlated errors — due to spatially correlated shocks and unobserved exogenous drivers (e.g., regional subsidy schemes, network charges, etc.) — further contribute to spatially diverging patterns of technology deployment.

[28] Business models based on third-party ownership already exist in Germany but are currently viable only for very large rooftops (above 600 m^2), where a full-injection model typically makes economic sense (see, e.g., energie-helde, 2024).

These findings are highly relevant from a policy perspective. The disparities in SBI-PV and S-BES deployment can, to a large extent, be attributed to distortions in the regulatory framework. Current regulations do not create a level playing field that would encourage the cost-efficient deployment of residential PV and BES—namely, installing relatively larger systems on buildings and in regions with higher self-consumption potential. On the contrary, the regulatory framework systematically favors smaller SBI-PV installations on owner-occupied one- and two-family buildings over larger installations on multifamily buildings. Moreover, most new SBI-PV installations are coupled with S-BES systems, which are operated to maximize household self-consumption regardless of grid and power market conditions, thereby misusing an increasingly important asset for a RES-dominated power system.

Beyond cost-efficiency considerations, such distorting regulatory arrangements entail distributional implications. On the one hand, individuals who are less educated, foreign, elderly, poorer, less well-connected, distrustful of institutions, living alone, or who simply do not belong to the STFHO demographic are largely excluded from the economic benefits of PV prosumage. On the other hand, the economic benefits for prosumers do not reflect lower system-level costs, but are rather financed directly and indirectly through taxes and non-cost-reflective energy tariffs.

Lastly, this paper discussed how a set of regulatory reforms could reshape the deployment and operation of energy technologies. In the context of the broader energy transition — and the projected expansion of PV in particular — the ambitious targets set by the German government may require a fundamental regulatory shift that creates the right incentives for effective, cost-efficient, and equitable decarbonization. A key outcome of such a shift would be the substantial uptake of SBI-PV — and potentially S-BES — in multifamily buildings and among less-advantaged demographic groups.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to improve the language and readability. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

Acknowledgments

This work was supported by the Helmholtz Association under the program "Energy System Design". The author would like to thank Prof. Valentin Bertsch for his supervision, suggestions and comments, which helped to improve the paper's methodology and the manuscript overall. The author would also like to thank Dr. Imke Rhoden for the detailed feedback on earlier versions of this paper, which also contributed significantly to improve the manuscript. The sole responsibility for the analysis and the implications of the findings lies with the author.

Appendix A. Description of variables

Weighting and dependent variables:

rbuild_2011 Stock of residential buildings according to the 2011 census[29] (Statistische Ämter des Bundes und der Länder, 2023), both available at municipal and district level. This variable was used as a fixed weight for the dependent variables, as well as for several independent variables. Time series of building stock were also available and were used for deriving other time-varying variables (e.g., ***rbuild_sdf***).

PV_cap Annual additional capacity (in kW) of SBI-PV installations per thousand of **rbuild_2011**. Data were available for the full period 2000–2023 from BNetzA (2023). This variable was also used as an explanatory variable for BES capacity deployment.

BES_cap. Annual additional capacity (in kWh) of S-BES installations per thousand of ***rbuild_2011***. Although data were available for the full period 2000–2023 from BNetzA (2023), the analysis used only data of the period 2013–2023, because of the extremely low number of installations in the preceding years.

Each of the independent variables is described in detail below:

PV output potential

glob_rad, i.e., average annual global radiation in kWh/m^2 over the period 1991–2020. This is a non-time-varying variable, which is based on a raster dataset with a 1 km x 1 km resolution retrieved from DWD (2021). The values of the raster data were matched with the coordinates of municipalities derived from Destatis (2021). Subsequently, a weighted average, with weights based on the municipal stock of residential buildings, was calculated in order to obtain a single value for each of the 400 NUTS-3 regions. This variable was included because it reflects the PV generation potential, which is why it is connected to the profitability of adoption. Therefore its expected impact is positive on SBI-PV uptake, but unclear for S-BES.

Built environment

nrbuild, i.e., new buildings per thousand of ***rbuild_2011***. Data are available for the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023).[30] In line with the literature, this variable was included because SBI-PV might be installed either more or less frequently on new buildings in comparison to existing ones. Therefore its expected impact is unclear.

rbuild_sdf, i.e., single-family homes plus dwellings in two-family homes as a share of the residential building stock. Two-family homes are therefore counted twice, as they may offer a chance for installing a SBI-PV system for each of the two households inhabiting the building. Raw data were available over the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023). This variable is connected to the presence of STFHO, which are the main demographic that can aspire to become PV prosumers. Therefore, it is expected to have a positive impact on SBI-PV uptake.

rbuild_dens, i.e., density of residential buildings, namely the number of residential buildings per km^2 of the district's area assigned to settlements and transport infrastructure. Residential building data were available over the period 2000–2022, whereas data on land use were missing for the periods 2001–2003, 2005–2007 and for 2022. Missing observations were filled via linear interpolation up to 2007, and 2021 values were used for 2022–2023 All data were retrieved from Statistische Ämter des Bundes und der Länder (2023). This variable reflects the degree of urbanization and correlates negatively with the presence of STFHO. Furthermore, building density is also negatively associated with the potential availability of suitable rooftops for PV installation: higher density may lead to increased shadowing and smaller roof surface area due to building contiguity.

[29] The latest available census data are from 2011.

[30] Except for 10 missing observations for the federal state of Sachsen-Anhalt for the year 2000. In the cross-sectional regression, the first 4 years were aggregated, meaning that this variable was averaged and therefore the model could be still estimated with all the 400 districts.

Therefore, it is expected to have a negative impact on SBI-PV uptake.

ratio_res2wor, i.e., the ratio between employed persons at the place of residence[31] and employed persons at the place of work.[32] Raw data are available for the 2008–2022 period from 1u Statistische Ämter des Bundes und der Länder (2023). This variable aims to reflect the extent to which the district's building stock — as well as its energy demand — is residential rather than non-residential. Such a variable was chosen because no data on non-residential buildings was publicly available, while SBI-PV installations may also be deployed on non-residential buildings. Its expected impact is unclear, as more non-residential districts are expected to have more buildings (and energy demand), yet more residential districts might have more STFHO and be generally more impacted by peer effects.

livestock, i.e., a variable reflecting the number of livestock units (*Großvieheinheiten*)[33] per thousand of residential buildings (**rbuild_2011**). Raw data were generally[34] available for 2010, 2016 and 2020 from Statistische Ämter des Bundes und der Länder (2023). The values of 2010 were used for the period 2000–2009, linear interpolation was employed for the periods 2011–2015 and 2017–2019, and the values of 2020 were used for the following years. This variable serves as a proxy for farm-related buildings, such as barns, on which SBI-PV systems may also be installed. Therefore, it is expected to have a positive impact.

Socioeconomics and demographics

fGDR, i.e., a dummy variable indicating whether the district was formerly part of the German Democratic Republic (GDR).[35] This variable aims to capture differences in attitudes, which go beyond measurable socioeconomic and demographic differences between former West and East Germany districts. Its expected impact is either negative or non-significant.

low_edu, i.e.,a non-time-varying variable aiming at measuring the level of education, which was available only for the census year 2011. The raw data consist of the population aged 15 and older, assigned to three categories based on educational attainment. The category with neither vocational training nor an academic degree (i.e., *Ohne beruflichen Ausbildungsabschluss*, "professional degree") was selected. After removing individuals aged 15–25 (obtained from another dataset from the same source) both from the selected category and the total, the share of the population without a professional degree was calculated. This adjustment was made because districts with many young students would otherwise tend to have a high share of people without a professional degree. As a robustness check, the variable was also calculated after removing only those aged 15–18, with no significant change in the results. Given that raw data regarding education from Statistische Ämter des Bundes und der Länder (2023) were available only for 2011, 2011 values were used for the entire time series. In line with the literature, a low level of education is expected to have a negative impact on SBI-PV and S-BES uptake.

income, i.e., per capita gross income of private households (*Primäreinkommen der privaten Haushalte je Einwohnerin bzw. Einwohner*), namely the income before income tax and social contributions paid by households, and before social benefits and other transfers paid to households. In contrast to disposable income (*Verfügbares Einkommen*), this variable has a higher spatial variability and it is also more relevant for SBI-PV and S-BES adoption, as its costs can be deducted from taxable income. The squared variable ***income2*** is also used to control for non-linear effects. Data were available over the period 2000–2021 from VGRdL (2022). The values of 2021 were used for the following years. Income is expected to have a positive impact on SBI-PV and S-BES uptake, not only because more affluent households may have more financial resources to invest in such technologies, but also because income may be positively correlated with power demand. The impacts of income might have decreasing returns, which is why its squared term is expected to have a negative effect.

pop_tot, i.e., number of inhabitants per thousand of residential buildings (**rbuild_2011**). Raw data were available over the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023). This variable aims to reflect residential demand. Its expected impact is unclear as higher residential demand reflects self-consumption potential, yet higher demand per building reflects also households living in multifamily buildings that normally cannot become prosumers.

pop_over75, i.e., the share of the population over 75 years of age. Compared to other studies, this represents a much higher age threshold than the 60–75 interval used in Dharshing (2017) or the 65+ threshold in Stein et al. (2023). Raw data were available over the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023). In line with the literature, this variable is expected to have a negative impact.

pop_for, i.e., the share of the foreign population. Raw data were available over the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023). Foreign residents may encounter more difficult to become homeowners and/or to navigate the complexities of investing in PV. They also may be less prone to conducting a long-term investment in Germany. Therefore, this variable is expected to have a negative impact on SBI-PV.

pop_minor, i.e., the share of the population under 18 years of age. Raw data were available over the period 2000–2022 from Statistische Ämter des Bundes und der Länder (2023). This variable is a proxy for families with underage children. This demographic is not only overrepresented among STFHO, but is also expected to have a higher self-consumption potential. Therefore, this variable is expected to have a positive impact on SBI-PV and S-BES uptake.

gdiff_emp, i.e., gender-based[36] difference in the employment rate (in terms of *Sozialversicherungspflichtig Beschäftigte am Wohnort*, namely employees subject to social security contributions[37] whose place of residence is in the NUTS-3 region).

[31] *Sozialversicherungspflichtig Beschäftigte am Wohnort*, namely employees subject to social security contributions, whose place of residence is in the NUTS-3 region.

[32] *Sozialversicherungspflichtig Beschäftigte am Arbeitsort*, namely employees subject to social security contributions, whose place of work is in the NUTS-3 region.

[33] The conversion to *Großvieheinheiten* (GV) allows the comparison across several species of animals, for instance an adult bovine equals 1 GV, whereas a chicken corresponds to 0.004 GV (BMEL, 2023).

[34] Out of 1200 observations (400 districts×3 years), 60 values were missing: such missing observations were filled with either interpolated values (in the case of values missing only for 2016), or using previous/following values, or with estimates of livestock unities based on the number of farms (in the case of 2 districts, for which values were missing for all the 3 years).

[35] Although East Berlin was part of the GDR, the dummy variable has a value of 0 for the current city-state of Berlin.

[36] According to the binary gender classification of the raw data from Statistische Ämter des Bundes und der Länder (2023).

[37] Employed persons who are not employees and persons working a so-called *Minijob* (i.e., a part-time job with low earnings) are not included in these statistics.

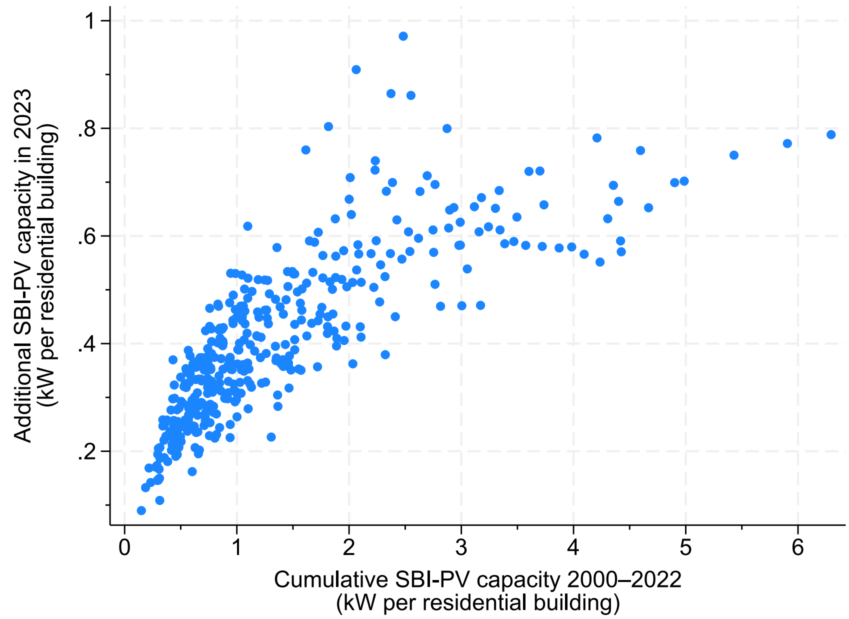

Fig. 6. Additional and preexisting PV capacity per residential building in 2023.
Source: Own elaboration based on data from BNetzA (2023).

Raw data were available 2008–2022 from Statistische Ämter des Bundes und der Länder (2023). This variable aims to reflect households with a stay-at-home adult, which are expected to have a higher self-consumption potential during PV generation. Therefore, this variable is expected to have a positive impact on SBI-PV uptake, but not necessarily on S-BES uptake.

Politics

green_pol, i.e., the share of votes for the Green party (as a share of *Gültige Zweitstimmen*) in the German Federal elections. Raw data from Statistische Ämter des Bundes und der Länder (2023) covered the elections from 1998 until 2021,[38] which occurred in 4-year intervals. The years between 2000 and 2020 without elections were filled through linear interpolation, whereas the values of 2021 were used for the following years. In line with the related literature, this variable is used as a proxy for environmentalist attitudes, which is why it is expected to have a positive impact.

afd_pol, i.e., the share of votes for the AfD party (as a share of *Gültige Zweitstimmen*) in German Federal elections. Data from Statistische Ämter des Bundes und der Länder (2023) covered the elections from 2013 (the first federal elections in which this party participated) to 2021. The years from 2014 to 2020 without elections were filled using linear interpolation, while the 2021 values were carried forward for subsequent years. This variable is intended to capture attitudes of climate change skepticism, as well as general distrust of institutions and anti-establishment sentiment. Accordingly, it is expected to have a negative impact on SBI-PV uptake, though not necessarily on S-BES uptake.

Sector-coupling technologies

nrbuild_hp, i.e., the share of new residential building with an air–water heat pump (*Umweltthermie (Luft/Wasser))* as primary heating source (*primär verwendeter Heizenergie*). This variable was available for the period 2016–2022 from Statistische Ämter des Bundes und der Länder (2023). This variable reflects additional self-consumption potential, which is why its expected impact on SBI-PV uptake is positive.

ecars, i.e., the share of electric cars in the stock of passenger vehicles (*Bestand an Personenkraftwagen*), which was mainly derived using data on registered car from Kraftfahrt-Bundesamt (2023).[39] Raw data were available for the period 2016—2022. This variable reflects additional self-consumption potential, which is why its expected impact on SBI-PV uptake is positive.

Furthermore, several variables (e.g., homeownership rate, population density, dwelling size, unemployment rate, employment rate, average seasonal temperatures, age of residential buildings) were considered in the regression model specification but discarded, as they did not improve explanatory power — either in terms of coefficient significance or the model's pseudo-R^2 — most likely due to multicollinearity. Other geographically heterogeneous variables were excluded due to the lack of freely available data—namely, network charges (which account for most of the regional variation in retail electricity prices), the uptake of electric heating in existing buildings, and subnational promotion schemes (particularly grants for S-BES). These missing variables likely play an important role in determining the profitability of SBI-PV and S-BES for residential prosumers and may therefore be relevant drivers of diffusion.

Appendix B. Additional results

See Fig. 6 and Tables 6–8.

[38] In the 10 districts of the federal state of Saarland, the Green Party did not participate in the 2021 elections. Therefore, the values of 2021 were filled by increasing the 2017 data by 62.3%, namely the average increase in the share of green voters in the districts of the neighboring state of Rhineland-Palatinate. Such an increase was also similar to the nation-wide increase.

[39] Given that the data do not distinguish between cars owned by private households and company cars, a number of outliers in terms of the share of electric cars were identified and capped. The upper limit was calculated annually as $Q_3 + 2IQR$, where Q_3 is the upper quartile and IQR is the interquartile range. Such outliers appear to be due to companies' fleets, for instance in regions where large car manufacturers are based (e.g., Wolfsburg) or where rental car companies registered their fleet (e.g., Weimar, see Seide, 2022). Moreover, the data of the city of Trier and the district of Trier-Saarburg were aggregated, although these areas correspond to 2 distinct NUTS-3 regions. Disaggregated values were estimated based on Stadtverwaltung Trier (2023).

Table 6
Estimation results of OLS model for *PV_cap*.

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
glob_rad	0.590[a]	0.584[a]	0.561[a]	0.580[a]	0.592[a]	0.563[a]	0.519[a]	0.514[a]	0.498[a]	0.541[a]
nrbuild	−0.074[c]	−0.067[c]	−0.029	−0.077[c]	−0.041	−0.055	−0.037	−0.084[b]	−0.042	−0.083[b]
rbuild_sdf	−0.055	0.094	0.189	0.101	−0.07	0.024	0.031	0.065	0.091	0.102
rbuild_dens	−0.149[a]	−0.191[a]	−0.165[a]	−0.197[a]	−0.162[a]	−0.139[a]	−0.183[a]	−0.251[a]	−0.298[a]	−0.320[a]
ratio_res2wor					−0.113[b]	−0.123[a]	−0.124[a]	−0.102[a]	−0.062[c]	0.001
livestock	0.231[a]	0.194[a]	0.177[a]	0.147[a]	0.179[a]	0.294[a]	0.328[a]	0.264[a]	0.206[a]	0.068[c]
fGDR	−1.078[a]	−0.829[a]	−0.575[b]	−0.767[a]	−0.972[a]	−1.380[a]	−1.371[a]	−1.489[a]	−1.419[a]	−1.072[a]
low_edu	−0.217[a]	0.023	−0.018	−0.051	−0.074	−0.09	−0.04	−0.075	−0.07	−0.162[a]
income	0.454[c]	0.447	0.501[c]	0.574[b]	0.526[c]	0.265	0.207	0.298	0.368	0.454[c]
income2	−0.512[b]	−0.492[b]	−0.580[b]	−0.618[b]	−0.542[b]	−0.319	−0.251	−0.346[c]	−0.430[b]	−0.493[b]
pop_tot	0.234[b]	0.379[a]	0.335[a]	0.300[b]	0.107	0.244[b]	0.250[a]	0.234[b]	0.208[b]	0.165[c]
pop_over75	0.047	0.007	0.06	−0.026	−0.115[b]	−0.099[b]	−0.093[b]	−0.139[a]	−0.118[b]	−0.123[b]
pop_for	−0.222[a]	−0.385[a]	−0.258[a]	−0.249[a]	−0.383[a]	−0.408[a]	−0.421[a]	−0.374[a]	−0.342[a]	−0.265[a]
pop_minor	0.316[a]	0.301[a]	0.361[a]	0.275[a]	−0.009	0.001	0.052	0.076	0.043	0.088
gdiff_emp					0.281[a]	0.196[a]	0.173[a]	0.084[b]	0.112[a]	0.127[a]
green_pol	−0.067	−0.084[c]	−0.051	−0.163[a]	−0.098[c]	−0.181[a]	−0.193[a]	−0.261[a]	−0.231[a]	−0.210[a]
afd_pol										−0.137[a]
nrbuild_hp										
ecars										
_cons	0.202[a]	0.155[a]	0.108[c]	0.144[b]	0.182[a]	0.259[a]	0.257[a]	0.279[a]	0.266[a]	0.201[a]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
R2	0.665	0.681	0.68	0.625	0.64	0.695	0.761	0.792	0.776	0.761
Adjusted R2	0.653	0.67	0.668	0.612	0.625	0.682	0.751	0.783	0.767	0.751
Moran's I	81.76951	97.26377	122.1853	119.1649	126.484	170.7599	144.595	174.0393	137.083	102.0065

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
glob_rad	0.581[a]	0.625[a]	0.559[a]	0.508[a]	0.531[a]	0.501[a]	0.472[a]	0.379[a]	0.319[a]	0.282[a]
nrbuild	−0.066[c]	−0.017	0.013	0.068[c]	0.090[b]	0.108[a]	0.109[a]	0.106[a]	0.086[b]	0.079[b]
rbuild_sdf	0.004	−0.085	−0.192[c]	−0.157	−0.198[b]	−0.086	−0.143	−0.053	0.118	0.166[c]
rbuild_dens	−0.337[a]	−0.310[a]	−0.219[a]	−0.253[a]	−0.262[a]	−0.255[a]	−0.239[a]	−0.229[a]	−0.196[a]	−0.117[b]
ratio_res2wor	−0.005	0.002	−0.008	−0.058	−0.044	−0.035	−0.048	−0.039	−0.052	−0.023
livestock	0.075[c]	0	0.081[b]	0.113[a]	0.151[a]	0.164[a]	0.157[a]	0.128[a]	0.101[a]	0.228[a]
fGDR	−1.081[a]	−1.052[a]	−0.767[a]	−1.125[a]	−1.247[a]	−1.056[a]	−1.135[a]	−0.928[a]	−0.606[a]	−0.262
low_edu	−0.262[a]	−0.332[a]	−0.242[a]	−0.202[a]	−0.230[a]	−0.162[a]	−0.190[a]	−0.188[a]	−0.212[a]	−0.161[a]
income	0.537[b]	0.606[b]	0.686[a]	0.609[a]	0.632[a]	0.550[b]	0.657[a]	0.540[b]	0.660[a]	0.751[a]
income2	−0.536[b]	−0.604[a]	−0.650[a]	−0.578[a]	−0.636[a]	−0.585[a]	−0.666[a]	−0.546[b]	−0.675[a]	−0.735[a]
pop_tot	0.102	−0.068	−0.129	−0.063	−0.071	0.045	0.025	0.049	0.12	0.121
pop_over75	−0.114[b]	−0.134[b]	−0.085[c]	−0.143[a]	−0.140[a]	−0.111[b]	−0.143[a]	−0.158[a]	−0.099[b]	−0.047
pop_for	−0.244[a]	−0.187[a]	−0.218[a]	−0.253[a]	−0.275[a]	−0.313[a]	−0.343[a]	−0.334[a]	−0.316[a]	−0.314[a]
pop_minor	0.105[b]	0.088[c]	0.104[b]	0.064	0.062	0.070[c]	0.092[b]	0.080[b]	0.154[a]	0.155[a]
gdiff_emp	0.170[a]	0.135[a]	0.171[a]	0.133[a]	0.128[a]	0.159[a]	0.115[a]	0.170[a]	0.154[a]	0.189[a]
green_pol	−0.190[a]	−0.158[a]	−0.046	−0.106[b]	−0.108[c]	−0.107[c]	−0.223[a]	−0.237[a]	−0.229[a]	−0.106[c]
afd_pol	−0.101[b]	−0.065	−0.007	0.072	0.07	−0.002	−0.049	−0.081	−0.156[b]	−0.236[a]
nrbuild_hp			0.175[a]	0.176[a]	0.124[a]	0.127[a]	0.121[a]	0.111[a]	0.074[b]	0.096[a]
ecars			0.065	0.063	0.068[c]	0.094[b]	0.134[a]	0.209[a]	0.241[a]	0.170[a]
_cons	0.203[a]	0.197[a]	0.144[a]	0.211[a]	0.234[a]	0.198[a]	0.213[a]	0.174[a]	0.114[b]	0.049
Statistics										
N	400	400	400	400	400	400	400	400	400	400
R2	0.754	0.726	0.747	0.771	0.774	0.77	0.793	0.774	0.756	0.76
Adjusted R2	0.743	0.714	0.734	0.759	0.763	0.759	0.783	0.762	0.744	0.748
Moran's I	109.8377	67.20557	49.06694	30.62268	65.96435	120.5229	144.8997	227.268	230.3153	233.1761

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1. Moran's I is the Chi-square test statistics computed using the spatial weighting matrix **W_cdt50_row**: all corresponding p-values < 0.000.

Table 7
Estimation results of SARAR model for *PV_cap*.

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
glob_rad	0.320^{a}	0.299^{a}	0.259^{a}	0.302^{a}	0.274^{a}	0.315^{a}	0.332^{a}	0.332^{a}	0.347^{a}	0.410^{a}
nrbuild	−0.112^{a}	−0.096^{a}	−0.038	−0.091^{a}	−0.064^{c}	−0.048	−0.077^{b}	−0.132^{a}	−0.063^{c}	−0.074^{b}
rbuild_sdf	−0.147	−0.009	0.074	−0.007	−0.152^{c}	−0.043	−0.048	−0.012	0.031	−0.018
rbuild_dens	−0.133^{a}	−0.146^{a}	−0.116^{a}	−0.153^{a}	−0.155^{a}	−0.133^{a}	−0.172^{a}	−0.232^{a}	−0.268^{a}	−0.293^{a}
ratio_res2wor					0.06	0.032	0.014	0.032	0.063^{b}	0.108^{a}
livestock	0.141^{b}	0.081	0.074	0.064	0.088	0.202^{a}	0.246^{a}	0.186^{a}	0.162^{a}	0.061
fGDR	−0.657^{a}	−0.153	−0.068	−0.296	−0.271	−0.564^{b}	−0.655^{a}	−0.771^{a}	−0.866^{a}	−0.670^{a}
low_edu	−0.108	0.063	−0.006	−0.049	−0.066	−0.033	0.001	−0.033	−0.033	−0.064
income	0.027	0.088	0.051	0.137	0.102	0.003	0.075	0.118	0.007	0.152
income2	−0.065	−0.102	−0.097	−0.162	−0.111	−0.02	−0.076	−0.13	−0.057	−0.185
pop_tot	0.088	0.210^{b}	0.165^{c}	0.159^{c}	0.024	0.161^{b}	0.170^{b}	0.172^{b}	0.155^{b}	0.072
pop_over75	−0.088^{c}	−0.076^{c}	−0.05	−0.097^{b}	−0.121^{b}	−0.079^{c}	−0.095^{b}	−0.121^{a}	−0.097^{b}	−0.126^{a}
pop_for	−0.250^{a}	−0.329^{a}	−0.209^{a}	−0.239^{a}	−0.239^{a}	−0.296^{a}	−0.333^{a}	−0.305^{a}	−0.290^{a}	−0.284^{a}
pop_minor	0.306^{a}	0.381^{a}	0.396^{a}	0.354^{a}	0.155^{b}	0.116^{c}	0.164^{a}	0.221^{a}	0.168^{a}	0.172^{a}
gdiff_emp					0.208^{a}	0.181^{a}	0.142^{a}	0.058^{c}	0.084^{b}	0.102^{a}
green_pol	0.025	−0.018	−0.036	−0.096^{c}	−0.006	−0.052	−0.098^{b}	−0.162^{a}	−0.130^{a}	−0.117^{a}
afd_pol										−0.074^{b}
nrbuild_hp										
ecars										
_cons	0.149^{a}	0.067	0.055	0.099	0.094	0.140^{a}	0.158^{a}	0.188^{a}	0.202^{a}	0.162^{a}
W: Wcdt50_pop_row										
λ	0.535^{a}	0.577^{a}	0.590^{a}	0.566^{a}	0.633^{a}	0.498^{a}	0.424^{a}	0.422^{a}	0.359^{a}	0.306^{a}
M: Wcdt50_row										
ρ	−0.013	−0.087	0.022	0.137	0.13	0.22	0.267^{c}	0.357^{a}	0.425^{a}	0.419^{a}
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R2	0.663	0.693	0.687	0.618	0.622	0.7	0.768	0.797	0.773	0.755
Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
glob_rad	0.409^{a}	0.438^{a}	0.350^{a}	0.310^{a}	0.345^{a}	0.324^{a}	0.321^{a}	0.261^{a}	0.215^{a}	0.158^{a}
nrbuild	−0.076^{b}	−0.028	0.008	0.046	0.053	0.079^{b}	0.061^{c}	0.065^{c}	0.094^{b}	0.083^{b}
rbuild_sdf	−0.069	−0.093	−0.210^{a}	−0.169^{b}	−0.207^{a}	−0.093	−0.119	−0.007	0.128^{c}	0.196^{a}
rbuild_dens	−0.288^{a}	−0.263^{a}	−0.172^{a}	−0.183^{a}	−0.195^{a}	−0.203^{a}	−0.181^{a}	−0.169^{a}	−0.123^{a}	−0.045
ratio_res2wor	0.114^{a}	0.101^{a}	0.077^{b}	0.027	0.047	0.065^{b}	0.041	0.05	0.03	0.072^{b}
livestock	0.045	−0.016	0.046	0.082^{b}	0.116^{a}	0.110^{a}	0.110^{a}	0.075^{b}	0.026	0.125^{a}
fGDR	−0.561^{a}	−0.678^{a}	−0.306	−0.653^{a}	−0.789^{a}	−0.598^{a}	−0.601^{a}	−0.420^{b}	−0.248	0.18
low_edu	−0.145^{b}	−0.245^{a}	−0.141^{b}	−0.141^{a}	−0.179^{a}	−0.118^{b}	−0.132^{b}	−0.148^{a}	−0.190^{a}	−0.137^{b}
income	0.195	0.267	0.363	0.318^{c}	0.213	0.035	0.209	0.002	0.194	0.351^{b}
income2	−0.201	−0.274	−0.321^{c}	−0.293^{c}	−0.231	−0.081	−0.228	−0.036	−0.218	−0.322^{b}
pop_tot	0.026	−0.094	−0.170^{b}	−0.086	−0.092	0.004	−0.014	0.017	0.041	0.07
pop_over75	−0.110^{b}	−0.141^{a}	−0.097^{c}	−0.135^{a}	−0.139^{a}	−0.096^{b}	−0.126^{a}	−0.129^{a}	−0.076^{b}	−0.006
pop_for	−0.240^{a}	−0.165^{b}	−0.219^{a}	−0.239^{a}	−0.276^{a}	−0.320^{a}	−0.353^{a}	−0.358^{a}	−0.315^{a}	−0.285^{a}
pop_minor	0.217^{a}	0.155^{a}	0.159^{a}	0.129^{a}	0.138^{a}	0.149^{a}	0.172^{a}	0.182^{a}	0.235^{a}	0.216^{a}
gdiff_emp	0.110^{a}	0.059	0.103^{a}	0.084^{b}	0.084^{b}	0.121^{a}	0.082^{b}	0.121^{a}	0.090^{b}	0.095^{b}
green_pol	−0.098^{c}	−0.132^{a}	−0.038	−0.091^{b}	−0.089^{c}	−0.046	−0.142^{a}	−0.155^{a}	−0.169^{a}	−0.103^{b}
afd_pol	−0.091^{b}	−0.092^{c}	−0.058	0.001	−0.015	−0.086^{c}	−0.131^{a}	−0.184^{a}	−0.246^{a}	−0.347^{a}
nrbuild_hp			0.166^{a}	0.171^{a}	0.123^{a}	0.119^{a}	0.118^{a}	0.083^{a}	0.059^{b}	0.086^{a}
ecars			0.068	0.054	0.056	0.064^{c}	0.099^{a}	0.175^{a}	0.167^{a}	0.097^{b}
_cons	0.143^{a}	0.157^{a}	0.083^{c}	0.146^{a}	0.175^{a}	0.142^{a}	0.139^{a}	0.113^{b}	0.084^{c}	0.011
W: Wcdt50_pop_row										
λ	0.372^{a}	0.357^{a}	0.388^{a}	0.406^{a}	0.400^{a}	0.414^{a}	0.394^{a}	0.408^{a}	0.396^{a}	0.480^{a}
M: Wcdt50_row										
ρ	0.353^{a}	0.298^{a}	0.126	−0.145	0.118	0.288^{a}	0.310^{a}	0.495^{a}	0.513^{a}	0.520^{a}
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R2	0.75	0.719	0.75	0.775	0.777	0.766	0.795	0.76	0.737	0.721

^{a} denotes a p-value < 0.01, ^{b} denotes a p-value < 0.05, ^{c} denotes a p-value < 0.1.

Table 8
Estimation results of SARAR model for *BES_cap*.

Variable	2013–14	2015	2016	2017	2018	2019	2020	2021	2022	2023
PV_cap	0.466[a]	0.655[a]	0.514[a]	0.669[a]	0.674[a]	0.585[a]	0.746[a]	0.819[a]	0.941[a]	1.045[a]
glob_rad	−0.093	−0.118[c]	0.082	0.011	0.082	0.151[a]	0.139[a]	0.022	0.016	−0.021
nrbuild	0.097[b]	0.015	−0.05	0.029	0.052	0.067[b]	−0.016	0.011	0.045	0.024
rbuild_sdf	−0.271[a]	−0.111	−0.025	−0.097	0.005	0.002	0.006	0.061	−0.014	−0.008
rbuild_dens	−0.043	−0.051	−0.088[c]	−0.03	−0.028	−0.045	−0.003	0.046[c]	0.056[c]	0.078[a]
ratio_res2wor	0.096[c]	0.049	−0.004	0.061[c]	0.03	0.057[b]	0.040[c]	0.017	0.013	0.007
livestock	−0.006	0.064	0.058	−0.026	−0.045	−0.081[b]	−0.089[a]	0	−0.029	−0.046[c]
fGDR	0.046	−0.449	−0.899[a]	−0.413[b]	−0.418[b]	0.041	0.121	0.053	0.223[c]	0.489[a]
low_edu	0.002	−0.064	−0.204[b]	−0.123[c]	−0.087	−0.026	−0.02	−0.032	−0.002	0.003
income	0.186	−0.075	0.018	0	0.238	0.418[a]	0.201	0.316[a]	0.480[a]	0.445[a]
income2	−0.138	0.099	−0.073	0.012	−0.219	−0.399[a]	−0.153	−0.219[b]	−0.373[a]	−0.359[a]
pop_tot	−0.196[b]	−0.066	0.079	−0.004	0.046	−0.014	0.001	0.056	−0.032	−0.044
pop_over75	−0.01	−0.024	−0.062	−0.03	0.002	0.083[b]	0.049	0.050[c]	0.025	0.062[b]
pop_for	−0.086	0.033	−0.105	−0.140[b]	−0.101	−0.101	−0.094[c]	−0.064	0.003	0.093[b]
pop_minor	0.125[b]	0.043	0.101[c]	0.054	0.091[b]	0.149[a]	0.142[a]	0.060[b]	0.031	0.035
gdiff_emp	0.004	−0.051	−0.069	−0.064[c]	−0.068[c]	−0.023	−0.067[b]	0.002	−0.017	−0.049[b]
green_pol	0.093	0.036	−0.127[b]	−0.047	−0.053	0.025	0.004	−0.023	0.026	0.014
afd_pol	0.116[b]	0.123	0.048	0.044	0.059	−0.001	−0.044	−0.002	0.04	−0.007
nrbuild_hp			0.015	0.015	0	0.008	−0.023	−0.01	−0.004	0.003
ecars			0.069	0.142[a]	0.105[a]	0.124[a]	0.067[b]	0.037	−0.029	0.003
_cons	0.022	0.097	0.177[a]	0.083[c]	0.079[c]	−0.001	−0.021	−0.009	−0.05	−0.099[a]
W: Wcdt50_pop_row										
λ	0.576[a]	0.259[b]	0.241[a]	0.162[b]	0.071	0.179[a]	0.133[b]	0.067	−0.034	−0.041
M: Wcdt50_row										
ρ	−0.103	0.11	0.197	0.108	0.263[c]	0.374[a]	0.491[a]	0.534[a]	0.523[a]	0.608[a]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R2	0.547	0.609	0.699	0.786	0.807	0.83	0.881	0.907	0.919	0.919

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1.

Appendix C. Robustness checks and out-of-sample validation

The multiple, year-specific regressions, which were run and reported above, are the first evidence of robust findings, as independent variables vary greatly over time, whereas the estimated coefficients are much slower to change. In order to further test the robustness of the results, additional model specifications were tested.

Firstly, the robustness to spatial weighting matrices was tested employing the alternative spatial matrix **Wc_row**, namely the row-normalized, queen-contiguity spatial matrix. **Wc_row** is a simpler and far more common spatial weighting matrix, in which only contiguous spatial units are considered to be neighbors, whereas neither distance nor population size affect weights (i.e., all non-zero weights are equal to 1 before row-normalization). This matrix was used to assign weight to both the spatial lags of the dependent variable and the spatial lags of the errors. The results of the SARAR2 with this alternative spatial matrix (see Table 9) demonstrate that the estimated coefficients were largely similar to those of Table 2: the most notable difference concerns the autoregressive coefficients λ, whose magnitude appeared to be lower when population- and distance-based weighting was not applied. Similarly, for S-BES diffusion, the alternative specification with **Wc_row** yields very similar results (cf. Tables 3 and 10).

Secondly, since similar studies limited the scope of their analysis to smaller PV systems (e.g., up to 10 kW_p in Dharshing, 2017; Baginski and Weber, 2019), the robustness of the results to the cutoff in terms of SBI-PV system size was also analyzed. Table 11 reports the estimation results for SBI-PV installations up to 10 kW_p: while the coefficients are generally quite similar to those of Table 2, the lower magnitude of the coefficient *livestock* and the higher magnitude of the coefficient of *rbuild_sdf* highlight the lesser relevance of farm-related installations and the higher relevance of residential installations on STFH, respectively. A SBI-PV size cutoff at 100 kW_p was also considered, finding, conversely, a higher magnitude of the coefficient *livestock* and a lower magnitude of the coefficient of *rbuild_sdf* (see Table 12).

The *Pseudo-R^2* reported in all the regression tables allows for comparing the goodness of fit of all the different SARAR2 models' specifications: while the SBI-PV size cutoff at 30 kW_p performs best among the alternative thresholds considered, the **Wc_row** spatial weighting performs very similarly to the preferred spatial weighting based on inverse distance and population size.

Such *pseudo-R^2* scores computed by Stata consist of the squared correlation between the dependent variable (i.e., ***PV_cap***) and its reduced-form[40] prediction, namely the prediction based on the independent variables X and the spatial weighting matrices W and M, as well as the estimates of λ and β parameters (see Eq. (5)) (Drukker et al., 2013b).

$$\hat{Y}_t = (I - \hat{\lambda}_t \mathbf{W}_t)^{-1} \mathbf{X} \hat{\beta} \tag{5}$$

In addition to *pseudo-R^2* statistics based on in-sample predictions, the model was further validated by estimating out-of-sample predictions. The spatial model is endogenous by design, which is why out-of-sample predictions represent a challenge: following global spillover effects, technology deployment in each of the 400 spatial units is affected by technology deployment in the other 399 spatial units. In order to estimate out-of-sample predictions, the following approach was therefore implemented:

1. The sample was divided randomly in 20 sub-samples, each of them containing 20 observations.
2. For each of the 20 sub-samples, the 20 "selected" observations were replaced by mean values (in the case of both endogenous and exogenous variables), such means were calculated over the whole sample.
3. For each of the 20 sub-samples, 20 separate SARAR2 models were estimated using the 380 "true" observations and the 20 "fictive" observations with mean values.

[40] The best predictor is however the full-information predictor described in Kelejian and Prucha (2007). The full-information prediction is conditional on the independent variables, on the spatial weighting matrix and on the dependent-variable values of all the other spatial units. While the full-information predictor produces more accurate fitted values, the reduced-form predictor is more relevant to assess the forecasting potential of the model, as its computation does no rely on the observed dependent variable.

Table 9
Estimation results for *PV_cap* with spatial weighting matrix Wc_row.

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
$\hat{\epsilon}_{04}$		0.732^{a}	0.529^{a}	0.657^{a}	0.612^{a}	0.602^{a}	0.573^{a}	0.455^{a}	0.470^{a}	0.412^{a}
$\hat{\eta}_{t-1}$		0	0.837^{a}	0.553^{a}	0.776^{a}	0.414^{a}	0.784^{a}	0.760^{a}	0.893^{a}	0.890^{a}
glob_rad	0.352^{a}	0.298^{a}	0.284^{a}	0.331^{a}	0.349^{a}	0.298^{a}	0.307^{a}	0.324^{a}	0.327^{a}	0.378^{a}
nrbuild	−0.109^{a}	−0.066^{a}	−0.004	−0.054^{a}	−0.068^{a}	−0.045^{b}	−0.052^{a}	−0.054^{b}	−0.018	−0.027
rbuild_sdf	−0.126	0.084^{c}	0.168^{a}	0.100^{c}	−0.012	0.052	0.048	0.095^{c}	0.133^{a}	0.044
rbuild_dens	−0.122^{b}	−0.122^{a}	−0.104^{a}	−0.145^{a}	−0.145^{a}	−0.119^{a}	−0.159^{a}	−0.210^{a}	−0.233^{a}	−0.262^{a}
ratio_res2wor					0.034	0.031	0.013	0.018	0.050^{a}	0.098^{a}
livestock	0.185^{b}	0.126^{a}	0.128^{a}	0.117^{a}	0.147^{a}	0.242^{a}	0.278^{a}	0.239^{a}	0.212^{a}	0.123^{a}
fGDR	−0.620^{b}	−0.191	−0.147	−0.446^{b}	−0.479^{a}	−0.585^{a}	−0.651^{a}	−0.864^{a}	−0.913^{a}	−0.710^{a}
low_edu	−0.097	0.084^{c}	0.018	−0.035	−0.032	−0.022	0.019	−0.001	−0.008	−0.018
income	0.178	0.037	0.057	0.076	0.142^{c}	0.041	0.051	0.048	−0.02	0.145
income2	−0.233	−0.091	−0.143^{c}	−0.153^{c}	−0.200^{a}	−0.087	−0.087^{c}	−0.104	−0.07	−0.193
pop_tot	0.107	0.283^{a}	0.246^{a}	0.242^{a}	0.148^{a}	0.244^{a}	0.246^{a}	0.246^{a}	0.234^{a}	0.127^{b}
pop_over75	−0.052	−0.035	−0.001	−0.057	−0.076^{a}	−0.043^{c}	−0.056^{a}	−0.082^{a}	−0.062^{a}	−0.106^{a}
pop_for	−0.237^{a}	−0.303^{a}	−0.185^{a}	−0.206^{a}	−0.230^{a}	−0.249^{a}	−0.283^{a}	−0.278^{a}	−0.249^{a}	−0.272^{a}
pop_minor	0.286^{a}	0.320^{a}	0.330^{a}	0.267^{a}	0.149^{a}	0.107^{a}	0.142^{a}	0.142^{a}	0.109^{a}	0.094^{b}
gdiff_emp					0.086^{a}	0.123^{a}	0.095^{a}	0.041^{c}	0.060^{a}	0.100^{a}
green_pol	0.032	−0.007	−0.021	−0.087^{b}	−0.05	−0.061^{c}	−0.096^{a}	−0.148^{a}	−0.128^{a}	−0.105^{a}
afd_pol										−0.03
nrbuild_hp										
ecars										
_cons	0.078	−0.011	−0.026	0.045	0.053^{c}	0.06	0.077^{a}	0.124^{a}	0.133^{a}	0.097^{b}
W: Wc_row										
$\hat{\epsilon}_{04}$		0.075	0.125	0.301^{a}	0.368^{a}	0.219^{b}	0.186^{a}	0.320^{a}	0.343^{a}	0.307^{a}
$\hat{\eta}_{t-1}$		0	0.141	0.217^{c}	0.419^{a}	0.243	0.351^{a}	0.400^{b}	0.597^{a}	0.314^{b}
λ	0.376^{a}	0.483^{a}	0.450^{a}	0.390^{a}	0.375^{a}	0.395^{a}	0.361^{a}	0.298^{a}	0.283^{a}	0.255^{a}
M: Wc_row										
ρ	0.297*	−0.068	0.008	0.148	0.087	0.329^{b}	0.228^{b}	0.413^{a}	0.146^{c}	0.317^{a}
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.664	0.874	0.879	0.827	0.914	0.869	0.958	0.903	0.931	0.869

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{04}$	0.430^{a}	0.267^{a}	0.309^{a}	0.351^{a}	0.401^{a}	0.318^{a}	0.301^{a}	0.211^{a}	0.093^{a}	0.043
$\hat{\eta}_{t-1}$	0.719^{a}	0.708^{a}	0.570^{a}	0.593^{a}	0.583^{a}	0.733^{a}	0.730^{a}	0.784^{a}	0.921^{a}	0.715^{a}
glob_rad	0.410^{a}	0.384^{a}	0.379^{a}	0.338^{a}	0.391^{a}	0.366^{a}	0.305^{a}	0.278^{a}	0.190^{a}	0.143^{a}
nrbuild	−0.035	−0.042	0.028	0.038	0.027	0.057^{b}	0.019	0.050^{c}	0.090^{a}	0.089^{a}
rbuild_sdf	−0.014	−0.049	−0.138^{b}	−0.107	−0.120^{b}	−0.036	−0.074	0.011	0.108^{b}	0.149^{b}
rbuild_dens	−0.260^{a}	−0.225^{a}	−0.191^{a}	−0.169^{a}	−0.180^{a}	−0.178^{a}	−0.160^{a}	−0.147^{a}	−0.099^{a}	−0.03
ratio_res2wor	0.101^{a}	0.104^{a}	0.073^{b}	0.008	0.03	0.036	0.036^{c}	0.033	0.017	0.059^{b}
livestock	0.091^{a}	0.021	0.057^{c}	0.127^{a}	0.161^{a}	0.165^{a}	0.147^{a}	0.122^{a}	0.080^{b}	0.171^{a}
fGDR	−0.511^{a}	−0.462^{b}	−0.333^{b}	−0.549^{a}	−0.676^{a}	−0.536^{a}	−0.491^{a}	−0.375^{a}	−0.181	0.159
low_edu	−0.090^{c}	−0.185^{a}	−0.103^{b}	−0.087^{b}	−0.132^{a}	−0.084^{c}	−0.076^{c}	−0.104^{b}	−0.122^{a}	−0.069
income	0.271^{b}	0.316^{c}	0.358^{c}	0.369^{a}	0.297^{b}	0.07	0.259^{b}	0.104	0.285^{b}	0.430^{a}
income2	−0.288^{a}	−0.323^{c}	−0.324^{c}	−0.350^{a}	−0.323^{a}	−0.117	−0.263^{a}	−0.132	−0.295^{b}	−0.386^{a}
pop_tot	0.08	−0.042	−0.091	−0.031	−0.016	0.056	0.04	0.06	0.079^{c}	0.093
pop_over75	−0.071^{b}	−0.105^{b}	−0.054	−0.114^{a}	−0.106^{a}	−0.079^{a}	−0.110^{a}	−0.110^{a}	−0.051^{b}	0.002
pop_for	−0.238^{a}	−0.155^{b}	−0.205^{a}	−0.239^{a}	−0.279^{a}	−0.323^{a}	−0.366^{a}	−0.370^{a}	−0.343^{a}	−0.323^{a}
pop_minor	0.144^{a}	0.136^{a}	0.123^{a}	0.113^{a}	0.117^{a}	0.123^{a}	0.150^{a}	0.141^{a}	0.205^{a}	0.175^{a}
gdiff_emp	0.111^{a}	0.058^{c}	0.103^{a}	0.064^{b}	0.075^{a}	0.114^{a}	0.061^{b}	0.119^{a}	0.086^{a}	0.110^{a}
green_pol	−0.081^{b}	−0.097^{b}	−0.004	−0.039	−0.035	−0.012	−0.122^{a}	−0.168^{a}	−0.163^{a}	−0.092^{b}
afd_pol	−0.086^{a}	−0.098^{b}	−0.062	−0.003	−0.028	−0.094^{b}	−0.127^{a}	−0.190^{a}	−0.208^{a}	−0.272^{a}
nrbuild_hp			0.112^{a}	0.165^{a}	0.101^{a}	0.108^{a}	0.087^{a}	0.074^{a}	0.082^{a}	0.104^{a}
ecars			0.002	0.004	0.021	0.023	0.075^{a}	0.172^{a}	0.162^{a}	0.089^{a}
_cons	0.057^{c}	0.034	0.017	0.061^{c}	0.087^{a}	0.055	0.033	0.021	−0.03	−0.108^{a}
W: Wc_row										
$\hat{\epsilon}_{04}$	0.247^{a}	0.184	0.144^{b}	0.266^{a}	0.244^{a}	0.327^{a}	0.201^{a}	0.140^{b}	0.159^{a}	0.091
$\hat{\eta}_{t-1}$	0.571^{a}	0.280^{c}	0.319^{b}	−0.046	0.290^{b}	0.433^{a}	0.289^{a}	0.729^{a}	0.467^{a}	0.865^{a}
λ	0.298^{a}	0.389^{a}	0.345^{a}	0.325^{a}	0.304^{a}	0.295^{a}	0.385^{a}	0.314^{a}	0.368^{a}	0.433^{a}
M: Wc_row										
ρ	0.023	−0.062	−0.031	−0.199^{b}	−0.028	0.127^{c}	0.230^{b}	0.399^{a}	0.385^{a}	0.139^{c}
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.899	0.815	0.846	0.869	0.884	0.895	0.902	0.876	0.875	0.861

^{a} denotes a p-value < 0.01, ^{b} denotes a p-value < 0.05, ^{c} denotes a p-value < 0.1.

4. For each of the 20 sub-samples, the "fictive" mean values were re-replaced with the original "true" values; after which a reduced-form prediction was computed based on the estimated coefficients derived in 3, in which 380 "true" observations and 20 "fictive" observations were used.
5. The 20 out-of-sample predictions for each of the 20 model's run were grouped in a new variable containing the 400 out-of-sample predictions.

The same approach was implemented with fewer and therefore larger sub-sample sizes (i.e., 80 and 200 observations). Table 13 reports the computed correlations between the observed dependent variables and their reduced-form predictions both in-sample and out-of-sample. Even with two random sub-samples of 200 observations — i.e., half of the observations with a "fictive" mean values — the out-of-sample prediction performs very well, especially in the case of BES, for which endogenous spillover effects play a lesser role.

Table 10
Estimation results for *BES_cap* with spatial weighting matrix Wc_row.

Variable	2013–14	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{14}$		0.375[c]	0.224[c]	0.195[c]	0.170[c]	0.146[c]	0.122[c]	0.082[c]	0.083[c]	0.081[c]
$\hat{\eta}_{t-1}$		0	0.336[c]	0.276[c]	0.502[c]	0.461[c]	0.472[c]	0.634[c]	0.734[c]	0.616[c]
PV_cap	0.464[c]	0.560[c]	0.493[c]	0.631[c]	0.694[c]	0.629[c]	0.736[c]	0.838[c]	0.913[c]	1.058[c]
glob_rad	−0.098[c]	−0.111[b]	0.046	−0.019	0.01	0.100[b]	0.076[b]	−0.015	0.002	−0.026
nrbuild	0.079[c]	−0.004	−0.053	0.012	0.044	0.035	−0.01	−0.011	0.044[b]	0.018
rbuild_sdf	−0.223[b]	−0.083	−0.009	−0.1	0.01	−0.009	−0.033	0.038	−0.039	−0.044
rbuild_dens	−0.026	−0.058	−0.057	−0.021	0	−0.024	0.011	0.051[b]	0.048[b]	0.068[c]
ratio_res2wor	0.087[c]	0.068[c]	−0.002	0.070[b]	0.042	0.073[c]	0.056[c]	0.038[b]	0.026[c]	0.026[c]
livestock	0.029	0.078[c]	0.075[c]	−0.02	−0.047[c]	−0.074[c]	−0.085[c]	0.001	−0.036[c]	−0.054[b]
fGDR	0.121	−0.427[c]	−0.808[c]	−0.324[c]	−0.304[c]	0.199	0.111	0.112	0.186[c]	0.494[c]
low_edu	0.044	−0.05	−0.155[b]	−0.104[c]	−0.056	0.009	−0.018	−0.023	−0.013	0.002
income	0.329	−0.027	−0.013	0.033	0.262[c]	0.484[c]	0.145	0.261[c]	0.481[c]	0.416[c]
income2	−0.288	0.047	−0.031	−0.007	−0.221	−0.439[c]	−0.089	−0.163[c]	−0.368[c]	−0.333[c]
pop_tot	−0.131	−0.026	0.091	0.008	0.037	−0.037	−0.028	0.038	−0.05	−0.071[b]
pop_over75	0.027	−0.036	−0.064	−0.016	−0.019	0.098[c]	0.038	0.047[b]	0.022	0.072[c]
pop_for	−0.095	0.018	−0.127[c]	−0.145[c]	−0.089	−0.075	−0.095[b]	−0.06	−0.011	0.097[c]
pop_minor	0.087	0.034	0.075	0.063[c]	0.067[b]	0.137[c]	0.125[c]	0.061[c]	0.046[b]	0.056[c]
gdiff_emp	0.017	−0.051	−0.072[c]	−0.053[c]	−0.076[b]	−0.025	−0.060[b]	−0.004	−0.022	−0.050[b]
green_pol	0.115[b]	0.017	−0.115[b]	−0.028	−0.042	0.049	0.019	−0.016	0.019	0.035
afd_pol	0.129[c]	0.115[c]	0.057	0.043	0.085[b]	0.013	−0.005	0.013	0.04	0.012
nrbuild_hp			0.029	0.013	−0.016	−0.014	−0.026	−0.02	−0.006	−0.002
ecars			0.056	0.104[b]	0.084[c]	0.114[c]	0.062[c]	0.046[b]	−0.034	0.001
_cons	−0.073	0.047	0.121[b]	0.038	0.038	−0.069[c]	−0.049[c]	−0.043	−0.042	−0.095[c]
W: Wc_row										
$\hat{\epsilon}_{14}$		−0.014	0.067	−0.153[b]	0.085	0.134[c]	0.035	0.071[c]	0.053	0.033
$\hat{\eta}_{t-1}$		0	0.039	0.034	0.086	0.272[b]	0.164	0.333[c]	0.425[c]	0.407[c]
λ	0.543[c]	0.351[c]	0.293[c]	0.250[c]	0.149[c]	0.214[c]	0.206[c]	0.133[c]	0.029	−0.007
M: Wc_row										
ρ	−0.224[c]	−0.163	−0.023	0.031	0.041	0.063	0.286[b]	0.334[c]	0.378[c]	0.485[c]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.56	0.678	0.77	0.821	0.867	0.881	0.922	0.946	0.948	0.944

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1.

Table 11
Estimation results for *PV_cap_u10* (SBI-PV installations up to 10 kW_p)

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
$\hat{\epsilon}_{04}$		0.666[a]	0.410[a]	0.399[a]	0.433[a]	0.504[a]	0.442[a]	0.342[a]	0.328[a]	0.289[a]
$\hat{\eta}_{t-1}$		0	0.830[a]	0.571[a]	0.620[a]	0.450[a]	0.674[a]	0.506[a]	0.823[a]	0.758[a]
glob_rad	0.260[a]	0.204[a]	0.186[a]	0.238[a]	0.268[a]	0.305[a]	0.306[a]	0.343[a]	0.307[a]	0.345[a]
nrbuild	−0.136[a]	−0.081[a]	−0.016	−0.023	−0.041[c]	−0.037[c]	−0.069[a]	−0.066[b]	−0.044[b]	−0.067[b]
rbuild_sdf	−0.150[c]	0.039	0.121[b]	0.079	0.107[c]	0.175[a]	0.142[a]	0.157[b]	0.121[b]	0.025
rbuild_dens	−0.112[b]	−0.103[a]	−0.084[a]	−0.102[a]	−0.099[a]	−0.108[a]	−0.176[a]	−0.162[a]	−0.202[a]	−0.254[a]
ratio_res2wor					0.045	0.021	0.034	0.014	0.055[b]	0.106[a]
livestock	0.051	−0.058[b]	−0.127[a]	−0.156[a]	−0.109[a]	−0.03	−0.034	0.032	0.001	−0.018
fGDR	−0.481[b]	0.005	0.028	0.043	−0.066	−0.246[c]	−0.475[a]	−0.858[a]	−1.065[a]	−0.736[a]
low_edu	−0.086	0.066	−0.009	−0.041	−0.018	−0.025	−0.065[c]	−0.084	−0.165[a]	−0.130[a]
income	0.005	0.021	0.043	0.119	0.13	0.193	0.249[b]	0.137	0.071	0.125
income2	−0.013	−0.02	−0.088	−0.186	−0.202[c]	−0.217[c]	−0.269[a]	−0.175[c]	−0.137	−0.177
pop_tot	0.062	0.179[a]	0.110[a]	0.021	0.091[c]	0.200[a]	0.198[a]	0.182[a]	0.102[b]	0.031
pop_over75	−0.103[b]	−0.084[b]	−0.077[a]	−0.099[a]	−0.107[a]	−0.026	−0.036	−0.078[b]	−0.095[a]	−0.147[a]
pop_for	−0.274[a]	−0.332[a]	−0.230[a]	−0.215[a]	−0.235[a]	−0.259[a]	−0.264[a]	−0.264[a]	−0.191[a]	−0.240[a]
pop_minor	0.321[a]	0.379[a]	0.379[a]	0.391[a]	0.296[a]	0.256[a]	0.319[a]	0.260[a]	0.213[a]	0.227[a]
gdiff_emp					0.059[c]	0.106[a]	0.094[a]	−0.004	−0.012	0.056[c]
green_pol	0.041	−0.007	−0.014	−0.018	−0.061[c]	−0.064[c]	−0.096[a]	−0.190[a]	−0.228[a]	−0.164[a]
afd_pol										−0.034
nrbuild_hp										
ecars										
_cons	0.118[a]	0.053	0.037	0.038	0.061	0.095[a]	0.139[a]	0.208[a]	0.251[a]	0.179[a]
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$		−0.194[c]	−0.097	0.061	0.054	−0.099	−0.216[a]	0.093	0.036	0.124
$\hat{\eta}_{t-1}$		0	−0.025	0.159	0.228[b]	−0.002	0.621[a]	−0.12	0.228[c]	0.187
λ	0.667[a]	0.745[a]	0.714[a]	0.672[a]	0.671[a]	0.568[a]	0.510[a]	0.440[a]	0.454[a]	0.383[a]
M: Wcdt50_row										
ρ	−0.241	−0.287[b]	−0.300[a]	−0.058	−0.133	0.245[c]	−0.042	0.219[b]	−0.084	0.265[b]
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.696	0.774	0.854	0.736	0.848	0.828	0.907	0.839	0.909	0.816

(*continued on next page*)

Table 11 (*continued*).

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{04}$	0.381^{a}	0.255^{a}	0.275^{a}	0.270^{a}	0.275^{a}	0.228^{a}	0.248^{a}	0.136^{a}	0.081	−0.064
$\hat{\eta}_{t-1}$	0.667^{a}	0.682^{a}	0.534^{a}	0.623^{a}	0.654^{a}	0.688^{a}	0.754^{a}	0.762^{a}	0.802^{a}	0.603^{a}
glob_rad	0.361^{a}	0.399^{a}	0.365^{a}	0.365^{a}	0.415^{a}	0.330^{a}	0.324^{a}	0.297^{a}	0.141^{a}	0.090^{b}
nrbuild	−0.047^{c}	−0.01	0.046^{c}	0.032	0.017	0.059^{b}	0.049^{b}	0.025	0.079^{b}	0.114^{a}
rbuild_sdf	−0.051	−0.081	−0.196^{a}	−0.156^{a}	−0.154^{a}	−0.093	−0.041	0.092	0.163^{a}	0.238^{a}
rbuild_dens	−0.290^{a}	−0.241^{a}	−0.192^{a}	−0.171^{a}	−0.167^{a}	−0.144^{a}	−0.109^{a}	−0.111^{a}	−0.045	0.047
ratio_res2wor	0.144^{a}	0.135^{a}	0.116^{a}	0.053^{c}	0.093^{a}	0.102^{a}	0.069^{a}	0.065^{a}	0.041	0.03
livestock	−0.052^{b}	−0.068^{b}	−0.021	0.019	0.026	0.031	0.039	0	0.015	0.089^{a}
fGDR	−0.538^{a}	−0.639^{a}	−0.392^{a}	−0.392^{a}	−0.519^{a}	−0.174	−0.334^{b}	−0.02	0.131	0.621^{a}
low_edu	−0.215^{a}	−0.256^{a}	−0.199^{a}	−0.153^{a}	−0.164^{a}	−0.114^{a}	−0.149^{a}	−0.181^{a}	−0.220^{a}	−0.257^{a}
income	0.207	0.232	0.207	0.302^{b}	0.256^{c}	0.228^{c}	0.144	0.211	0.453^{b}	0.823^{a}
income2	−0.195	−0.209	−0.204	−0.279^{b}	−0.270^{b}	−0.239^{b}	−0.146	−0.197	−0.445^{b}	−0.742^{a}
pop_tot	−0.065	−0.108	−0.190^{a}	−0.137^{b}	−0.112^{b}	−0.088	−0.031	−0.012	0.011	−0.031
pop_over75	−0.105^{a}	−0.115^{a}	−0.079^{c}	−0.124^{a}	−0.111^{a}	−0.050^{c}	−0.098^{a}	−0.083^{b}	−0.059^{c}	0.048
pop_for	−0.147^{a}	−0.149^{b}	−0.179^{a}	−0.265^{a}	−0.314^{a}	−0.327^{a}	−0.365^{a}	−0.360^{a}	−0.264^{a}	−0.233^{a}
pop_minor	0.222^{a}	0.189^{a}	0.201^{a}	0.179^{a}	0.193^{a}	0.212^{a}	0.206^{a}	0.249^{a}	0.265^{a}	0.278^{a}
gdiff_emp	0.056^{c}	0.033	0.068^{b}	0.081^{a}	0.054^{b}	0.091^{a}	0.067^{b}	0.105^{a}	0.067^{c}	0.117^{a}
green_pol	−0.109^{a}	−0.142^{a}	−0.064	−0.03	−0.073	−0.011	−0.108^{a}	−0.092^{c}	−0.146^{a}	0.01
afd_pol	−0.092^{a}	−0.110^{b}	−0.111^{a}	−0.072^{b}	−0.098^{a}	−0.173^{a}	−0.208^{a}	−0.227^{a}	−0.254^{a}	−0.398^{a}
nrbuild_hp			0.130^{a}	0.157^{a}	0.088^{a}	0.126^{a}	0.088^{a}	0.061^{b}	0.072^{a}	0.071^{b}
ecars			0.046	0.052^{c}	0.079^{b}	0.074^{a}	0.076^{a}	0.138^{a}	0.123^{a}	0.037
_cons	0.146^{a}	0.146^{a}	0.105^{a}	0.094^{a}	0.125^{a}	0.069^{c}	0.098^{a}	0.053	0.033	−0.072^{c}
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$	*0.084*	0.021	−0.047	0.037	−0.008	0.023	−0.097	−0.105	−0.103	−0.02
$\hat{\eta}_{t-1}$	*0.384*^{a}	0.429^{b}	0.419^{a}	0.075	0.351^{b}	0.404^{a}	0.378^{a}	0.768^{a}	0.464^{a}	0.782^{a}
λ	0.432^{a}	0.395^{a}	0.421^{a}	0.383^{a}	0.404^{a}	0.483^{a}	0.474^{a}	0.455^{a}	0.556^{a}	0.483^{a}
M: Wcdt50_row										
ρ	0.121	0.121	0.043	−0.026	0.031	0.193^{b}	0.293^{a}	0.322^{a}	0.207^{c}	0.233^{a}
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.871	0.81	0.842	0.87	0.877	0.87	0.877	0.838	0.801	0.771

^{a} denotes a p-value < 0.01, ^{b} denotes a p-value < 0.05, ^{c} denotes a p-value < 0.1.

Table 12
Estimation results for *PV_cap_u100* (SBI-PV installations up to 100 kW_p).

Variable	2000–04	2005	2006	2007	2008	2009	2010	2011	2012	2013
$\hat{\epsilon}_{04}$		0.745^{a}	0.512^{a}	0.642^{a}	0.629^{a}	0.601^{a}	0.527^{a}	0.444^{a}	0.462^{a}	0.379^{a}
$\hat{\eta}_{t-1}$		0	0.803^{a}	0.590^{a}	0.722^{a}	0.405^{a}	0.780^{a}	0.669^{a}	0.868^{a}	0.874^{a}
glob_rad	0.337^{a}	0.295^{a}	0.235^{a}	0.278^{a}	0.310^{a}	0.309^{a}	0.286^{a}	0.319^{a}	0.327^{a}	0.351^{a}
nrbuild	−0.105^{a}	−0.070^{a}	0	−0.053^{a}	−0.061^{a}	−0.029	−0.044^{b}	−0.049^{b}	−0.012	−0.024
rbuild_sdf	−0.144	0.01	0.136^{b}	0.038	−0.082^{c}	0.022	0.042	0.089^{c}	0.100^{b}	−0.004
rbuild_dens	−0.135^{a}	−0.140^{a}	−0.084^{a}	−0.144^{a}	−0.151^{a}	−0.112^{a}	−0.146^{a}	−0.186^{a}	−0.224^{a}	−0.236^{a}
ratio_res2wor					0.042^{c}	0.009	−0.018	−0.009	0.027	0.081^{a}
livestock	0.157^{b}	0.113^{a}	0.102^{a}	0.083^{a}	0.127^{a}	0.290^{a}	0.317^{a}	0.287^{a}	0.251^{a}	0.129^{a}
fGDR	−0.752^{a}	−0.262^{b}	−0.059	−0.325	−0.372^{a}	−0.748^{a}	−0.734^{a}	−0.792^{a}	−0.864^{a}	−0.595^{a}
low_edu	−0.122^{c}	0.025	−0.007	−0.071	−0.063^{c}	−0.074	−0.036	−0.027	−0.041	−0.027
income	−0.005	0.031	0.009	0.023	0.05	−0.07	0.033	0.072	0.054	0.196
income2	−0.054	−0.065	−0.078	−0.081	−0.092	0.028	−0.057	−0.118^{c}	−0.128	−0.211^{c}
pop_tot	0.079	0.184^{a}	0.192^{a}	0.144^{b}	0.053	0.210^{a}	0.220^{a}	0.233^{a}	0.215^{a}	0.07
pop_over75	−0.092^{c}	−0.073^{a}	−0.021	−0.099^{a}	−0.114^{a}	−0.058^{b}	−0.071^{a}	−0.089^{a}	−0.068^{a}	−0.110^{a}
pop_for	−0.243^{a}	−0.269^{a}	−0.160^{a}	−0.154^{a}	−0.186^{a}	−0.252^{a}	−0.257^{a}	−0.265^{a}	−0.254^{a}	−0.262^{a}
pop_minor	0.283^{a}	0.321^{a}	0.342^{a}	0.306^{a}	0.193^{a}	0.150^{a}	0.196^{a}	0.205^{a}	0.169^{a}	0.163^{a}
gdiff_emp					0.085^{a}	0.113^{a}	0.072^{a}	0.039^{c}	0.057^{a}	0.065^{b}
green_pol	0.031	−0.016	−0.024	−0.095^{b}	−0.058^{b}	−0.098^{a}	−0.149^{a}	−0.175^{a}	−0.154^{a}	−0.124^{a}
afd_pol										−0.022
nrbuild_hp										
ecars										
_cons	0.165^{a}	0.090^{a}	0.059^{c}	0.104^{b}	0.114^{a}	0.176^{a}	0.178^{a}	0.184^{a}	0.202^{a}	0.152^{a}
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$		−0.109	−0.125	0.074	0.084	−0.131	−0.168^{a}	0.05	0.082	0.08
$\hat{\eta}_{t-1}$		0	−0.03	0.302^{c}	0.412^{a}	0.092	0.334^{a}	0.412^{c}	0.253^{c}	0.642^{a}
λ	0.503^{a}	0.581^{a}	0.633^{a}	0.586^{a}	0.573^{a}	0.449^{a}	0.418^{a}	0.359^{a}	0.335^{a}	0.386^{a}
M: Wcdt50_row										
ρ	0.042	−0.148	−0.144	−0.053	−0.084	0.290^{b}	0.054	0.246^{b}	0.280^{a}	0.01
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.658	0.885	0.872	0.837	0.916	0.892	0.958	0.92	0.924	0.877

(*continued on next page*)

Table 12 (*continued*).

Variable	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
$\hat{\epsilon}_{04}$	0.368[a]	0.183[a]	0.345[a]	0.414[a]	0.430[a]	0.377[a]	0.312[a]	0.228[a]	0.113[a]	0.072[b]
$\hat{\eta}_{t-1}$	0.728[a]	0.492[a]	0.385[a]	0.430[a]	0.628[a]	0.651[a]	0.677[a]	0.649[a]	0.785[a]	0.620[a]
glob_rad	0.338[a]	0.381[a]	0.320[a]	0.289[a]	0.308[a]	0.255[a]	0.257[a]	0.223[a]	0.158[a]	0.134[a]
nrbuild	−0.048[c]	−0.008	−0.015	0.032	0	0.006	0.031	0.049[c]	0.067[b]	0.082[a]
rbuild_sdf	0.027	−0.028	−0.091	−0.138[c]	−0.182[a]	−0.04	−0.069	−0.018	0.112[b]	0.143[b]
rbuild_dens	−0.228[a]	−0.233[a]	−0.175[a]	−0.167[a]	−0.175[a]	−0.117[a]	−0.125[a]	−0.107[a]	−0.075[b]	−0.028
ratio_res2wor	0.075[a]	0.043	0.007	−0.012	−0.004	0.013	0.017	0.033	0.001	0.042
livestock	0.084[a]	0.047	0.052	0.159[a]	0.204[a]	0.254[a]	0.192[a]	0.126[a]	0.070[a]	0.149[a]
fGDR	−0.417[a]	−0.476[b]	−0.142	−0.515[a]	−0.558[a]	−0.314[b]	−0.307[b]	−0.441[a]	−0.254[c]	0.224
low_edu	−0.087[c]	−0.150[b]	−0.106[c]	−0.130[a]	−0.170[a]	−0.099[b]	−0.113[b]	−0.152[a]	−0.168[a]	−0.120[a]
income	0.303[b]	0.173	0.575[a]	0.253	0.275[b]	0.132	0.196	0.068	0.293[b]	0.524[a]
income2	−0.299[a]	−0.147	−0.520[a]	−0.256[c]	−0.269[b]	−0.161	−0.212[c]	−0.098	−0.315[b]	−0.477[a]
pop_tot	0.120[b]	−0.072	−0.092	−0.018	−0.071	0.056	0.057	0.049	0.085	0.067
pop_over75	−0.073[b]	−0.106[b]	−0.081[c]	−0.162[a]	−0.167[a]	−0.133[a]	−0.130[a]	−0.135[a]	−0.052[c]	−0.014
pop_for	−0.201[a]	−0.134[b]	−0.125[b]	−0.236[a]	−0.235[a]	−0.274[a]	−0.304[a]	−0.337[a]	−0.306[a]	−0.269[a]
pop_minor	0.191[a]	0.113[b]	0.150[a]	0.116[a]	0.111[a]	0.133[a]	0.159[a]	0.153[a]	0.257[a]	0.225[a]
gdiff_emp	0.076[b]	0.031	0.044	0.091[a]	0.087[a]	0.084[b]	0.076[a]	0.109[a]	0.061[b]	0.066[b]
green_pol	−0.096[b]	−0.076[c]	−0.035	−0.048	−0.080[b]	−0.059	−0.150[a]	−0.182[a]	−0.180[a]	−0.125[a]
afd_pol	−0.075[b]	−0.077	−0.084[c]	−0.037	−0.061[c]	−0.102[b]	−0.176[a]	−0.159[a]	−0.198[a]	−0.312[a]
nrbuild_hp			0.121[a]	0.159[a]	0.104[a]	0.100[a]	0.096[a]	0.069[a]	0.073[a]	0.090[a]
ecars			−0.046	−0.023	−0.025	−0.006	0.048[c]	0.157[a]	0.159[a]	0.097[a]
_cons	0.131[a]	0.134[a]	0.066[c]	0.125[a]	0.142[a]	0.099[a]	0.094[a]	0.123[a]	0.100[a]	0.014
W: Wcdt50_pop_row										
$\hat{\epsilon}_{04}$	*−0.014*	0.248	−0.119	0.024	−0.066	−0.021	−0.084	−0.207[b]	−0.164[b]	−0.046
$\hat{\eta}_{t-1}$	*0.354*[b]	0.880[a]	0.295[b]	−0.212	0.246[b]	0.127	0.129	0.674[a]	0.319[b]	0.785[a]
λ	0.491[a]	0.426[a]	0.503[a]	0.462[a]	0.473[a]	0.531[a]	0.520[a]	0.492[a]	0.534[a]	0.539[a]
M: Wcdt50_row										
ρ	−0.142	−0.148	−0.19	−0.344[b]	−0.315[a]	0.014	−0.048	0.259[a]	0.239[a]	0.106
Statistics										
N	400	400	400	400	400	400	400	400	400	400
pseudo-R^2	0.867	0.754	0.78	0.815	0.879	0.822	0.897	0.844	0.858	0.858

[a] denotes a p-value < 0.01, [b] denotes a p-value < 0.05, [c] denotes a p-value < 0.1.

Table 13
Correlation between observed dependent variables and their in-sample and out-of-sample (oos) predictions by regression's period and according to sub-samples size.

Period	PV (*PV_cap*)				BES (*BES_cap*)			
	in-sample	oos_20s	oos_80s	oos_200s	in-sample	oos_20s	oos_80s	oos_200s
2000–04	0.814	0.808	0.810	0.787				
2005	0.931	0.926	0.922	0.900				
2006	0.937	0.929	0.914	0.906				
2007	0.909	0.901	0.893	0.872				
2008	0.952	0.944	0.935	0.920				
2009	0.926	0.914	0.909	0.889				
2010	0.978	0.973	0.966	0.951				
2011	0.949	0.941	0.938	0.935				
2012	0.962	0.956	0.955	0.941				
2013	0.936	0.927	0.925	0.904	0.740	0.724	0.722	0.722
2014	0.944	0.937	0.934	0.932				
2015	0.906	0.891	0.889	0.887	0.824	0.8038801	0.804	0.800
2016	0.918	0.906	0.904	0.883	0.877	0.8568978	0.854	0.838
2017	0.930	0.919	0.916	0.912	0.906	0.8917657	0.892	0.880
2018	0.939	0.932	0.927	0.907	0.931	0.918659	0.918	0.914
2019	0.944	0.936	0.931	0.911	0.938	0.9299903	0.927	0.918
2020	0.947	0.939	0.937	0.928	0.960	0.9535	0.954	0.948
2021	0.936	0.931	0.930	0.903	0.973	0.9676236	0.967	0.966
2022	0.927	0.920	0.918	0.900	0.974	0.9701082	0.970	0.969
2023	0.931	0.926	0.920	0.903	0.972	0.9682628	0.967	0.966
average	0.931	0.923	0.919	0.904	0.909	0.882	0.882	0.876

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.109031.

References

Andor, M., Frondel, M., Vance, C., 2015. Installing photovoltaics in Germany: A license to print money? Econ. Anal. Policy 48, 106–116. http://dx.doi.org/10.1016/j.eap.2015.09.003, Energy.

Aniello, G., Bertsch, V., 2023. Shaping the energy transition in the residential sector: Regulatory incentives for aligning household and system perspectives. Appl. Energy 333, 120582. http://dx.doi.org/10.1016/j.apenergy.2022.120582, URL https://www.sciencedirect.com/science/article/pii/S0306261922018396.

Aniello, G., Bertsch, V., Ball, C., Kuckshinrichs, W., 2024. Subsidies or cost-reflective energy tariffs? Alternative pathways for decarbonizing the residential sector and implications for cost efficiency. Appl. Energy 358, 122273. http://dx.doi.org/10.1016/j.apenergy.2023.122273, URL https://www.sciencedirect.com/science/article/pii/S0306261923016379.

Aniello, G., Shamon, H., Kuckshinrichs, W., 2021. Micro-economic assessment of residential PV and battery systems: The underrated role of financial and fiscal aspects. Appl. Energy 281, 115667. http://dx.doi.org/10.1016/j.apenergy.2020.115667.

Arnold, F., Jeddi, S., Sitzmann, A., 2022. How prices guide investment decisions under net purchasing — An empirical analysis on the impact of network tariffs on residential PV. Energy Econ. 112, 106177. http://dx.doi.org/10.1016/j.eneco.2022.106177, URL https://www.sciencedirect.com/science/article/pii/S0140988322003292.

Baginski, J.P., Weber, C., 2019. Coherent estimations for residential photovoltaic uptake in Germany including spatial spillover effects.

Balta-Ozkan, N., Watson, T., Mocca, E., 2015. Spatially uneven development and low carbon transitions: Insights from urban and regional planning. Energy Policy 85, 500–510. http://dx.doi.org/10.1016/j.enpol.2015.05.013, URL https://www.sciencedirect.com/science/article/pii/S0301421515002062.

Balta-Ozkan, N., Yildirim, J., Connor, P.M., Truckell, I., Hart, P., 2021. Energy transition at local level: Analyzing the role of peer effects and socio-economic factors on UK solar photovoltaic deployment. Energy Policy 148, 112004. http://dx.doi.org/10.1016/j.enpol.2020.112004, URL https://www.sciencedirect.com/science/article/pii/S0301421520307151.

BMEL, 2023. 3100100-0000 Umrechnungsschlüssel zur Ermittlung der Großvieheinheiten (GV. https://www.bmel-statistik.de/landwirtschaft/tierhaltung. (Accessed: 26 January 2024).

BMWK, 2023. Photovoltaik-strategie handlungsfelder und maßnahmen für einen beschleunigten ausbau der photovoltaik.

BNetzA, 2023. Marktstammdatenregister. https://www.marktstammdatenregister.de/MaStR/Datendownload. (Accessed: 03 May 2024).

BNetzA, 2024. Mieterstrom. https://www.bundesnetzagentur.de/DE/Vportal/Energie/Vertragsarten/Mieterstrom/start.html. (Accessed: 30 April 2024).

Böhringer, C., Landis, F., Reaños, M.A.T., 2017. Economic impacts of renewable energy promotion in Germany. Energy J. 38, 189–209, URL http://www.jstor.org/stable/26294157.

Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Mark. Sci. 31 (6), 900–912. http://dx.doi.org/10.1287/mksc.1120.0727.

Borenstein, S., 2022. It's time for rooftop solar to compete with other renewables. Nat. Energy 7 (4), 298–298.

Bund, 2000. Gesetz für den vorrang erneuerbarer energien (erneuerbare-energien-gesetz – EEG) sowie zur änderung des energiewirtschaftsgesetzes und des mineralölsteuergesetzes vom 29. märz 2000 (bgbl. I s. 305).

Bund, 2004. Gesetz zur neuregelung des rechts der erneuerbaren energien im strombereich (bgbl. I 2004, s. 1918).

Bund, 2014. Gesetz zur grundlegenden reform des EEG und zur änderung weiterer bestimmungen des energiewirtschaftsrechts (bgbl. I s. 1066)).

Bund, 2020. Gesetz zur änderung des erneuerbare-energien-gesetzes und weiterer energierechtlicher vorschriften (bgbl. I 2020 s. 3138).

Bund, 2022. Jahressteuergesetz 2022 vom 16. Dezember 2022 (BGBl. I S. 2294).

Bund, 2023. Gesetz zu sofortmaßnahmen für einen beschleunigten ausbau der erneuerbaren energien und weiteren maßnahmen im stromsektor vom 20. Juli 2022 (BGBl. I S. 1237).

Burger, S.P., Luke, M., 2017. Business models for distributed energy resources: A review and empirical analysis. Energy Policy 109, 230–248. http://dx.doi.org/10.1016/j.enpol.2017.07.007, URL https://www.sciencedirect.com/science/article/pii/S030142151730438X.

Decker, F., 2023. Wahlergebnisse und Wählerschaft der GRÜNEN. https://www.bpb.de/themen/parteien/parteien-in-deutschland/gruene/42159/wahlergebnisse-und-waehlerschaft-der-gruenen/. (Accessed: 22 May 2024).

Destatis, 2019. Wohnverhältnisse privater haushalte - fachserie 15 sonderheft 1 - 2018. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Wohnen/Publikationen/Downloads-Wohnen/evs-wohnverhaeltnis-haushalte-2152591189004.html. (Accessed: 30 May 2024).

Destatis, 2021. Gemeindeverzeichnis. Gebietsstand: 31.12.2020 (Jahr).

Destatis, 2025. NUTS classification. https://www.destatis.de/Europa/EN/Methods/Classifications/OverviewClassification_NUTS.html. (Accessed: 04 August 2025).

Dharshing, S., 2017. Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. Energy Res. Soc. Sci. 23, 113–124. http://dx.doi.org/10.1016/j.erss.2016.10.012, URL https://www.sciencedirect.com/science/article/pii/S2214629616302547.

Dietrich, A., Weber, C., 2018. What drives profitability of grid-connected residential PV storage systems? A closer look with focus on Germany. Energy Econ. 74, 399–416. http://dx.doi.org/10.1016/j.eneco.2018.06.014.

Drukker, D.M., Peng, H., Prucha, I.R., Raciborski, R., 2013a. Creating and managing spatial-weighting matrices with the spmat command. Stata J. 13 (2), 242–286. http://dx.doi.org/10.1177/1536867X1301300202.

Drukker, D.M., Prucha, I.R., Raciborski, R., 2013b. Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. Stata J. 13 (2), 221–241. http://dx.doi.org/10.1177/1536867X1301300201.

Drury, E., Miller, M., Macal, C.M., Graziano, D.J., Heimiller, D., Ozik, J., Perry IV, T.D., 2012. The transformation of southern California's residential photovoltaics market through third-party ownership. Energy Policy 42, 681–690. http://dx.doi.org/10.1016/j.enpol.2011.12.047, URL https://www.sciencedirect.com/science/article/pii/S0301421511010536.

DWD, 2021. DWD climate data center (CDC): Gridded multi annual monthly mean sums and multi annual yearly mean sum of incoming shortwave radiation (global radiation) on the horizontal plain for Germany based on ground and satellite measurements, version V003, current year. https://opendata.dwd.de/climate_environment/CDC/grids_germany/multi_annual/radiation_global/. (Accessed: 31 August 2023).

Eicke, A., Hirth, L., Mühlenpfordt, J., 2024. Mehrwert dezentraler flexibilität – oder: Was kostet die verschleppte flexibilisierung von wärmepumpen, elektroautos und heimspeichern?. https://neon.energy/mehrwert-flex. (Accessed: 08 July 2024).

EnBW, 2024. Mieterstrom: So funktioniert das versorgungsmodell. https://www.enbw.com/blog/energiewende/erneuerbare-energie/mieterstrom-so-funktioniert-das-versorgungsmodell/#was-ist-mieterstrom. (Accessed: 30 April 2024).

Energie-Experten, 2022. Stromspeicher-Förderung: Kredite und Zuschüsse 2022/ 2023 im Überblick. https://www.energie-experten.org/erneuerbare-energien/photovoltaik/stromspeicher/foerderung. (Accessed: 11 May 2022).

energie-helde, 2024. Dach vermieten für Solar: Nur für große Flächen zu empfehlen?. https://www.energieheld.de/solaranlage/mieten/ratgeber/dachvermietung#allgemeines. (Accessed: 30 April 2024).

Fett, D., Keles, D., Kaschub, T., Fichtner, W., 2019. Impacts of self - generation and self - consumption on german household electricity prices. J. Bus. Econ. 89, 867–891. http://dx.doi.org/10.1007/s11573-019-00936-3.

Figgener, J., Haberschusz, D., Kairies, K.-P., Wessels, O., Tepe, B., Sauer, D.U., 2018. Wissenschaftliches Mess- und Evaluierungsprogramm Solarstromspeicher 2.0.. Jahresbericht 2018, Institut für Stromrichtertechnik und Elektrische Antriebe - RWTH Aachen.

Figgener, J., Stenzel, P., Kairies, K.P., Linßen, J., Haberschusz, D., Wessels, O., Robinius, M., Stolten, D., Sauer, D.U., 2021. The development of stationary battery storage systems in Germany – status 2020. J. Energy Storage 33, http://dx.doi.org/10.1016/j.est.2020.101982.

Friedrich, L., 2008. Wohnen und innerstädtische segregation von migranten in deutschland aus der reihe "integrationsreport", teil 4. https://www.bamf.de/SharedDocs/Anlagen/DE/Forschung/WorkingPapers/wp21-wohnen-innerstaedtische-segregation.html?nn=283560. (Accessed: 26 June 2024).

Frondel, M., Schmidt, C.M., Vance, C., 2014. Revisiting Germany's solar cell promotion: An unfolding disaster. Econ. Anal. Policy 44 (1), 3–13. http://dx.doi.org/10.1016/j.eap.2014.02.001.

Godron, P., Herrndorff, M., Müller, S., Schaber, K., Zackariat, M., Jooß, N., Köppl, S., Müller, M., Reinhard, J., Serafin von Roon, A.W., 2024. Haushaltsnahe flexibilitäten nutzen – wie elektrofahrzeuge, wärmepumpen und co. die stromkosten für alle senken können. https://www.agora-energiewende.de/publikationen/haushaltsnahe-flexibilitaeten-nutzen. (Accessed: 08 July 2024).

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

Graziano, M., Gillingham, K., 2015. Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. J. Econ. Geogr. 15 (4), 815–839. http://dx.doi.org/10.1093/jeg/lbu036.

Green, R., Staffell, I., 2017. "Prosumage" and the british electricity market. Econ. Energy Environ. Policy 6 (1), 33–50. http://dx.doi.org/10.5547/2160-5890.6.1.rgre.

Grösche, P., Schröder, C., 2014. On the redistributive effects of Germany's feed-in tariff. Empir. Econ. 46, 1339–1383.

Gunkel, P.A., Kachirayil, F., Bergaentzlé, C.-M., McKenna, R., Keles, D., Jacobsen, H.K., 2023. Uniform taxation of electricity: incentives for flexibility and cost redistribution among household categories. Energy Econ. 127, 107024. http://dx.doi.org/10.1016/j.eneco.2023.107024, URL https://www.sciencedirect.com/science/article/pii/S0140988323005224.

Günther, C., Schill, W.-P., Zerrahn, A., 2021. Prosumage of solar electricity: Tariff design, capacity investments, and power sector effects. Energy Policy 152, 112168. http://dx.doi.org/10.1016/j.enpol.2021.112168.

Huckebrink, D., Bertsch, V., 2021. Integrating behavioural aspects in energy system modelling—A review. Energies 14 (15), http://dx.doi.org/10.3390/en14154579, URL https://www.mdpi.com/1996-1073/14/15/4579.

IEA, 2023a. Evolution of solar PV module cost by data source, 1970–2020. https://www.iea.org/data-and-statistics/charts/evolution-of-solar-pv-module-cost-by-data-source-1970-2020. (Accessed: 31 August 2023).

IEA, 2023b. Renewables 2022 — Analysis and forecast to 2027. https://www.iea.org/reports/renewables-2022. (Accessed: 31 August 2023).

Irwin, N.B., 2021. Sunny days: Spatial spillovers in photovoltaic system adoptions. Energy Policy 151, 112192. http://dx.doi.org/10.1016/j.enpol.2021.112192, URL https://www.sciencedirect.com/science/article/pii/S0301421521000616.

Jacksohn, A., Grösche, P., Rehdanz, K., Schröder, C., 2019. Drivers of renewable technology adoption in the household sector. Energy Econ. 81, 216–226. http://dx.doi.org/10.1016/j.eneco.2019.04.001, URL https://www.sciencedirect.com/science/article/pii/S0140988319301070.

Jägemann, C., Hagspiel, S., Lindenberger, D., 2013. The economic inefficiency of grid parity: The case of German photovoltaics. EWI Working Paper No 13/19, Institute of Energy Economics at the University of Cologne (EWI).

Kelejian, H.H., Prucha, I.R., 2007. The relative efficiencies of various predictors in spatial econometric models containing spatial lags. Reg. Sci. Urban Econ. 37 (3), 363–374. http://dx.doi.org/10.1016/j.regsciurbeco.2006.11.005, URL https://www.sciencedirect.com/science/article/pii/S0166046206001013.

Kelejian, H.H., Prucha, I.R., 2010. Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. J. Econometrics 157 (1), 53–67. http://dx.doi.org/10.1016/j.jeconom.2009.10.025, Nonlinear and Nonparametric Methods in Econometrics, URL https://www.sciencedirect.com/science/article/pii/S0304407609002784.

KfW, 2022. Erneuerbare energien – standard. https://www.kfw.de/inlandsfoerderung/Unternehmen/Energie-Umwelt/F%c3%b6rderprodukte/Erneuerbare-Energien-Standard-(270)/. (Accessed: 11 May 2022).

Klein, M., Ziade, A., de Vries, L., 2019. Aligning prosumers with the electricity wholesale market – the impact of time-varying price signals and fixed network charges on solar self-consumption. Energy Policy 134, 110901. http://dx.doi.org/10.1016/j.enpol.2019.110901.

Konzen, G., Best, R., de Castro, N.J., 2024. The energy injustice of household solar energy: A systematic review of distributional disparities in residential rooftop solar adoption. Energy Res. Soc. Sci. 111, 103473. http://dx.doi.org/10.1016/j.erss.2024.103473, URL https://www.sciencedirect.com/science/article/pii/S2214629624000641.

Kost, C., 2024. PHOTOVOLTAIK- UND BATTERIESPEICHERZUBAU IN DEUTSCHLAND IN ZAHLEN – Auswertung des Marktstammdatenregisters – Stand Februar 2024. https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/2024-02-photovoltaik-und-batteriespeicherzubau-in-deutschland.pdf. (Accessed: 08 July 2024).

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

Kraftfahrt-Bundesamt, 2023. Bestand nach Zulassungsbezirken (FZ 1). https://www.kba.de/DE/Statistik/Produktkatalog/produkte/Fahrzeuge/fz1_b_uebersicht.html. (Accessed: 26 January 2024).

Kubli, M., 2018. Squaring the sunny circle? On balancing distributive justice of power grid costs and incentives for solar prosumers. Energy Policy 114, 173–188. http://dx.doi.org/10.1016/j.enpol.2017.11.054.

Kucher, O., Lacombe, D., Davidson, S.T., 2021. The residential solar PV in the mid-atlantic: a spatial panel approach. Int. Reg. Sci. Rev. 44 (2), 262–288.

Lan, H., Gou, Z., Liu, T., 2021. Residential solar panel adoption in Australia: spatial distribution and socioeconomic factors. Aust. Geogr. 52 (3), 315–332. http://dx.doi.org/10.1080/00049182.2021.1964161.

Lerbs, O.W., Oberst, C.A., 2012. Explaining the spatial variation in homeownership rates: Results for german regions. Reg. Stud. 48 (5), 844–865. http://dx.doi.org/10.1080/00343404.2012.685464.

Müller, S., Rode, J., 2013. The adoption of photovoltaic systems in wiesbaden, Germany. Econ. Innov. New Technol. 22 (5), 519–535. http://dx.doi.org/10.1080/10438599.2013.804333.

Müller, J., Trutnevyte, E., 2020. Spatial projections of solar PV installations at subnational level: Accuracy testing of regression models. Appl. Energy 265, 114747. http://dx.doi.org/10.1016/j.apenergy.2020.114747, URL https://www.sciencedirect.com/science/article/pii/S0306261920302592.

Mundaca, L., Samahita, M., 2020. What drives home solar PV uptake? Subsidies, peer effects and visibility in Sweden. Energy Res. Soc. Sci. 60, 101319. http://dx.doi.org/10.1016/j.erss.2019.101319, URL https://www.sciencedirect.com/science/article/pii/S2214629619301975.

OECD, 2022. Homeownership rate by income quintile, 29 OECD countries. http://dx.doi.org/10.1787/1258dc19-en, URL https://www.oecd-ilibrary.org/content/component/1258dc19-en.

OECD, 2023. Homeownership rates vary considerably across OECD countries. http://dx.doi.org/10.1787/cbb976a3-en, URL https://www.oecd-ilibrary.org/content/component/cbb976a3-en.

Olivier, D., Del Lo, G., 2022. Renewable energy drivers in France: a spatial econometric perspective. Reg. Stud. 56 (10), 1633–1654. http://dx.doi.org/10.1080/00343404.2021.1998415.

Ossenbrink, J., 2017. How feed-in remuneration design shapes residential PV prosumer paradigms. Energy Policy 108 (June), 239–255. http://dx.doi.org/10.1016/j.enpol.2017.05.030.

Palm, A., 2017. Peer effects in residential solar photovoltaics adoption—A mixed methods study of Swedish users. Energy Res. Soc. Sci. 26, 1–10. http://dx.doi.org/10.1016/j.erss.2017.01.008, URL https://www.sciencedirect.com/science/article/pii/S2214629617300087.

Paul Elhorst, J., 2014. Spatial econometrics: from cross-sectional data to spatial panels. Springer Berlin, Heidelberg, http://dx.doi.org/10.1007/978-3-642-40340-8.

Pérez-Arriaga, I.J., Jenkins, J.D., Batlle, C., 2017. A regulatory framework for an evolving electricity sector: Highlights of the MIT utility of the future study. Econ. Energy Environ. Policy 6 (1), 71–92. http://dx.doi.org/10.5547/2160-5890.6.1.iper.

Pronti, A., Zoboli, R., 2024. Something new under the sun. a spatial econometric analysis of the adoption of photovoltaic systems in Italy. Energy Econ. 134, 107582. http://dx.doi.org/10.1016/j.eneco.2024.107582, URL https://www.sciencedirect.com/science/article/pii/S0140988324002901.

Rode, J., Weber, A., 2016. Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany. J. Environ. Econ. Manag. 78, 38–48. http://dx.doi.org/10.1016/j.jeem.2016.02.001, URL https://www.sciencedirect.com/science/article/pii/S0095069616000073.

Say, K., Schill, W.P., John, M., 2020. Degrees of displacement: The impact of household PV battery prosumage on utility generation and storage. Appl. Energy 276 (March), 115466. http://dx.doi.org/10.1016/j.apenergy.2020.115466, arXiv:2003.06987.

Schaffer, A.J., Brun, S., 2015. Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. Energy Res. Soc. Sci. 10, 220–227. http://dx.doi.org/10.1016/j.erss.2015.06.010, URL https://www.sciencedirect.com/science/article/pii/S2214629615300037.

Scheller, F., Graupner, S., Edwards, J., Weinand, J., Bruckner, T., 2022. Competent, trustworthy, and likeable? Exploring which peers influence photovoltaic adoption in Germany. Energy Res. Soc. Sci. 91, 102755. http://dx.doi.org/10.1016/j.erss.2022.102755, URL https://www.sciencedirect.com/science/article/pii/S2214629622002584.

Schill, W.-P., Zerrahn, A., Kunz, F., 2017. Prosumage of solar electricity: Pros, cons, and the system perspective. Econ. Energy Environ. Policy 6 (1), 7–31. http://dx.doi.org/10.5547/2160-5890.6.1.wsch.

Seide, S., 2022. Rekord: Fast 40.000 fahrzeuge auf weimars straßen unterwegs. https://www.pressreader.com/germany/thuringische-landeszeitung-weimar/20220106/281913071457484. (Accessed: 26 January 2024).

Sovacool, B.K., Barnacle, M.L., Smith, A., Brisbois, M.C., 2022. Towards improved solar energy justice: Exploring the complex inequities of household adoption of photovoltaic panels. Energy Policy 164, 112868. http://dx.doi.org/10.1016/j.enpol.2022.112868.

Stadtverwaltung Trier, 2023. KFZ-bestand in der stadt trier zum 01.01.2023. https://www.trier.de/rathaus-buerger-in/trier-in-zahlen/informationsblaetter/. (Accessed: 26 January 2024).

Statistische Ämter des Bundes und der Länder, 2023. Regionaldatenbank Deutschland. https://www.regionalstatistik.de/genesis/online. (Accessed: 31 August 2023).

Stein, T., Sieger, L., Weber, C., 2023. Disentangling small-scale solar photovoltaic adoption: A spatial analysis of decision factors and localized interactions in Germany.

Stewart, F., 2022. Friends with benefits: How income and peer diffusion combine to create an inequality "trap" in the uptake of low-carbon technologies. Energy Policy 163, 112832. http://dx.doi.org/10.1016/j.enpol.2022.112832, URL https://www.sciencedirect.com/science/article/pii/S030142152200057X.

Thomsen, J., Weber, C., 2021. Getting prices for prosumers right? Incentivizing investment and operation of small-scale PV-battery storage systems through prices, charges and levies. Z. Energiewirtschaft 35–59. http://dx.doi.org/10.1007/s12398-020-00295-5.

Többen, J., 2017. Regional net impacts and social distribution effects of promoting renewable energies in Germany. Ecol. Econom. 135, 195–208. http://dx.doi.org/10.1016/j.ecolecon.2017.01.010, URL https://www.sciencedirect.com/science/article/pii/S0921800916302178.

VGRdL, 2022. Einkommen der privaten Haushalte in den kreisfreien Städten und Landkreisen der Bundesrepublik Deutschland 1995 bis 2021 Reihe 2, Kreisergebnisse Band 3. https://www.statistikportal.de/de/vgrdl/ergebnisse-kreisebene/einkommen-kreise. (Accessed: 31 August 2023).

Winter, S., Schlesewsky, L., 2019. The german feed-in tariff revisited - an empirical investigation on its distributional effects. Energy Policy 132, 344–356. http://dx.doi.org/10.1016/j.enpol.2019.05.043, URL https://www.sciencedirect.com/science/article/pii/S0301421519303477.

Wirth, H., 2023. Aktuelle fakten zur photovoltaik in deutschland.

Zhang, J., Ballas, D., Liu, X., 2023. Neighbourhood-level spatial determinants of residential solar photovoltaic adoption in the netherlands. Renew. Energy 206, 1239–1248. http://dx.doi.org/10.1016/j.renene.2023.02.118, URL https://www.sciencedirect.com/science/article/pii/S0960148123002690.