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Spatio-temporal diffusion of solar thermal systems in Germany: A spatial panel data analysis

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**Spatio-temporal diffusion of solar thermal systems in Germany:
A spatial panel data analysis**

HEMF Working Paper No. 04/2019

by

Jan Paul Baginski

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Spatio-temporal diffusion of residential solar thermal systems in Germany: A spatial panel data analysis

by Jan Paul Baginski

Abstract

Solar thermal roof-top installations offer the potential to meet an important share of residential water and space heating demand in Germany. These systems are subsidised with grants under the so-called market incentive program. The political goal is to encourage the adoption of renewable energy and to reduce CO₂-emissions in the heating market in view of a low-carbon building stock. Solar thermal adoption levels are currently rather low after a high period in 2008 and 2009. Also, solar thermal adoption rates distinctly vary between regions. This paper tries to disentangle influences governing regional and temporal differences in residential solar thermal uptake. Spatial panel regression models are estimated to capture spatial interactions, while controlling for potential adoption determinants, including economic considerations, household characteristics and climatic suitability. The panel data contain observations for over 1 million solar thermal installations across 402 German regions covering the period from 2001 to 2015. Results indicate that differences in profitability influence the spatial and temporal patterns of solar thermal uptake. Regional diffusion is mainly driven by solar radiation. The development of fossil fuel prices is accountable for different adoption rates over time. New constructions do not seem to foster solar thermal use, indicating that solar heating is easily applied to existing houses. Larger households are more inclined to use solar heating, given that they use more efficiently solar generated heat. Results also show that spatial dependence drives the diffusion of solar thermal systems. These findings imply that there is potential for new policies and business models to increase the geographic and social diversification of solar thermal adoption.

Keywords: solar energy, domestic solar thermal heating, spatial econometrics, panel data

JEL-Classification: C23, D12, Q28, Q42

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Content

Abstract	I
Content	II
1 Introduction	1
2 Solar thermal: policy framework and customer choices	3
2.1 Policy framework	3
2.2 Residential heating system choice studies	5
3 Methodological approach	8
4 Data description and variable specification	10
4.1 Solar thermal data	10
4.2 Investment profitability index	12
4.3 Explanatory variables	15
5 Empirical estimation and results	18
5.1 Static and dynamic panel model results	18
5.2 Spatial model results	22
5.3 Sensitivity and robustness results	24
6 Conclusion and Implications	26
References	III
Appendix A: Input data	VIII
Appendix B: Sensitivity analyses	XI

1 Introduction

In view of a sustainable energy supply and climate protection, the German government introduced a “directive to promote the use of renewable energies” in 1994. The use of renewable energy should reduce CO₂-emissions, decrease fossil fuel dependence and provide sustainable heat and electricity generation. The directive targeted solar thermal (ST) and geothermal heating as well as water and wind power plants. Heat pumps, combined heat and power plants as well as photovoltaic (PV) systems enlarged the promotion portfolio in 1995. In the year 2000, the directive has been revised and the caption *Marktanreizprogramm (MAP)* (market incentive program) adopted. It has been directed towards the promotion of renewable heating systems, whereas subsidies in the electricity sector have been organised under the *Erneuerbare-Energien-Gesetz* (renewable energy act).

The *MAP* has become the most important funding instrument for the use of renewable energy in the heating sector. It provides direct grants and low-interest loans for innovative and sustainable heating technologies. Potential buyers can apply for direct grants to the *Bundesamt für Wirtschaft und Ausfuhrkontrolle* (BAFA) (federal office for economics and export control) or for loans to the *Kreditanstalt für Wiederaufbau* (reconstruction loan corporation). The *MAP* aims to provide investment incentives for private users, to boost sales and to reduce costs of renewable heating technologies. Subsidised technologies include ST systems, biomass boilers, heat pumps and geothermal heating plants. In 2016, ST systems accounted for 35% of investment subsidies, followed by biomass boilers (35%) and heat pumps (27%) (BMWI 2017a). Besides financial incentives, a specific regulation stimulates the diffusion of renewable energy in the German heating market since 2009: The *Erneuerbare-Energien-Wärmegesetz (EEWärmeG)* (renewable energies heating act) introduced a renewable use obligation in new constructions.¹ The required share of renewable energy to cover space and water heating demand varies between energy sources. In the case of harnessing solar radiation, a minimum of 15% is legally binding.

The German government has set the goal of increasing the share of renewable energy in heating and cooling supply to 14% in the year 2020. This target seems to be achievable as in 2016, the share of renewable energy amounts to 13% (BMWI 2017a). However, this share has been 12% in 2011 already and only increased marginally ever since. Compared to the electricity sector, where the share of renewable energy in electricity consumption keeps rising and exceeded 30% in 2016, the heating sector lags behind (BMWI 2017a). Residential heating is still dominated by fossil fuels (BMWI 2017b) and only a few households use renewable

¹ *Erneuerbare-Energien-Wärmegesetz (EEWärmeG)* of 7th August 2008 (BGBl. I p. 1658), and revised by paragraph 2, section 68 of this law on 22nd December 2011 in order to fulfil European law (BGBl. I p. 3044).

heating technologies. The long-term target of an almost climate neutral building stock in the year 2050 seems thus rather ambitious when compared to the past development of renewables in the heating market.

Hence, this paper seeks to identify drivers for the uptake of renewable heating systems in German households. Determining enabling and constraining factors is crucial in learning how to best promote renewable energy in the heating market and consequently to decarbonise the building stock. Notably, the analysis focusses on ST systems. First, because solar thermal heat generation is an established technology, which has a huge untapped potential. Currently solar generated heat amounts to 28 Petajoule per year (PJ/a) (BMW 2017b). Estimations quantify only the domestic roof-mounted ST potential in Germany to be between 127 PJ/a and 174 PJ/a (Corradini 2013). Second, because a sound data basis for ST installations is attainable. This study uses data on over 1 million ST household installations funded with a direct grant under the *MAP*. Installations are allocated to 402 German NUTS3 regions over the period from 2001 to 2015.

The acceptance of *MAP*-grants and the adoption of ST systems respectively show great differences over the years (cf. section 2, Figure 2) and between regions (cf. section 4.1, Figure 3). A first explanation addressed in this study builds on economic considerations. As the use of ST energy entails heating cost savings, the purchase is potentially profitable and cost savings can recoup investment expensed. Hence, a profitability index is developed to capture the relationship between ST uptake and economic viability. It incorporates system costs, *MAP*-grants, solar radiation, interest rates, energy prices and price expectations. Yet, households' adoption decisions cannot be reduced to a pure economic calculus (Zundel and Stieß 2011; Welsch and Kühling 2009) and a broader approach to examine ST uptake should be applied. Hence, non-financial determinants, like peer-effects, climatic and household characteristics are included in the analysis. In addition, it is tested whether spatial effects influence the purchase of ST systems and hence drive regional diffusion. This presumption builds on the insight that spatial spillover is present in PV adoption (e.g. Allan and McIntyre (2017); Dharshing (2017); see Baginski & Weber (2018) for a literature review). Also, the geographic distribution of residential ST installations in Germany indicates spatial clustering. This study therefore employs traditional panel estimations, which are extended to spatial panel models. Thereby, potential adoption determinants are captured, while controlling for spatial interactions. The analysis is based on NUTS3-year combinations as the smallest unit of observation.² The paper contributes to literature in performing the first econometric analysis of regional ST uptake in Germany using a granular panel dataset on real adoption decisions. In

² This is mainly due to data availability. Data on smaller units e.g. postcode regions is not available or free of charge for all variables. A NUTS3 region within the European Union is equivalent to a German county ("Landkreis").

addition, it adds to the rather topical research stream of spatial econometrics in energy related decisions.

The remainder of the paper is structured as follows: Section 2 gives an overview of the policy framework, especially the *MAP* and section 2.2 reviews related literature. Section 3 describes the empirical strategy. Section 4 provides data, descriptive statistics and profitability calculations. Results, including sensitivity and robustness checks are presented in section 5. The final chapter concludes.

2 Solar thermal: policy framework and customer choices

There are two solar technologies types available for residential use offering the potential to tap an almost limitless source of energy. PV cells use sunlight to generate electricity, whereas ST collectors convert direct and indirect solar radiation into useful heat. Over 95% of ST applications in Germany are collectors on single- or double-family houses (Solar Heating & Cooling Program 2018). The market is dominated by flat plate collectors with a share of about 90% (Stuible et al. 2016). Since solar radiation substantially fluctuates daily (and yearly), collectors are usually combined with a hot water storage to balance daily demand. Smaller ST systems with average collector sizes of 4-7 m² are only used to heat tap water. Larger ST installations with average collector areas of 10-14 m² are used to heat tap water and to provide space heating support (combi-systems). Residential ST applications in Germany are usually not the main heating system but are operated in combination with another residential heating system (RHS) (e.g. a gas boiler). Since both systems feed heat into the same hot water storage, heating energy provided by the ST system replaces conventional heat generation to some extent. Depending on the design of collectors and storage, ST systems can cover around 20% to 40% of annual heat demand (Corradini 2013).

2.1 Policy framework

Under the *MAP*, the installation or expansion of ST systems equipped with a heat meter is subsidised with a direct grant.³ The grants in 2001 amounted to 128 €/m² for flat-plate collectors, 166 €/m² for evacuated tube collectors and 51 €/m² for system-expansions.⁴ However, the *MAP* was revised and grant levels changed almost annually between 2001 and 2015 (cf. Figure 1). In the revision of 2004, grants were no longer differentiated between collector types. In 2005, the use of solar energy for space heating was incentivised with higher grants, while grants for water heating were reduced. The *MAP* 2005 was well received and funds were exhausted by October. This led to an upscaling of funds and a degression of

³ As a technical requirement, systems need a “Keymark-Certificate” showing a yearly solar yield of at least 525 kWh/m².

⁴ Directive to promote the use of renewable energy in the heating market, 23rd March 2001. An exchange rate of 1 Euro = 1,95583 DM was used.

funding rates in 2006. Yet, the high number of grant applications continued in 2006; funds were again exhausted and rates reduced in June 2006. These cutbacks held in 2007. However, as the number of applications declined drastically, grants were restored (cf. Figure 1). Further, a bonus of 750 € was added, if the existing RHS was replaced by a condensing boiler in the course of the ST installation.

Because of the use obligation under the *EEWärmeG*, the *MAP* as a political funding instrument had to be enshrined in the law, entailing two major implications: First, renewable heating systems that merely comply with the obligation are no longer subsidised.⁵ Second, grants are differentiated between existing and new buildings, as new buildings are subject to the *EEWärmeG*. Subsidies were reduced by 25% for renewable heating systems in new buildings.

A temporary suspension of the *MAP* took place in 2010 (May 3, 2010 to July 11, 2010), so the program came into force only in August. Notably, this *MAP* version entailed a disruption for solar energy: Water heating systems were dropped from the *MAP* and funding was only granted for combi-systems (cf. Figure 1). In addition, still with respect to the *EEWärmeG*, subsidies for new buildings were abandoned completely. In the current version of the *MAP* 2015, ST system for only water heating purposes are readmitted.⁶ Combi-system grants are 140 €/m² with a minimum of 2000 € for new systems. The bonus for additional replacement of the existing RHS is still in place but decreased to 500 €.

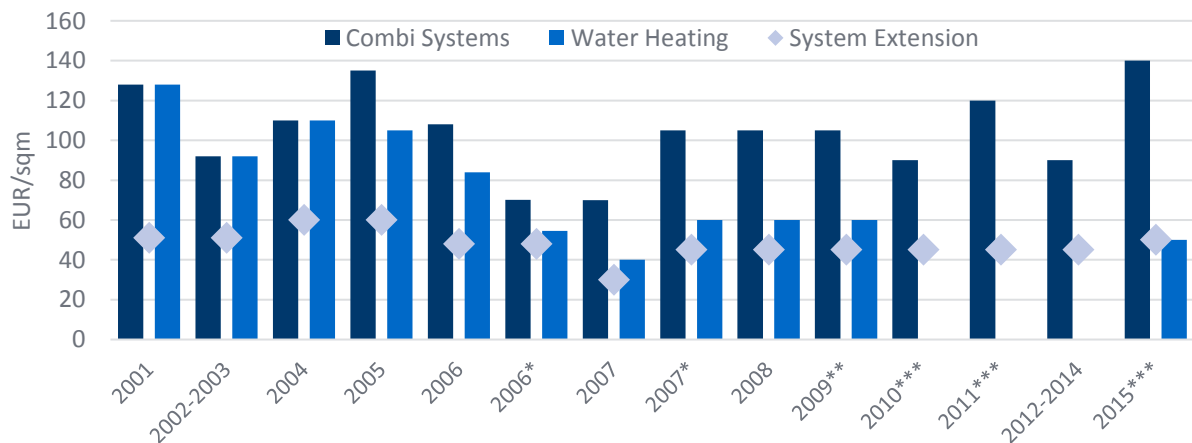


Figure 1: MAP-grants for solar thermal systems (*Grants changed within year, **Grants for new buildings reduced by 25%, ***Grants only applicable for building stock); Own illustration based on MAP directives

The funding under the *MAP* hence has shown several structural breaks, which lead to unstable market conditions. The installed collector area of ST systems subsidised under the *MAP* shows great variations between 2001 and 2015 (cf. Figure 2). While many ST systems were erected in 2008 and 2009, a huge drop is reported in 2010 (cf. Figure 2). An essential reason is the suspended funding between May and June 2010. Additionally, the dropped support for pure

⁵ For technically sophisticated systems and for over-accomplishing obligations, funding is still granted.

⁶ Directive to promote the use of renewable energy in the heating market, 11th March 2015.

water heating systems, as well as the dropped support in new buildings took a toll on supported installations (Langniß et al. 2011). Besides *MAP* installations, total annual solar installations in Germany are falling since 2011. According to the BDH, reasons for a declining ST market are too little (or no) cost decreases, high installer margins and high workload of artisans (Stuible et al. 2016).

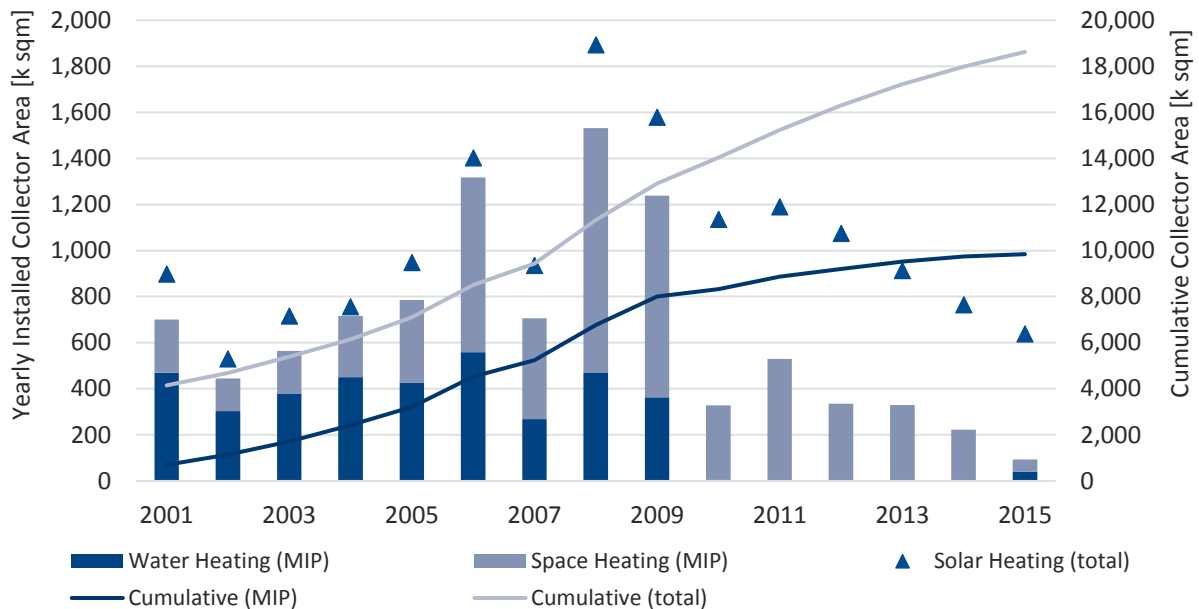


Figure 2: Solar thermal installations in Germany from 2001 to 2016, own illustration with data from (BSW 2017) for *MAP* installations and (BMWI 2017b) for all solar thermal installations⁷

2.2 Residential heating system choice studies

Existing studies investigate decisions on RHS in Germany (Braun 2010; Michelsen and Madlener 2012; Decker and Menrad 2015; Michelsen and Madlener 2017), Austria (Hecher et al. 2017), Norway (Lillemo et al. 2013), Ireland (Curtis et al. 2018) and other European countries. As the decision is a discrete appliance choice, they usually specify a (multinomial) logit or probit model to identify drivers and barriers. Mostly, large surveys are used and revealed or stated RHS preferences together with building and household characteristics are analysed. Building characteristics (e.g. type: detached or terraced, single- or multi-family) and settlement structure (e.g. populations density) are key determinants for RHS choice (cf. (Braun 2010)). The decision to install a RHS differs between new and existing buildings, as technical features are easier to account for during construction. Michelsen and Madlener (2012) find that in existing homes, the decision is driven by socio-demographic, home and spatial characteristics while in new buildings, preferences about RHS specific attributes are more

⁷ With regards to the entire ST collector area in Germany installed between 2001 and 2015 (BMWI 2017b), almost 60% is attributable to domestic ST applications, subsidised by the *MAP*. While this share was higher between 2001 and 2009 (83%), it fell to 27% after 2009. This again is due to the changed support scheme, dropping subsidies for new buildings and water heating systems.

relevant. Depending on the type of RHS households choose, different determinants seem to be important. Adopters of gas- and oil-fired condensing boilers with ST support have a strong preference for energy savings, while adopters of heat pumps or wood pellet-fired boilers prefer being more independent from fossil fuels (Michelsen and Madlener 2012). In the same vein, Decker and Menrad (2015) find that economic aspects are important to users of oil heating but less relevant for users of wood pellets. The latter seem to accept higher investment costs and regard ecological advantages as more important.⁸ Belonging to an ecology cluster is one of the most significant variables separating the users of different RHS (Decker and Menrad 2015). In contrast Curtis et al. (2018) find that past environmental behaviours, socioeconomic and dwelling characteristics have only little explanatory power in determining RHS choice, whereas the proximity to a fuel network, specifically natural gas, is the key determinant. Ambiguous results are provided regarding the influence of household income. Curtis et al. (2018) find no substantial difference in the likelihood of choosing a particular RHS between income groups. In contrast, Michelsen and Madlener (2012) find that income affects RHS choice.

Obviously, ST systems are hardly comparable to other RHS as they usually support a main heating system. Solar collectors are moreover preferably installed on unshaded roofs directly exposed to sunlight. Such conditions may be more prevalent in rural areas with higher shares of detached houses. Determinants for the addition of ST heating may thus deviate from drivers and barriers for other (main) heating systems. Three studies specifically study the adoption of ST heating and are briefly examined in the following. Mills and Schleich (2009) build a probit model based on a 2002 survey regarding energy usage of 20,325 German households to identify characteristics that favour the adoption of ST systems. 114 respondents reported having a solar combi-system and 423 having a solar water heating system. Results indicate that ST adoption decreases with heating degree-days (HDD) and city size (local population density). HDD are a measure of local climate based on daily temperatures and are broadly proportional to the heating energy demand in a residence. Households in rented residences show a lower propensity to adopt ST systems (Mills and Schleich 2009). In general, the apportion of costs and savings between tenants and landlords hampers the adoption of energy efficient investments in rented dwellings (Jaffe and Stavins 1994). Mills and Schleich (2009) find that higher levels of solar radiation, household size and a recent construction year (in occurrence the years 2001-2002) positively affect ST adoption. Household income on the contrary is found to have no impact on ST adoption.

⁸ Within Decker and Menrad's 2015 survey, respondents had to evaluate 11 statements addressing topics such as climate change, sustainability, environmental pollution, and environmental protection and are grouped to five ecology clusters afterwards: Environmentally indifferent consumers; environmentally nihilistic consumers; ecologically minded, active altruists; ecologically-minded, active egoists and miserly pseudo environmentalists.

Schelly (2009) uses logistic regressions to test residential ST adoption at the county level throughout the United States. The author employs three indices to capture socioeconomic circumstances, environmental concern, and ecological conditions.⁹ The socioeconomic index is the most robust predictor for ST use. It indicates that counties with higher education levels, less unemployment, and higher levels of disposable or investment income (measured through income and home value) are more likely to entail households who adopt ST systems. As the author uses the absolute number of ST systems, a positive impact of the number of households within a county is found, which is purely a consequence of having more dwellings. Yet, populous counties are also more likely to have businesses to provide the necessary technology and services available to inform and assist in renewable energy investments (Schelly 2009).

Woersdorfer and Kaus (2011) analyse the adoption of solar thermal systems with a probit model building on a survey of nearly 500 consumers, undertaken between July and September 2007 in the region of Hannover (north-western Germany). The study distinguishes pioneers and potential imitators among the respondents and classifies outcomes into the categories “interest to purchase” and “plan to purchase” a ST system. The authors summarize that product knowledge, environmental attitude, and income seem to be important but not sufficient determinants of prospective purchases of ST systems. Only peer group behaviour proves essential to trigger the concrete adoption plan. Once potential adopters show an interest for ST systems, the activities in the social environment decide if the installation is actually envisaged or not.

Several authors suggest that peer-effects determine the ST adoption decision, indicated by a higher likeliness of adoption when peers (e.g. neighbours, friends) have already adopted the technology. Mills and Schleich (2009) find that households’ propensity to adopt solar water heating increases with installed ST capacity per-capita within that Federal State. Also, Michelsen and Madlener (2013) and Woersdorfer and Kaus (2011) state that peers influence renewable heating system choices. In the same vein authors claim that regional characteristics i.e. conditions that cannot be assigned to an individual home or homeowner, influence the RHS adoption decision. Braun (2010) states that spatial aspects are important as clear differences prevail between East and West Germany. Schelly (2009) plots ST adoption at the county level across America. Although her plots indicate that ST use shows regional clusters (it is concentrated in the Southwest of the U.S., in the Northeast and in the state of Florida), the

⁹ The socioeconomic index encompasses employment rates, median household income, median home value, and education rates in a county. The environmental concern index includes the use of “soft transportation” (public transports, biking, or walking), support for environmental causes, the percentage of county residents who claim to recycle, county participation in the International Council for Local Environmental Initiatives, the number of environmental non-profits within the county, and the percentage of the county that voted for a Democratic candidate. The environmental index encapsulates the natural-environmental factors that may influence ST technology adoption, notably solar radiation and temperature averages.

author does not suggest regional spatial spillover as a predictor. Hence, more research is needed to disentangle the sources of regional ST system diffusion, especially focusing on peer effects and other sources of spatial spillover.

3 Methodological approach

There has been a growing interest in the specification and estimation of econometric relationships based on panel data (Elhorst 2003). Panel data offer extended modelling possibilities compared to cross-sectional or time-series data, since they are more informative, contain more variation and less collinearity among the variables (Baltagi 2005). They consist of observations on the same $i \in \{1, \dots, n\}$ entities (cross-section dimension) at more than one period $t \in \{1, \dots, T\}$ (time dimension). In the present data, n corresponds to 402 geographically delimited NUTS3 regions and t to the years 2001 to 2015, which leads to $N = n \times T = 6030$ observations.¹⁰ A linear estimation approach pools all the data across i and t and performs an ordinary least squares (OLS) regression. The main objection to this model is that it does not account for individual or temporal heterogeneity (Elhorst 2014). In panel data, individual units are likely to differ in their background variables, which are usually space-specific and time-invariant variables that affect the dependent variable (Elhorst 2003). Further, time specific events (e.g. structural breaks in support policies or nationwide policy announcements) apply to all regions and influence the dependent variable, but are difficult to measure or hard to obtain. Failing to account for these variables increases the risk of obtaining biased estimation results. One remedy is to assume that the error term has separate components. Depending on the properties of the error component, individual and temporal heterogeneity can be introduced as fixed or random effects. In a random effects model, it is assumed that effects are rather unobserved random variables which follow a probability distribution with finite parameters. Observed panel units should be representative of a larger population, and the number of units should potentially be able to go to infinity in a regular fashion (Elhorst 2003). When panels are specified for a given set of spatial units, such as regions in a country, the population is sampled exhaustively (Nerlove and Balestra 1996), and the individual units have characteristics that actually set them apart from a larger population (Anselin 1988). Hence, in the present study, the random effects model is not appropriate and the primary focus will be on fixed effects estimations.

A fixed effects model incorporating variable intercepts to model regional and time-period heterogeneity (two-way FE), takes the form:

¹⁰ Estimation of the models and all the spatial data analyses were done using “plm”, “splm” (Croissant and Millo, 2015; Millo and Piras, 2015) and “spdep” packages (Bivand, 2016) implemented in R statistical software. The packages are available on the CRAN package repository (www.cran.r-project.org) while codes used to obtain reported results and all additional information useful to make research reproducible will be made available by the authors on request.

$$y_{it} = \beta^T x_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} \sim N(0, \sigma^2 I_n)$$

y_{it} contains observations on the dependent variable and x_{it} observations on the K independent variables. β is a $K \times 1$ vector with regression coefficients, μ_i are (time-invariant) individual fixed effects for each region (regional FE) and η_t are time-period fixed effects (space-invariant) for each year (time FE). The coefficients in a regional FE model declare how Y given X within a region changes over time, while controlling for individual departure points. Coefficients of any variable x , which does not change over time are eliminated as they are implicitly included in the regional FE μ_i (Elhorst 2014). Impacts of time-invariant variables, which may be important to the analysis, cannot be estimated and evaluated. Similarly, in a time FE model, the coefficients of variables that do not change across space cannot be estimated when controlling for time FE η_t (Elhorst 2014). Hence, the focus lies on the development of Y given X between regions over time. Given this study wants to particularly derive explanations for ST uptake over space, including time-invariant, the focus will be on time FE estimation. In addition, regional FE and two-way FE models are deployed.

In order to capture the possibility that the dependent variable y_{it} depends on previous outcomes, i.e. $y_{i,t-1}$, a lagged dependent variable may be introduced, leading to a dynamic panel model (cf. Eq. 2). Not including a lagged dependent variable may lead to omitted variable bias and makes results less reliable.

$$y_{i,t} = \tau y_{i,t-1} + \beta^T x_{i,t} + \mu_i + \eta_t + \varepsilon_{it} \quad (2)$$

$$\varepsilon_{it} \sim N(0, \sigma^2 I_n)$$

The effect of the time lag in the dependent variable is captured in τ . Still, a problem may arise when panel data incorporate a locational component because spatial dependence may exist between the regions (Elhorst 2003). A $N \times N$ spatial weights matrix W_N is required to reproduce the neighbourhood structure of the panel regions, to test for spatial dependence, and to specify spatial models. In this study, a queen contiguity matrix is used, meaning two regions are defined as neighbours when they share a border. The spatial weights matrix takes the form:

$$w_{i,j} = \begin{cases} 1, & \text{if neighbour to } j \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Since the selection of the spatial weights matrix W is to some extent arbitrary, it is a common practice to examine whether results are robust to other specifications (Elhorst 2010b). Therefore, the applied models are also tested with an inverse distance weights matrix.¹¹

¹¹ Plots of neighbourhood structures and the definition of the inverse distance matrix are presented in the Appendix A.

The time FE estimation are tested for spatial error and spatial lag dependence with Lagrange Multiplier tests (LM error and LM lag) together with their robust versions (Anselin et al. 1996).¹² Subsequently, the model is extended to incorporate these two types of spatial dependence. The first specification is the spatial lag model, where the dependent variable in a region i is affected by dependent variables in neighbouring regions j (spatial autoregressive model, SAR). The equation of the SAR including time FE takes the form (a SAR regional FE effects includes μ instead):

$$Y = \lambda(I_T \otimes W_N)Y + X\beta + \eta + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$
(4)

Subscripts i and t are dropped in view of readability. Since a spatial panel is present, W_N is extended with an identity matrix I_T of dimension T . \otimes denotes the Kronecker product. λ is the spatial autoregressive parameter, which measures the effect of spatial lag in the dependent variable.

The second type of spatial dependence implies that error terms across spatial units are correlated (spatial error model, SEM). This indicates unobserved or omitted variables that result in similar decisions in adjacent regions. The SEM time FE panel model can be represented as follows:

$$Y = X\beta + \eta + u$$

$$u = \rho(I_T \otimes W_N)u + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$
(5)

u denotes a vector of spatially autocorrelated error terms, with the spatial autocorrelation parameter ρ . It measures the effect of spatial error dependence.

4 Data description and variable specification

4.1 Solar thermal data

ST data is collected from an online platform called “Solaratlas” (BSW 2017). It provides information on ST installations, which received a *MAP*-grant. The platform offers data starting from the year 2001 and contains NUTS3 level sums of installations as well as collector area. Installations are distinguished according to collector type (flat-plate-collector, tube-collector, and air-collector), sectors (i.e. private households, trade and commerce, industry etc.) and

¹² Tests for a missing spatially lagged dependent variable (LM lag) test that $\lambda = 0$; tests for spatial autocorrelation of the error (LM error) test whether $\rho = 0$. RLM error tests for error dependence in the possible presence of a missing lagged dependent variable. RLM lag tests for a missing spatial lagged dependent variable in the possible presence of spatial error dependence.

application (space heating, water heating, process heat). Further, total investment costs and granted subsidies are available. Investment costs include components, assembly as well as installation expenses. Regrettably, it is not possible to distinguish between ST installations of property owners or tenants. Also, data does not separate installations in existing or new buildings. Hence, no separate estimations can be made, yet the impact of both factors is captured by including them as independent variables.

Annual installed combi-systems of all collector types in private households are specified as the dependent variable in this study. After cleaning the data, a total number of 487,110 systems with a collector area of 6.1 million m² remains.¹³ Yearly installations are normalized to the number of households, so the dependent variable represents the diffusion rate of ST systems within a region. The installation rate is preferred to a simple counting variable as the number of households varies considerably across NUTS3 regions. Dividing by the number of households controls for this variation.¹⁴ Further, the explanatory variables are normalized to households to achieve a coherent data basis for the econometric analysis. The number of households in a region is only available for the cross-section of 2011, the year of the last German census. It is assumed to be constant over time for the normalization of the variables.

The spatial pattern of households' ST uptake shows a North-South gradient and a divide between East and West Germany, with lower levels in the east (Figure 3). Cities also show a rather low adoption, presumably related to the higher number of households living in multi-storey dwellings. Clustering in southern Germany, (e.g. in Bavaria) is visible and increasing over time. ST systems have a relatively low penetration rate, with a maximum of 7% of households using ST combi systems in a region by the end of 2015.

¹³ Some installations are not clearly allocated to a NUTS3 region (below 1% of total installations) and not considered.

¹⁴ For the normalisation, the number of households is preferred over other regional characteristics. Some studies restrict their sample to homeowners, reflecting the concept that only owners are actually able to choose the RHS. Others also include renters. It can be argued that unobserved factors influencing the tenure chosen also influence the selection of RHS and accordingly both household types need to be included (Braun 2010). When a household seeks to rent, the available heating type can be supposed to influence the decision. It is plausible that the renter has only limited influence on the RHS decision of the landlord in the short term. In a longer term perspective, one can argue that the sum of the households' or renters' preferences will probably also influence decisions of building owners (Bauermann 2015). In that sense, a household not only actively decides to rent a particular home, but also consciously decides on the RHS attached to that unit (Braun 2010).

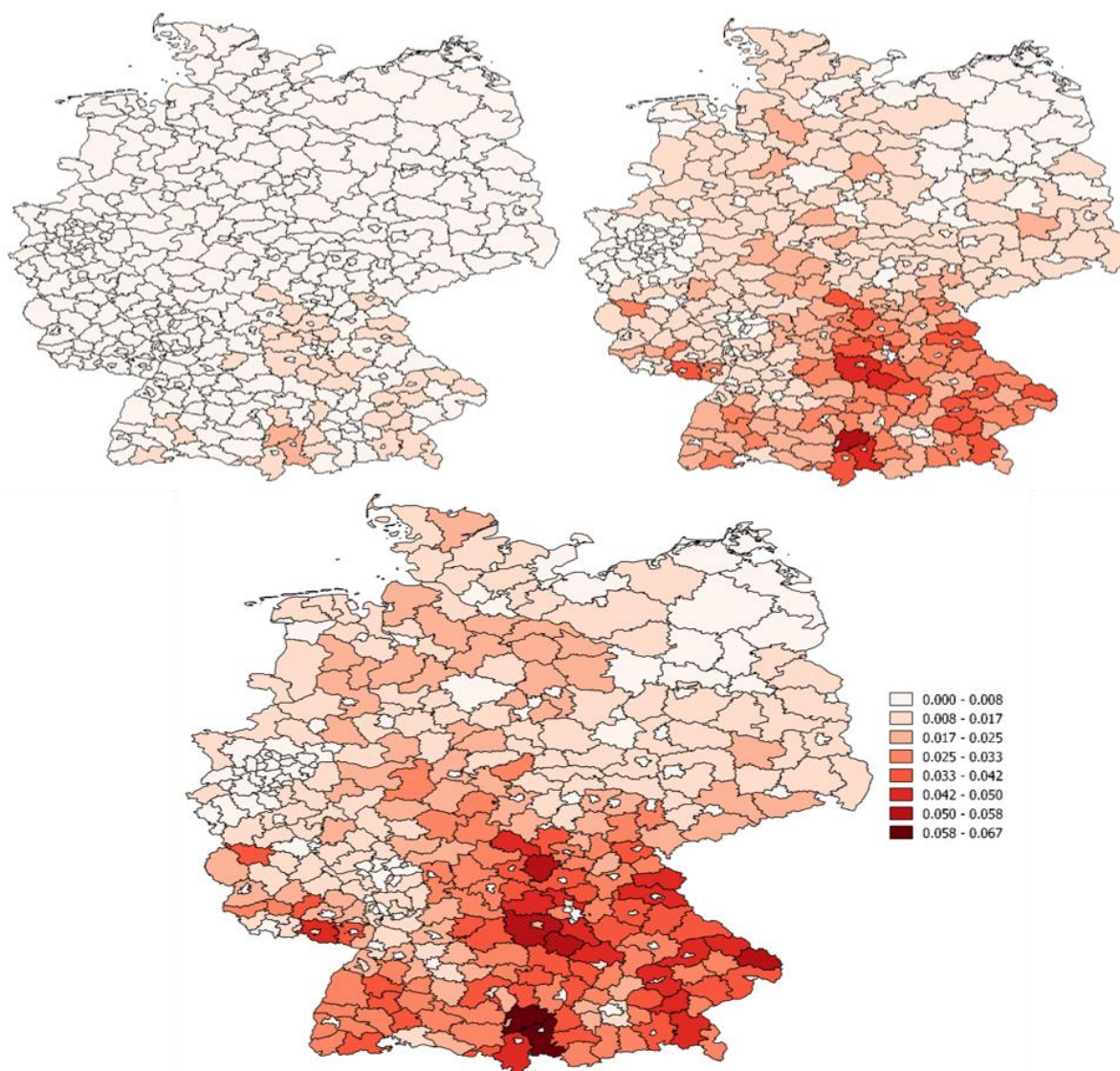


Figure 3: Regional distribution of household solar thermal Combi-systems in the years 2005, 2010 and 2015; Own illustration with data from BSW (2017)

4.2 Investment profitability index

A major barrier for a wider adoption of the ST technology are higher upfront costs in comparison with other RHS (Solar Heating & Cooling Program 2018). Overall, heating energy cost savings may recoup investment expensed, making ST systems a profitable investment – yet this depends on a number of factors. First, financial viability depends on upfront costs, the main heating energy source, energy prices and interest rates. Second, it depends on the usable energy output of the ST system, which in turn is subject to several factors inter alia heating demand, outdoor temperatures, collector area and storage size. A detailed profitability analysis of individual ST installations is not the focus of this study. Yet, the impact of changing energy prices and system costs over time and cross-sectional variation of solar radiation on ST adoption is to be captured in a consistent way.

The profitability of ST systems is modelled based on the following approach: In technical ST literature, a factor q_{sol} is defined as the usable solar net-energy amount in kWh per m² collector area in a year (Schabbach and Leibbrandt 2014). Heating losses of the collector circulation and pipe system are thereby already deducted. q_{sol} depends on individual characteristics including climatic factors (e.g. outdoor temperature, solar radiation), building characteristics (e.g. roof inclination, orientation, shadowing), and household behaviour (e.g. consumption profile, heating temperature). ST system features are furthermore important: inclination and orientation of collectors, collector size, storage size and system control (e.g. starting and stopping temperatures). Besides q_{sol} , a factor f_{sav} is used to capture the ratio between fossil energy consumption before and after the installation of a ST system.¹⁵ q_{sol} and f_{sav} can be determined by simulations or laboratory and field measurements (Corradini et al. 2014). Schabbach and Leibbrandt (2014) use simulations to determine q_{sol} for combi-systems in Germany. The authors obtain annual averages between 250 kWh/m²a and 400 kWh/m²a. For f_{sav} they report values between 19% and 46.4%, depending on the collector size. Based also on simulations, Drück and Müller-Steinhagen (2004) obtain similar values. Thür et al. (2011) measure 10 combi-systems in Austria and get q_{sol} values between 274 kWh/m²a and 428 kWh/m²a with an average of 322 kWh/m²a. This leads to fossil energy savings between 21% and 30%. Jordan and Vajen (2001) arrive at similar results. Tjaden et al. (2013) present savings between 5% and 28% based on simulations for German single family houses, with the numbers depending on the collector area and thermal storage volume. f_{sav} increases from 15% up to 50% with better insulation levels. Corradini et al. (2014) simulate different single-family houses in Germany and get results for f_{sav} between 15% and 35% for combi-systems.

Holding all other things constant (*ceteris paribus*), higher global radiation entails more usable solar energy, a higher q_{sol} (Tjaden et al. 2013). In the present study, this effect is captured and differences in solar radiation between NUTS3 regions are modelled. The usable thermal energy of a solar system in region i is defined as $q_{sol,i}$ [kWh/m²a] and represents the solar generated heat, which directly replaces thermal energy generation by the conventional heating system. It is calculated by multiplying the annual global solar radiation in a region rad_i with a reference usable energy $q_{sol,ref}$, divided by the reference radiation rad_{ref} :

¹⁵ The definition postulates, that both installations use the same conventional energy source, provide the same heating energy and thermal comfort. Definition of EN 12977-2: $f_{sav} = \frac{(Q_{conv} - Q_{aux})}{Q_{conv}}$ with $Q_{aux} = \frac{Q_{aux,net}}{\eta_{aux}}$ and $Q_{conv} = (Q_d + Q_{l,conv})/\eta_{conv}$; Q_{conv} denotes the energy demand of a fossil heating system without solar support. Q_{aux} gives the energy demand of a fossil heating system with solar thermal support. Q_d : Heat demand; $Q_{l,conv}$: Storage losses of conventional heating system; Energy savings: $Q_{sav} = Q_{conv} - Q_{aux}$

$$q_{sol,i} = \frac{rad_i}{rad_{ref}} \cdot q_{sol,ref} \quad (6)$$

In the present study, the reference usable solar heat $q_{sol,ref}$ is set to 300 kWh/m²a and rad_{ref} is set to 1091 kWh/m²a, the mean annual global radiation in our dataset.¹⁶ The derived $q_{sol,i}$ is in the range of 266 to 336 kWh/m²a, which is in line with the previously mentioned results of others and indicates realistic assumptions.

In line with a German standard for the calculation of economic efficiency of building installations (VDI 2067), profitability of ST systems is assessed with the annuity $A_{i,t}$ (Eq. 7). It represents the potential profitability in EUR/m² of a solar system in year t and region i . The term “profitability index” is used in this study. To calculate substituted fuel consumption (gas or oil) and finally avoided energy expenses (revenues), $q_{sol,i}$ is divided by the efficiency of the conventional heating system η_{conv} and multiplied with the energy price p_t in year t . η_{conv} is set to 75% (EN 12977-2). Revenues are multiplied with the price dynamic cash value factor b_t and the annuity factor a_t to account for annual changes in expected energy prices and interest rate effects.¹⁷ Investment expenditures (EUR/m²) result from average investment costs IC_t minus subsidies Sub_t and are annualized. Operation-related costs are calculated by multiplying investment costs with effort factors for servicing and inspection f_{W+Insp} and repair f_{Inst} (VDI 2067). Finally, annual capital and operation expenditures are subtracted from energy cost savings:

$$A_{i,t} = \left(\frac{q_{sol,i}}{\eta_{conv}} \cdot p_{i,t} \right) \cdot a_t \cdot b_t - (IC_t - Sub_t) \cdot a_t - IC_t \cdot (f_{Inst} + f_{W+Insp}) \cdot a_t \quad (7)$$

Figure 4 shows average values of the profitability index. It is obvious that investment costs (including MAP-grants) do not decrease over time. Further, price volatility of gas and oil including different price expectations leads to varying cost savings. The approximation of profitability in this study indicates that investments can only be recouped in the years 2008, 2012, 2013 and 2014. This is in line with other studies stating that investments in ST systems are hardly viable (Corradini et al. 2014).

¹⁶ $q_{sol,ref}$ values are varied in a sensitivity analysis leading to similar regression results. rad_{ref} of 1091 kWh/m²a corresponds to the global radiation of Würzburg. Climate factors of Würzburg are commonly used as reference values for heating system sizing in Germany (cf. Schabbach and Leibbrandt 2014, Corradini 2013.).

¹⁷ Price dynamic cash value factor $b_t = \frac{1 - \left(\frac{1+j_t}{1+i_t}\right)^T}{i_t - j_t}$ and annuity factor $a_t = \frac{(1+i_t)^{-1}}{1 - (1+i_t)^{-T}}$ both from VDI 2067. T : Lifetime, set to 20 years as supposed by VDI 2067 for flat plate collectors. j_t : expected energy price changes [%], i_t : interest rate [%]. Assumptions for annual interest, energy prices and expected price increases can be found in Appendix A.

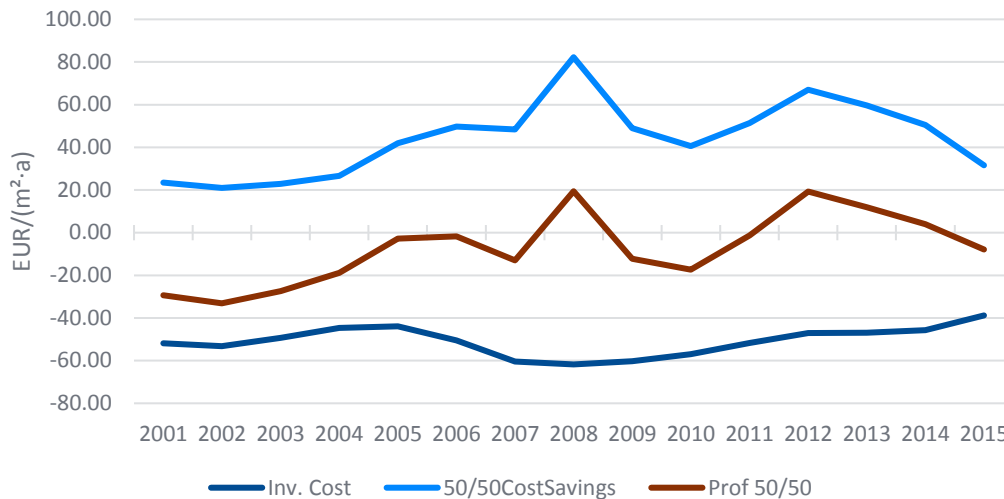


Figure 4: Average solar thermal system costs, generated energy cost savings and profitability index between 2001 and 2015

For the illustrated profitability index (used in the base estimations), the average of consumer gas and oil prices is used.¹⁸ As gas is the dominant heating technology in Germany (BMWI 2017b), gas prices are appropriate to calculate avoided energy expenses. However, especially single- and double family houses are equipped with oil-heating, making oil prices a similarly relevant indicator. Regional gas prices are obtained from a database which gathers prices of main gas providers on a zip code level (Michael Houben 2016).¹⁹ Oil prices are obtained from a provider for petroleum products but are only available on state level (mobene 2018).²⁰ Not only present but also expected future energy prices are a driver for RHS replacements (Achtnicht and Madlener 2014). Hence, annual expected price increases j_t are included in the profitability calculation. j_t are based on the historical consumer price development of the last ten years. As heating systems are a long term investment with an expected lifetime of 20 years, a price development of a rather long time period seems appropriate. However, more recent price developments (e.g. last three years) may be more present to consumers and have a greater impact on the decision. Thus, other time-frames of historical price developments are used to describe future price expectations and tested in the sensitivity analysis.

4.3 Explanatory variables

Besides economic incentives, different influences determining ST adoption are controlled for. Depending on the data source, a unique five-digit combination for municipalities (German term: Amtlicher Gemeindeschlüssel) or the postal code is used to match data to NUTS3 regions. As

¹⁸ Results using only gas, only oil prices or constant price increases and interest rates are also calculated (cf. section 5.3).

¹⁹ Regional prices include data from 2004 to 2015 for around 80% of NUTS3 regions. Missing NUTS3 data is approximated by state means. For the years 2001-2003, regional distribution factors of the years 2005-2008 are used and weighted with BMWI 2017b prices.

²⁰ A regional index for states is calculated based on oil prices between 2015 and 2017 and fitted to meet annual BMWI 2017b consumer energy prices for 2001 to 2015.

administrative district boundaries in Germany were redesigned between 2001 and 2015, the correct allocation of data is quite challenging. The NUTS3 version of 2013 is used and data are harmonized. However, while installation data are available in panel form, some of the characteristics are only available at NUTS3 level as cross-sectional data for the year 2011, the year of the last census in Germany (cf. Table 1). These include household size, owner-occupied houses, single-family houses and detached houses (Zensus 2011). These NUTS3 characteristics are included in the analysis as indicators for settlement structure. In addition, county area normalized to the number of households (the inverse of household density) is used to control for the effect of population density. To capture financial capability of a region, the share of welfare recipients is included, yet, due to data availability, only as a cross section of the year 2015 (Destatis 2018b). The share of social beneficiaries entails households who receive unemployment as well as other social benefits. As climatic characteristics, data on solar radiation and temperatures are retrieved from the German Weather Service (DWD 2015). They are almost time-invariant and average values of historical climate data are used when planning a ST system. Hence, long term averages are used in this study. Solar radiation represents the sum of global solar irradiation at the centre of a NUTS3 region. Heating Degree Days (HDD) are used to control for colder climates and extended heating needs. In this study they are defined as the sum of differences between 20° Celsius and the daily average outside temperature, when the daily average outside temperature is below 15° Celsius. Using these time-invariant NUTS3 characteristics entails the assumption that the factors are considered constant over the examined timeframe (2001-2015). It also implies that they are included in the regional FE and cannot be estimated in regional FE estimations. However, in time FE models, estimations allow insights into these (time-invariant) NUTS3 specific characteristics.

As household characteristics available in panel data form, average disposable household income (Destatis 2017) and share of green voters for the 2002, 2005, 2009 and 2013 federal election is included (Bundeswahlleiter 2016). Following the approach of previous studies (Schaffer and Brun 2015; Dharshing 2017), the share of Green voters (second votes for the Green party) is a proxy for environmental attitude. As a panel data variable for settlement structure, yearly residential constructions are considered (Destatis 2018a).

At last, to control for the effect of the *EEWärmeG*, which stopped subsidies for ST systems in new buildings by 2010, a *EEWärmeG*-dummy is introduced (as a time FE). As a sensitivity, only the period from 2001 to 2009 is examined to test whether the observed predictor variables have different impacts. As described in Sec. 3, potential spatial dependence might explain ST adoption. As a measure for spatial spillover of ST systems, the annual ST installations in adjacent regions are used. Table 1 provides descriptive statistics of the used variables.

Table 1: Descriptive statistics

Variable	Dimension (N x T)	Description	Mean	Std. Dev.	Min.	Max.	VIF ²¹
ST systems	15 x 402	Annual Adoption rate [-]	0.0011	0.0013	0.0000	0.0106	
Profitability Index	15 x 402	Annuity [EUR/m ²]	-7.37	16.37	-36.48	34.27	1.50
System costs	15 x 1	Installation costs [EUR/m ²]	871.92	93.65	714.20	992.25	
Subsidies	15 x 1	Grants [EUR/m ²]	130.62	27.27	89.80	199.38	
Energy price	15 x 402	Consumer price [EURCent/kWh]	6.16	1.34	3.68	9.17	
Price expectation	15 x 1	10 year price development [%]	5.67	2.12	1.92	10.30	
Interest rate	15 x 1	10-year German bonds [%]	3.25	1.34	0.53	4.98	
Solar radiation	1 x 402	Global radiation [kWh/m2a]	1,091	57	970	1,222	
New buildings	15 x 402	Annual built res. buildings/household	0.0037	0.0024	0.0000	0.0225	2.34
Income	15 x 402	Disposable household income [EUR]	41,529	7,436	23,529	86,212	2.71
Green voters	4 x 402	Green party second votes [%]	0.081	0.035	0.026	0.287	1.63
Household size	1 x 402	Household members [-]	2.20	0.19	1.77	2.74	9.29
Owner-occupied	1 x 402	Owner-occupied dwellings/household	0.519	0.144	0.128	0.769	14.44
Single family houses	1 x 402	Single family houses/household	0.388	0.152	0.085	0.753	8.29
Detached houses	1 x 402	Detached family houses/household	0.626	0.208	0.122	0.974	5.64
HDD	1 x 402	Measure for heating needs [-]	3,546	291	2,916	4,508	1.77
Inverse density	1 x 402	County area [m ²]/household	13,077	10,763	424	57,929	2.40
Welfare recipients	1 x 402	Social welfare recipients/household	0.171	0.075	0.038	0.423	1.59
PV systems	15 x 402	Annual adoption rate [-]	0.0020	0.0021	0.0000	0.0157	2.02

²¹ The variance inflation factor (VIF) is based on the square of the multiple correlation coefficients resulting from regressing a predictor variable against all other predictor variables. A VIF greater than 10 signals a collinearity problem in the model.

5 Empirical estimation and results

5.1 Static and dynamic panel model results

As a benchmark, a pooled OLS regression is estimated (cf. Table 2, all variables are standardized to improve comparability of coefficients). Collinearity causes instability in parameter estimation and must be avoided. It is tested using the variance inflation factor (VIF) (cf. Table 1). As household size, single-family houses, detached houses and owner-occupied houses are highly correlated only one variable is used. As household size entails the highest explanatory power, the corresponding results are shown. To investigate the null hypothesis that regional and time FE are jointly insignificant, Breusch-Pagan type Lagrange-Multiplier tests are performed. The hypothesis of insignificance of regional FE is rejected. Likewise, the insignificance of time FE is rejected and the influence of time FE seems to be bigger.²² The used variables seem to account for a larger share of regional characteristics than year-specific information.²³ This indicates that given the used dataset it is more important to include time FE than regional FE. Also, a practical aspect supports the use of time FE: Since *MAP* supported ST installations are considered, annual changes or announcements regarding the *MAP* funding rates may lead to time FE. A regional, a time and a two-way FE model are yet specified to compare results (cf. Table 2). As explained earlier, the RE model is not appropriate in this study. Yet, it is estimated and a Hausman specification test is performed to check that FE models provide a better fit to the data than the RE model.

In panel estimations, different R^2 can be defined. The shown within R^2 (cf. Table 2) represents the proportion of the within variance in ST uptake explained by the independent variables for a given FE, e.g. a NUTS3 region.²⁴ It can be used to compare the model fit of two regional FE models, but is inappropriate to compare the fit of different model types (e.g. a regional and a time FE model). The overall R^2 describes the proportion of the total variance in the dependent variable that is predictable from the independent variables and the fixed effects and can be used to compare different model types.²⁵ In addition, a between R^2 is computed by regressing the means of the ST uptake in a NUTS3 region (over the 15 year period) on the means of the individual independent variables. It amounts to 0.79, indicating that regional differences in ST uptake are explained quite well with the used variables.

²² Test regional FE: $\text{chisq} = 1,806$, $\text{df} = 1$, $p < 0.001$; test for time FE: $\text{chisq} = 76506$, $\text{df} = 1$, $p\text{-value} < 0.001$.

²³ By regressing the resulting 402 regional FE of the regional FE estimation with the variables HDD, household size, inverse population density and benefits, an R^2 of 70% is obtained.

²⁴ Here, the total sum of squares (TSS) for the regional FE model is defined as $TSS = \sum_{i=1}^N \sum_{t=1}^T (y_{it} - \bar{y}_i)^2$ with $\bar{y}_i = \frac{1}{T} \sum_{t=1}^T y_{i,t}$. For the time FE TSS is calculated with $\bar{y}_t = \frac{1}{N} \sum_{i=1}^N y_{i,t}$. R^2 is then defined as usual: $1 - \frac{RSS}{TSS}$ with RSS being the residual sum of squares.

²⁵ Here, TSS is defined as $TSS = \sum_{i=1}^N \sum_{t=1}^T (y_{it} - \bar{y})^2$ with $\bar{y} = \frac{1}{N \cdot T} \sum_{i=1}^N \sum_{t=1}^T y_{i,t}$. Wooldridge terms the within R^2 “centred” and the overall R^2 “uncentred” (Wooldridge 2002.)

Table 2: Estimation results of static panel models

	OLS (pooled)	Regional FE	Time FE	Two-way FE
Profitability index	0.4359*** (0.0098)	0.4130*** (0.0095)	0.9144*** (0.0405)	0.7507*** (0.0617)
New buildings	-0.2727*** (0.0110)	-0.3606*** (0.0145)	-0.1425*** (0.0100)	-0.1581*** (0.0136)
Income	-0.1101*** (0.0148)	-0.1112*** (0.0265)	-0.0685*** (0.0132)	-0.1572*** (0.0291)
Green	0.0813*** (0.0102)	0.4182*** (0.0225)	0.0040 (0.0091)	-0.0226 (0.0281)
EEWärmeG	-0.4154*** (0.0104)	-0.4754*** (0.0119)		
Household size	0.5021*** (0.0169)		0.4354*** (0.0149)	
Heating degree days	0.1637*** (0.0106)		0.1642*** (0.0089)	
Inverse population density	0.0878*** (0.0118)		0.0654*** (0.0100)	
Benefits	-0.2137*** (0.0142)		-0.1411*** (0.0134)	
Within R ²	0.5844	0.4763	0.5545	0.0473
Overall R ²	0.5844	0.7103	0.7085	0.8020
AIC	11836.14	10457.27	9727.96	8191.51
BIC	11909.89	13192.71	9888.87	11020.81

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

The ST uptake within a region is likely to depend on the previous adoptions in this region (e.g. because of peer effects), which may lead to autocorrelation in the static panel models. In fact, Wooldridge's test for serial correlation in FE panels (Wooldridge 2002) points to serial correlation in the estimated FE specifications which might bias results. One remedy is to include a lagged dependent variable, leading to a dynamic model (cf section 3). Hence, we include solar thermal uptake of the previous year as a predictor for ST uptake in a region (cf. Table 3). However, introducing a lagged dependent variable takes out a lot of variance and reduces the impact of other explanatory variables. Also, results must be regarded in face of potential “Nickell bias” as our panel is rather short (Nickell 1981). Comparing the static (cf. Table 2) and the dynamic estimation results (cf. Table 3), the coefficients' signs do not change, indicating robust estimation results when introducing the lagged dependent variable. Yet, as expected, coefficients are generally smaller. Notably, the introduction of time lagged ST uptake enhances the model fit of each FE specification, indicated by higher within and overall R² as well as by the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). So even model specifications including time FE are further enhanced by an autocorrelation

term which indicates the relevance of a time-lagged imitation or peer-group effect. Wooldridge's tests further show a reduced serial correlation, as expected.

Table 3: Estimation results of dynamic panel models

	OLS (pooled)	Regional FE	Time FE	Two-way FE
Profitability index	0.4370*** (0.0082)	0.4369*** (0.0088)	0.4789*** (0.0348)	0.6295*** (0.0579)
New buildings	-0.1039*** (0.0097)	-0.2112*** (0.0144)	-0.0610*** (0.0085)	-0.0987*** (0.0129)
Income	-0.0727*** (0.0123)	-0.1642*** (0.0247)	-0.0455*** (0.0110)	-0.1723*** (0.0272)
Green	0.0229*** (0.0085)	0.1796*** (0.0224)	-0.0009 (0.0076)	-0.0589** (0.0263)
EEWärmeG	-0.3860*** (0.0086)	-0.3988*** (0.0114)		
Household size	0.2632*** (0.0148)		0.2101*** (0.0132)	
Heating degree days	0.0864*** (0.0089)		0.0761*** (0.0076)	
Inverse population density	0.0307*** (0.0098)		0.0244*** (0.0083)	
Benefits	-0.0886*** (0.0120)		-0.0623*** (0.0113)	
Lag of ST uptake (tau)	0.4819*** (0.0093)	0.3274*** (0.0111)	0.5418*** (0.0106)	0.3431*** (0.0122)
Within R ²	0.7127	0.5469	0.6900	0.1648
Overall R ²	0.7127	0.7493	0.7970	0.8264
AIC	9614.96	9587.76	7544.65	7399.52
BIC	9695.42	12329.90	7712.27	10235.53

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

Looking at the results of the different FE specification, the following aspects are worth noting. Overall R² and AIC point out that the two-way FE performs best, as it includes regional and time FE. However, the impact of several time invariant predictor variables cannot be evaluated, as they are implicitly included in the individual intercepts u_i (cf. section 3). It is hence not possible to derive implications on which regional characteristics drive regional ST uptake. However, as these (time-variant) regional characteristics are of special interest in this study, the time FE model is favoured. Also, the model fit of the time FE comes close to the fit of the two-way FE in terms of overall R² and AIC. If the number of estimated parameters (including FE) is strongly penalized as done in the BIC, the time FE even renders the best result. Subsequently, the focus of the analysis is hence on the time FE model results and only

selected findings of other specifications are used to complement the analysis. It is worth noting that the estimated coefficients have the same sign and significance in all (static and) dynamic FE specifications, except the coefficient for Green voters (addressed in the next paragraph).

The effect of previous ST installations in a region is found to be positive in all dynamic specifications. Accordingly, adoption in one region predicts an increased likelihood of similar behaviour in this region. Recurrent visual perception or social contagion might explain the positive time lag as potential adopters follow decisions by peers. The effect of the profitability index conforms with expectations, as the coefficient is positive and indicative of a response of ST adoption to economic viability. Notably, high energy prices and price expectations seem to drive the installation of ST systems. Also higher solar radiation in a region, which implies larger solar yields and superior annuities favours ST uptake. The negative impact of new constructions on ST uptake indicates that the uptake of ST systems is less likely in NUTS3 regions with higher construction rates.²⁶ Also, the regional FE result implies that within a region, ST uptake is lower in years with high construction rates. This could be a result of financial constraints, which may especially prevail when constructing a house, making households choose comparatively lower priced heating systems. The official *MAP* evaluation covering the period 2007-2008, before the *EEWärmeG* was enacted, states that the building stock is accountable for 90% of *MAP* supported household ST installations (Nast et al. 2009). Also considering this finding, the estimation results show ST systems are easily applied in the building stock and adoption does not depend on new construction.

Household income has a negative impact on residential ST installations, showing that above average household income is no precondition for the adoption of ST systems. Based on the rationale that wealthier areas are more likely to adopt ST systems, this finding is surprising. However, the share of welfare recipients in a region affects negatively ST uptake. Hence, the share of welfare recipients seems to be a suitable negative proxy for wealth and financial capability in a region. It might not be income but rather wealth i.e. accumulated capital, which contributes to different regional ST diffusion levels.

No impact of Green voters is detected in the time FE model, implying that differences in Green votership do not explain varying ST adoption between regions. Yet, the result of the regional FE model indicates that the development of Green vote shares within a region positively affects ST uptake in a region over time, whereas in the two-way FE model the effect is negative. Hence, the effect of Green voters stays ambiguous.

²⁶ Although the effect of the *EEWärmeG* is captured in the time FE (or in a dummy-variable for the years 2010-2015 in the regional FE model), the terminated funding of ST systems in new constructions may contribute to this finding.

Next to profitability, especially household size qualifies to explain differences in regional ST adoption levels. It implies that larger households are more inclined to use ST systems. Water and space heating needs increase with the number of persons in a household, which usually increases utilization and efficiency of a ST system leading to higher profitability. As household size is positively correlated with detached houses, single-family houses and owner-occupied housing, the impact of these variables is also implicitly included in the finding. By replacing household size with these variables respectively, estimations show that all three have a positive impact on regional ST uptake.²⁷ Thus, households living in their own single-family house have a higher propensity to adopt ST systems. Further, results show that less densely populated regions favour ST uptake. Solar collectors need open areas that are clear of obstructions from sunlight; such areas may be more prevalent in less densely populated regions (with higher shares of detached houses and on average larger floor and roof area per dwelling). The coefficient of HDD is positive, which indicates a broader use of ST systems in regions with above average heating demand. This again may be a result of higher utilization of the ST system which positively influences economic viability.

The regional FE estimation results confirm that the *EEWärmeG* reduces *MAP* subsidised ST installations (cf. Figure 2). First, this is a direct result of terminating grants for combi-systems in existing buildings starting 2010. Second, the announcement of the *EEWärmeG* with the prospect of reduced subsidies, could have shifted ST adoptions to the years before the enactment (2008 and 2009), as households wanted to benefit from the higher grants. In addition, uncertain funding conditions mainly due to the temporary suspension in of *MAP*-grants in 2010 may have led to lacking trust in the *MAP*, roughly at the same time of the *EEWärmeG* enactment.

5.2 Spatial model results

If spatial dependence exists in a model, it may suffer from misspecification. To test for spatial correlation, Lagrange Multiplier (LM) tests are carried out for the time FE model (cf. Table 4). In the classical LM tests, the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatially autocorrelated error term are strongly rejected. It seems that although accounting for time FE and a time lag in ST adoptions, spatial spillover in ST uptake is present. Examining the LM tests' robust counterparts, the hypothesis of no autocorrelated error is still rejected. Yet, in presence of a spatially autocorrelated error, no spatially lagged dependent variable is present. Nevertheless, both the SEM and SAR model are estimated.

²⁷ Results are provided upon request. When considering all four variables in a single model (which should not be done because of collinearity), the effect of detached houses, single family houses and owner-occupied houses turns insignificant, while the coefficient of household size (and inverse population density) stays positive and significant. Therefore this variable is retained in the final specification.

Table 4: Tests for spatial dependence in the time FE model

Tests	
LM _{lag}	19.44***
LM _{error}	25.21***
rLM _{lag}	2.08
rLM _{error}	7.86***

*** Significance level at 1%

Considering the coefficients of the SAR and SEM with time FE, the detected signs of the predictor variables in the conventional time FE model are (cf. Table 5). A difference to the conventional FE model are slightly different coefficient values in the spatial models. Smaller coefficients indicate that the direct influence of a variable is less pronounced, and that their impact is partly attributable to spatial association.

The SAR model shows the effect of spatial lag in the dependent variable (number of ST systems). The positive and statistically significant estimate of the spatial autoregressive parameter λ reveals a positive correlation between the uptakes of solar collectors in neighbouring regions. According to this model specification, adoption levels in one region may serve to predict an increased likelihood of similar behaviours in neighbouring regions, implying that levels of ST uptake tend to spill over county borders. Recurrent visual perception, intensified social interactions and peer-effects might explain spatial lag as potential adopters follow decisions by actors in the proximity. The positive and statistically significant estimate of the autocorrelation parameter ρ in the SEM indicates spatial dependence in the residuals. According to this model, similar unobserved characteristics hence result in similar decisions in neighbouring regions. A local concentration of craft skills, solar initiatives, local ST supplier activities or advertising campaigns might lead to an accelerated ST diffusion in a region and its surroundings.

The spatial panel models confirm the hypothesis that residential ST systems form geographical clusters in certain regions. Both, the SAR and SEM specification improve the model fit and therefore both types of spatial spillover may be acknowledged when modelling ST uptake. Yet, by taking one type of spatial dependence into account, the explanatory power of the other is reduced drastically. Hence, it is advisable to consider either spatial lag or spatial error dependence in a specification. Addressing regional ST diffusion, overall R^2 , AIC and BIC point to the SEM as the preferable specification. This indicates that although spatial lag is present, spatial dependence in the residuals is more influential. Yet, on the basis of the available dataset, which relies on rather large spatial entities, a clear distinction between the two spillover types is challenging and requires further research.

Table 5: Estimation results with spatial interactions for dynamic time FE models

	Time FE	SAR Time FE	SEM Time FE
Profitability Index	0.4789*** (0.0348)	0.1627*** (0.0333)	0.2921*** (0.0407)
New buildings	-0.0610*** (0.0085)	-0.0528*** (0.0078)	-0.035*** (0.0084)
Income	-0.0455*** (0.0110)	-0.0228** (0.0102)	-0.0309*** (0.0107)
Green	-0.0009 (0.0076)	-0.0043 (0.0070)	0.0106 (0.0080)
Household size	0.2101*** (0.0132)	0.2016*** (0.0136)	0.1743*** (0.0130)
Heating degree days	0.0761*** (0.0076)	0.0210*** (0.0072)	0.0554*** (0.0084)
Inverse population density	0.0244*** (0.0083)	0.0562*** (0.0090)	0.0442*** (0.0091)
Benefits	-0.0623*** (0.0113)	-0.0156 (0.0106)	-0.0442*** (0.0107)
Lag of ST uptake (tau)	0.5418*** (0.0106)	0.4835*** (0.0103)	0.5817*** (0.0104)
Lambda		0.2927*** (0.0106)	
Rho			0.5217*** (0.0139)
Overall R ²	0.7970	0.8266	0.8528
AIC	7544.65	6596.56	5608.40
BIC	7712.27	6770.88	5782.72

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

5.3 Sensitivity and robustness results

The aim of this study is not to identify a best model specification but to derive resilient implications regarding the uptake of ST combi-systems building on several estimations. To test whether results are robust against input data variations a sensitivity analysis is performed. First, a constant energy price increase of 3% is employed, instead of expectations formed based on the development over the previous ten years. Also, a sensitivity with a price expectation based on the last three years is tested. The used interest rate is based on the interest of 10-year government securities. As a sensitivity, a constant interest rate of 3% is used throughout. In the base model, the average of oil and gas prices is employed, as these energy sources have the largest shares in the residential building stock. As a sensitivity, gas

prices and oil prices are considered separately. The majority of coefficient estimates do not change for the performed input data variations, implying robust results.²⁸

Similar to ST collectors, PV panels can also be roof mounted and are a possible competitor for roof area. However, visibility of PV panels in NUTS3 regions may also induce social imitation – including also installations of ST systems. Although ST and PV are very different technologies, they may look similar in a passers-by perspective. Thus, an estimation including panel data on PV installations up to 10 kW as a predictor is performed.²⁹ Results show that PV installations and ST systems positively correlate in all model specifications (cf. Appendix B, Tables 7-10). This indicates that PV uptake does not negatively affect ST adoption. Rather, imitative purchase behaviour could be present. By the year 2015, the two solar technologies hence do not seem to compete for roof space or possible adopters.

Studies suggest that households do not conduct profitability calculations when deciding on energy saving measures (e.g. (Zundel and Stieß 2011; Aravena et al. 2016); Baginski & Weber 2018). They exclude certain aspects and are possibly not fully aware of all costs during the purchase stage (Michelsen and Madlener 2012). To test, how the defined profitability index performs, the regression is also done using single variables for system costs (investment costs minus subsidies), solar radiation, interest rate, energy prices and price expectations. Thereby, effects can be singled out and argued whether the decision rather follows a business investment calculus or is driven by one or more single parameters. Results are referred to as the consumer model (cf. Appendix B, Tables 7-10). The estimated coefficients on energy prices, price expectations and solar radiation are positive and indicative of a response to economic viability. ST installations are more likely in regions with higher solar radiation and times with higher prices and price expectations. The impact of investment cost is negative, whereas the effect of subsidies is positive. Again, differences in profitability influence ST adoption. Interest rates seem to positively affect the decision to invest in ST systems, which is surprising from an economic perspective. It indicates that households do not consider capital costs for ST investments, which increase with rising interest rate.

In addition, a focus is put on the period until 2009, to exclude the effect of the *EEWärmeG* and the consecutive changes in the *MAP*. Some variations regarding the income variable are observed. First, in regional FE models, the income variable turns positive, indicating that until 2009, ST adoptions and income within a region are positively correlated (cf. Appendix B, Table 9 and Table 10). In the time FE models, the income variable is insignificant, entailing no effect of income on different adoption levels between regions. Finally, a different weights matrix is

²⁸ Results are made available upon request.

²⁹ In addition, I only included PV system costs, which decreased drastically in the observed period and may have made PV preferable over ST systems for some households. However, PV costs are only available in the time-dimension whereas PV installations are available in panel form, including more information.

applied (cf. Appendix A, Figure 5). Results are confirmed and seem robust against other NUTS3 neighbourhood structures.

6 Conclusion and Implications

Space heating accounts for a large fraction of the primary energy consumption and CO₂ emissions of residential buildings in Germany. Besides targeting the insulation of homes, renewable-based heating systems offer the potential to reduce conventional energy consumption and move towards a low-carbon building stock. Thus, understanding a broader set of determinants for households' heating system choice becomes increasingly important. This article studies drivers and barriers influencing the spatio-temporal diffusion of solar systems, using panel data, based on NUTS3-year combinations. Besides regional fixed effects and time fixed effects models, spatial panel models are estimated to capture regional clustering of ST adoption. The presented results might be exploited for future policy design or targeted marketing strategies. A few implications are derived here.

Estimation results indicate that ST uptake follows profitability causing differences in ST adoption rates between regions and over time. In particular, differing solar radiation levels and fossil fuel prices drive profitability. It implies that households' adoption decision can be at least to some extent explained by economic considerations. Thus, policy instruments providing financial support and enhancing economic viability (like the *MAP*) effectively contribute to ST uptake. However, the lack of cost effectiveness of residential ST heating - even when subsidies are taken into account - is still a major limitation for technology adoption. Additionally, price signals for conventional energy sources, e.g. induced by a CO₂-tax, improve economic viability of ST systems and are therefore a policy instrument likely to foster the diffusion of renewable heating systems. Also, the use of ST systems might increase if economies of scale and scope will result in substantial cost reductions, which are not accomplished to date.

A negative impact of new constructions on ST uptake is present in all estimated models. Other (renewable) RHS seem to be preferred and more (cost) attractive in new buildings. Notably, the finding indicates that ST systems are easily applied in the building stock, making it a suitable renewable technology for retrofit activities. Yet, if policy makers intend to increase the share of ST systems in new buildings, their installation needs to be more attractive, e.g. higher funding made available.

The results further show that larger households are more inclined to adopt ST systems, indicating a more efficient use of solar generated heat.³⁰ In addition, inverse population density increases the propensity to use solar heating. ST adopting households are likely to live in

³⁰ Further, results suggest that households with ST systems are homeowners and live in detached single-family houses.

spacious, rural areas, with possibly higher shares of detached single-family houses and large (unshaded) roof space. Further, regional ST installations positively correlate with HDD, indicating that higher heating needs are advantageous for ST systems. The share of green voters does not qualify to explain regional ST adoption levels, as the coefficient is insignificant in the time FE models. Also, disposable household income does not foster ST uptake, as the coefficient shows a negative sign. Based on the rationale that wealthier areas are more likely to be structurally enabled to adopt ST systems, this finding is surprising. However, high shares of social beneficiaries decelerate the regional diffusion of ST system. It might hence not be income but rather wealth i.e. accumulated capital, which contributes to different regional ST diffusion levels. The share of welfare recipients may be the better indicator for wealth or financial capability of a region compared to household income. It implies that ST uptake is constrained in financially disadvantaged regions. If a more evenly distributed spatial diffusion of ST systems is intended, differential NUTS3 level subsidies could be introduced or financially weak regions could be specifically targeted with monetary incentives, which need to be higher than *MAP*-grants. Delegating the effective design and implementation of instruments to the federal states or counties can be a meaningful strategy to better suit regional heterogeneity (Braun 2010). This is already done in Baden-Württemberg, where a state specific law was enacted in 2008.³¹

Besides the impact of the included predictor variables, it is shown that ST uptake follows an autoregressive process, since adoption rates in a region are positively influenced by past adoption decisions in this region. Recurrent visual perception or social contagion might induce potential adopters to follow decisions by actors nearby. As the adoption behaviour of others affects the use of solar heating, highly visible projects may promote diffusion effectively. Moreover, results show that these peer effects are not confined by NUTS3 borders, but are likely to spillover, indicated by spatial lag in ST adoption captured in the SAR model. Spatial model results point to spatial spillover between ST adoption levels in adjacent counties and confirm that residential ST forms local clusters in certain regions. Another and even more important reason for spatial dependence are unobserved spatially correlated effects, indicated by the SEM model. This might be e.g. a regional concentration of craft skills. The uptake of ST devices in an area likely means that neighbouring regions benefit from the technical installation expertise, leading to spillover across NUTS3 borders. Also, information dissemination activities in some regions (e.g. information campaigns, door-to-door energy advice) possibly lead to an accelerated ST diffusion in certain regions and its surroundings.

With the commencement of the *EEWärmeG*, (*MAP* subsidised) ST uptake drastically decreased, as funding for standard ST combi-systems in new buildings was discontinued and

³¹ Erneuerbare-Wärme-Gesetz (EWärmeG), of november 20th, 2008 (GBl. 19, p. 531), and revised march 17th, 2015 (GBl. 5, p. 151).

at the same time support for ST systems for water heating was generally stopped. A further major driver for decreasing ST uptake after 2009, which coincided with the *EEWärmeG*, may be the temporary suspension of *MAP*-grants in 2010. This disruption might also have reduced trust in the funding scheme and decreased acceptance. In this respect, it is recommendable to provide stable funding conditions, which was not the case for the *MAP* in the considered period. Yet, regulatory measures (like renewable use obligations established in the *EEWärmeG*) help to brake persisting behaviours (Michelsen and Madlener 2013) and increase the share of renewable heating technologies. A balanced bundle of policy instruments should be established and adverse repercussions prevented.

The present study deepens the understanding on the regional distribution of domestic ST systems. Yet, limitations leave room for further investigations. The variables employed are not the only possible predictors of ST technology use. Studies identifying a richer set of household attributes and preferences and models employing other socio-demographic variables could improve results. Yet, sensitivity analyses show rather robust results regarding the employed variables. Further research is needed to disentangle the sources of peer-effects, spatial dependence and regional clustering. When examining spillover effects, NUTS3 regions are rather large to control for neighbourhood effects and spillover between households. Smaller units could be employed to allow for more specific interpretations. Also, other spatial models, like the spatial Durbin specification could be tested, which includes a spatial lag in the independent variables (Elhorst 2010a). Moreover, the investigated ST sample only covers installations that received a *MAP*-grant. Until 2009, the majority of ST installations is covered (cf. Figure 2). After that, only half of the installed ST systems received a grant. Extending the sample to all domestic ST installations might enhance results and allow for more general conclusions – yet data is likely to be not available. Alternatively, the study could also be extended to other renewable heating technologies supported under the *MAP*.

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Appendix A: Input data

Neighbourhood structures

There are different options to define the spatial weights matrix W based on concepts of contiguity and distance; or a combination of both (Anselin and Bera 1998). The used inverse-distance matrix is defined as:

$$w_{i,j} = \frac{1}{d_{i,j}}; w_{i,j} = 0, \text{ if } d_{i,j} > 65 \text{ km}$$

By convention, the diagonal elements of the weights matrix ($w_{i,i}$) are set to zero as no spatial unit is viewed as its own neighbour and row elements are standardized such that they sum to one. NUTS3 centres are used to calculate distances. As the effect of spatial units on the entity of interest is expected to decrease with distance and eventually vanish, a cut-off distance at 65 km is introduced. Thereby each region has at least one neighbour.

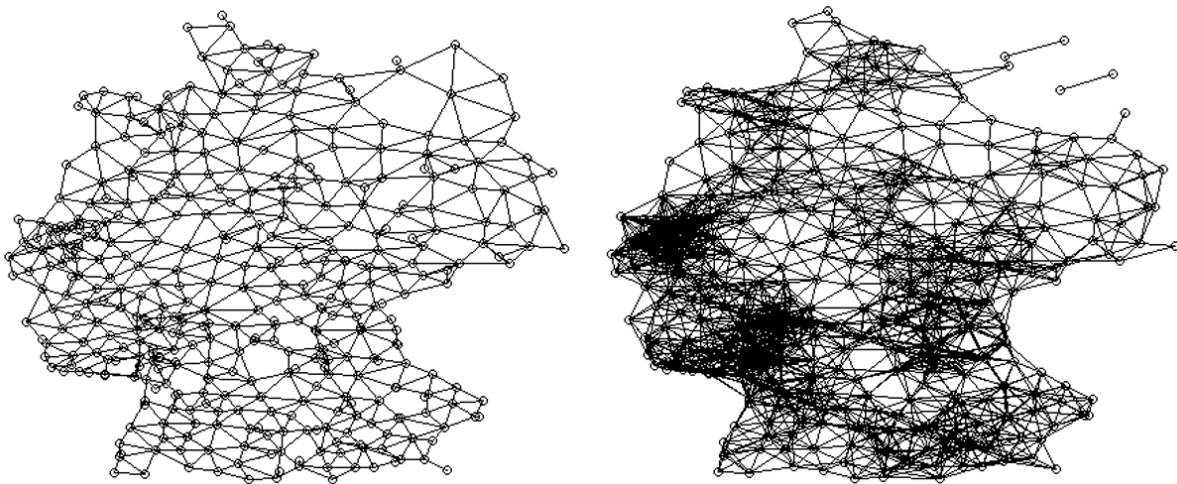


Figure 5: Neighbourhood structure of queen contiguity spatial weights matrix (left) and inverse distance spatial weights matrix with cut-off distance at 65 km (right) of German NUTS3 regions

Additional information on investment costs

Major driver of system costs are collectors, which are subject to the cost of primarily used materials like copper and aluminium. Besides production costs, system costs are determined by costs for marketing, retail etc. Cost developments of ST systems showed a steady decrease up to 2002. Since then, prices of some components increased and hence solar system prices remained constant or even went up (BSW – Bundesverband Solarwirtschaft e.V. 2012). According to the official evaluation of the *MAP*, no distinct explanation, e.g. like shortages, could be derived from discussions with industry representatives. However, some producers (with delays) presumably considered increased commodity prices of previous years, especially after high turnovers in 2007 and 2008 (Langniß et al. 2011). Although producers of flat plate

collectors claimed to have reduced production costs and due to price competition are forced to pass on price reduction to sales and distribution, these price reductions did not pass on to consumer prices. Somewhere in the distribution chain (wholesale, sale, installation) price reductions have been lost or even surpassed. Langniß et al. (2011) suggests that cost reduction potentials in the installation business are not realised by artisans. Due to high utilization, installers and plumbers do not perceive the need to reduce installations costs of ST systems (Langniß et al. 2011). In the ST data (cf. section 4.1), a wide spread between investment costs is present. One reason can be the use of different components (e.g. collectors with and without expensive antireflexion coating) or distinct system hydraulics (Stuible et al. 2016). Also, installation circumstances and profit margins of installers vary. Average specific investment costs in relation to average collector area for combi-systems subsidised under the *MAP* reveal that prices do not fall over the years (cf. Figure 6). Average costs lie between 671 and 983 €/m² and average sizes between 14.7 and 11.9 m².

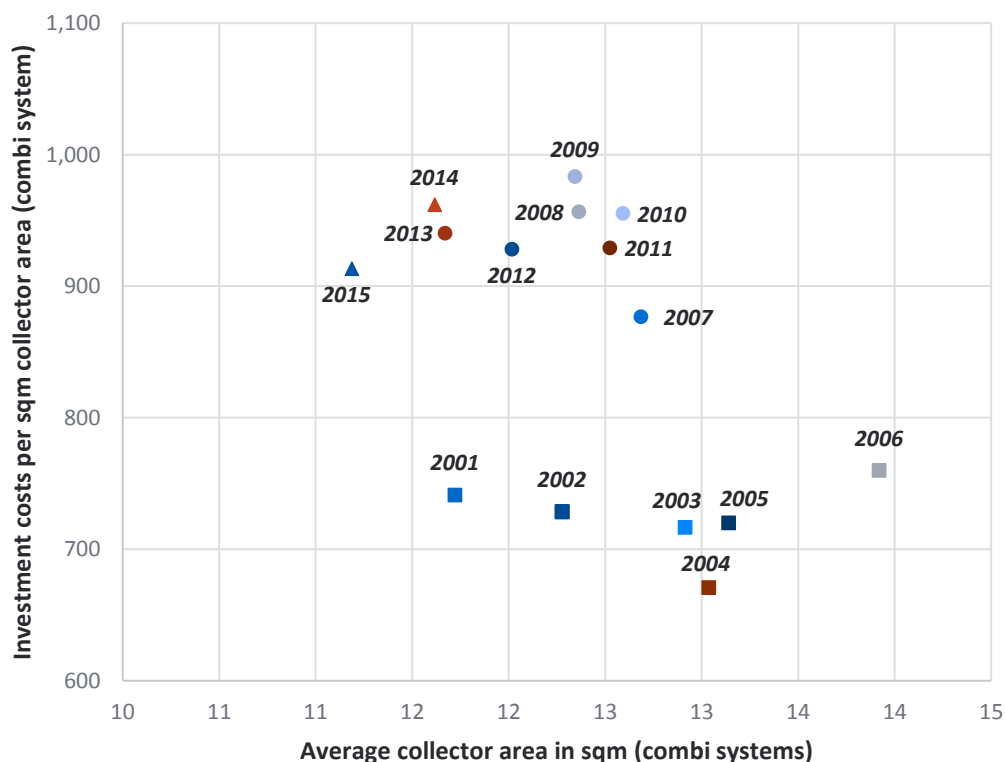


Figure 6: Collector area and specific investment costs of subsidised solar thermal Combi-systems; own illustration based on data from solaratlas.de

Usually, specific investment costs decrease with rising collector area. This is visible comparing costs of combi-systems and water heating systems, which usually have smaller collector sizes around 6 m². Offering turnkey-ST-systems with a smaller collector area in order to provide low-priced products might increase specific investments costs. However, average collector area of combi-systems did not change much between 2001 and 2015 (cf. Figure 6). Thus, specific cost increases are not due to smaller systems. Price increases are especially visible from 2006 to

2007. During the year 2007, in addition to the basic subsidy, a bonus was introduced in the *MAP*. It was paid for the supplementary installation of high efficient pumps or the replacement of the existent heating systems. Due to this linkage of other measures with ST systems, the declared investment costs turn out to be higher for the subsequent years, which is not only due to increasing system prices. Also, after 2007 subsidies in the used data are slightly higher than standard *MAP*-grants. As there is no itemization for investment costs in (BSW 2017) (i.e. solar thermal system, storage, heating boiler, pumps, hydraulic compensation), interpretation is rather difficult.

Input data profitability index

Table 6: Interest rates, energy prices and price expectations for the base profitability index

Year	Interest rate	Average gas price	Average oil price	Gas price increase	Oil price increase
2001	4.98%	4,84	3,87	3.84%	3.17%
2002	4.92%	4,53	3,54	3.74%	2.39%
2003	4.29%	4,76	3,67	3.94%	2.99%
2004	4.23%	4,82	4,09	5.81%	3.11%
2005	3.45%	5,34	5,40	9.34%	4.37%
2006	3.87%	6,33	5,97	8.63%	6.55%
2007	4.31%	6,51	5,91	8.24%	6.43%
2008	4.16%	7,10	7,77	13.32%	7.29%
2009	3.59%	6,98	5,39	7.26%	7.53%
2010	2.97%	6,36	6,60	4.85%	4.92%
2011	2.84%	6,66	8,22	7.82%	3.23%
2012	1.65%	7,03	8,95	9.72%	4.48%
2013	1.69%	7,13	8,41	8.64%	4.11%
2014	1.23%	7,14	7,75	6.60%	4.01%
2015	0.53%	7,06	5,96	1.00%	2.83%

Appendix B: Sensitivity analyses

Table 7: Sensitivity estimations for the time fixed effects spatial lag model

	Base model	No time lag	PV install.	Till 2009	Cons. model	Distance W.
Profitability index	0.1627*** (0.0333)	0.4563*** (0.0381)	0.1503*** (0.0336)	0.2507*** (0.0422)		0.1830*** (0.0345)
Solar radiation					0.0015 (0.0077)	
Energy price					0.0996*** (0.0293)	
New buildings	-0.0528*** (0.0078)	-0.1216*** (0.0091)	-0.0527*** (0.0078)	-0.0665*** (0.0097)	-0.0494*** (0.0079)	-0.0500*** (0.0080)
Income	-0.0228** (0.0102)	-0.0367*** (0.0121)	-0.0218** (0.0103)	0.0147 (0.0113)	-0.0183* (0.0103)	-0.0290*** (0.0105)
Green	-0.0043 (0.0070)	-0.0007 (0.0083)	-0.0047 (0.0070)	-0.0066 (0.0084)	-0.0037 (0.0070)	-0.0156** (0.0072)
Household size	0.2016*** (0.0136)	0.3943*** (0.0136)	0.1912*** (0.0128)	0.2080*** (0.0148)	0.1907*** (0.0124)	0.2109*** (0.0125)
HDD	0.0210*** (0.0072)	0.0828*** (0.0084)	0.0220*** (0.0072)	0.0317*** (0.0089)	0.0155** (0.0073)	0.0211*** (0.0075)
Inverse pop. density	0.0562*** (0.0090)	0.1006*** (0.0090)	0.0562*** (0.0078)	0.0661*** (0.0096)	0.0567*** (0.0078)	0.0523*** (0.0079)
Benefits	-0.0156 (0.0106)	-0.0714*** (0.0124)	-0.0137 (0.0106)	-0.0118 (0.0128)	-0.0266** (0.0111)	-0.0179* (0.0109)
Lag of ST uptake	0.4835*** (0.0103)		0.4751*** (0.0106)	0.5545*** (0.0136)	0.4888 (0.0103)	0.5022*** (0.0104)
PV installations			0.0289 (0.0098)			
Lambda	0.2927*** (0.0106)	0.3695*** (0.0121)	0.2880*** (0.0107)	0.2572*** (0.0133)	0.3051*** (0.0106)	0.3321*** (0.0134)
Overall R ²	0.8266	0.7618	0.8267	0.8430	0.8268	0.8180
AIC	6596.56	8510.39	6595.31	3608.08	6593.39	6890.13
BIC	6770.88	8678.00	6776.34	3731.95	6774.41	7064.45

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

Table 8: Sensitivity estimations for the time fixed effects spatial error model

	Base model	No time lag	PV install.	Till 2009	Cons. model	Distance W.
Profitability index	0.2921*** (0.0407)	0.5807*** (0.0492)	0.2659*** (0.0407)	0.3192*** (0.0502)		0.3312*** (0.0441)
Solar radiation					0.0583*** (0.0110)	
Energy price					0.0858*** (0.0283)	
New buildings	-0.035*** (0.0084)	-0.1185*** (0.0102)	-0.0316*** (0.0084)	-0.0554*** (0.0102)	-0.0349*** (0.0084)	-0.0376*** (0.0090)
Income	-0.0309*** (0.0107)	-0.0520*** (0.0502)	-0.0259*** (0.0107)	0.0007 (0.0116)	-0.0324*** (0.0107)	-0.0345*** (0.0110)
Green	0.0106 (0.0080)	0.0239** (0.0098)	0.0113 (0.0079)	0.0071 (0.0095)	0.0103 (0.0080)	0.0072 (0.0085)
Household size	0.1743*** (0.0130)	0.4159*** (0.0151)	0.1502*** (0.0135)	0.1882*** (0.0156)	0.1757*** (0.0131)	0.1804*** (0.0135)
HDD	0.0554*** (0.0084)	0.1295*** (0.0102)	0.0565*** (0.0084)	0.0585*** (0.0103)	0.0577*** (0.0086)	0.0611*** (0.0087)
Inverse pop. Density	0.0442*** (0.0091)	0.1039*** (0.0111)	0.0451*** (0.0091)	0.0483*** (0.0110)	0.0457*** (0.0092)	0.0371*** (0.0091)
Benefits	-0.0442*** (0.0107)	-0.1136*** (0.01301)	-0.0372*** (0.0107)	-0.0427*** (0.0127)	-0.0394*** (0.0111)	-0.0511*** (0.0111)
Lag of ST uptake	0.5817*** (0.0104)		0.5620 (0.0108)	0.6668*** (0.0135)	0.5814*** (0.0104)	0.5783*** (0.014)
PV installations			0.0687*** (0.0107)			
Rho	0.5217*** (0.0139)	0.4993*** (0.0143)	0.5205 (0.0139)	0.5215*** (0.0180)	0.5251*** (0.0139)	0.5815*** (0.0173)
Overall R ²	0.8528	0.7750	0.8538	0.9215	0.8528	0.8398
AIC	5608.40	8167.77	5570.90	2958.71	5612.98	6118.28
BIC	5782.72	8335.39	5751.92	3119.75	5794.00	6292.59

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

Table 9: Sensitivity estimations for the regional fixed effects spatial lag model

	Base model	No time lag	PV install.	Till 2009	Cons. model	Distance W.
Profitability index	0.1238*** (0.0073)	0.0907*** (0.0072)	0.1151*** (0.0075)	0.1285*** (0.0101)		0.1419*** (0.0086)
Invest. cost					-0.1299*** (0.0121)	
Subsidy					0.1151*** (0.0092)	
Interest					0.1445*** (0.0150)	
Price expectation					0.0824*** (0.0147)	
Energy price					0.1553*** (0.0233)	
New buildings	-0.0871*** (0.0101)	-0.1497*** (0.0100)	-0.0757*** (0.0102)	-0.1124*** (0.0128)	-0.0940*** (0.0104)	-0.0932*** (0.0107)
Income	-0.0813*** (0.0172)	-0.0499*** (0.0177)	-0.0685*** (0.0173)	0.0464* (0.0279)	-0.0234 (0.0213)	-0.0949*** (0.0183)
Green	-0.0301* (0.0158)	0.0696*** (0.0153)	-0.0570*** (0.0162)	-0.0513** (0.0255)	-0.0447*** (0.0162)	-0.0309* (0.0166)
EEWärmeG	-0.0976*** (0.0087)	-0.1135*** (0.0088)	-0.1190*** (0.0091)		-0.0120 (0.0164)	-0.1093*** (0.0097)
Lag of ST uptake	0.1673*** (0.1674)		0.1547*** (0.0088)	0.1999*** (0.0120)	0.1880*** (0.0095)	0.1827*** (0.0094)
PV installations			0.0686*** (0.0096)			
Lambda	0.6231*** (0.0111)	0.6664*** (0.0110)	0.6142*** (0.0113)	0.5507*** (0.0156)	0.6025*** (0.0118)	0.6970*** (0.0116)
Overall R ²	0.8686	0.8613	0.8692	0.8870	0.8702	0.8540
AIC	5695.90	6019.49	5666.54	3195.97	5629.30	6325.71
BIC	8444.75	8761.63	8422.09	5729.18	8404.97	9074.56

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

Table 10: Sensitivity estimations for the regional fixed effects spatial error model

	Base model	No time lag	PV install.	Till 2009	Cons. model	Distance W.
Profitability index	0.3162*** (0.0158)	0.2871*** (0.0179)	0.3109*** (0.0156)	0.2915*** (0.0159)		0.4532*** (0.0218)
Invest. cost					-0.0654*** (0.0248)	
Subsidy					0.1950*** (0.0227)	
Interest					0.2201*** (0.0353)	
Price expectation					0.3083*** (0.0254)	
Energy price					0.1249*** (0.0291)	
New buildings	-0.0696*** (0.0107)	-0.1283*** (0.0412)	-0.0559*** (0.0110)	-0.1185*** (0.0131)	-0.0649*** (0.0108)	-0.0800*** (0.0116)
Income	-0.0714*** (0.0262)	-0.0437 (0.0282)	-0.0827** (0.0262)	0.2280*** (0.0333)	-0.0579** (0.0271)	-0.0906** (0.0276)
Green	0.0549** (0.0252)	0.0968*** (0.0273)	0.0474 (0.0251)	0.0603* (0.0365)	0.0018 (0.0253)	0.0359 (0.0277)
EEWärmeG	-0.2680*** (0.0177)	-0.2766*** (0.0110)	-0.2830*** (0.0175)		-0.0323 (0.0353)	-0.4035*** (0.0239)
Lag of ST uptake	0.3471*** (0.0117)		0.3308*** (0.0119)	0.3746*** (0.0144)	0.3220*** (0.0119)	0.3485*** (0.0117)
PV installations			0.0822*** (0.0127)			
Rho	0.6751*** (0.0113)	0.6987*** (0.0108)	0.6858*** (0.0111)	0.6356*** (0.0155)	0.6400*** (0.0119)	0.7284*** (0.0114)
Overall R ²	0.8764	0.8599	0.8770	0.9396	0.8769	0.8615
AIC	5324.96	6077.62	5298.03	2776.62	5308.63	6010.02
BIC	8073.81	8819.76	8053.58	5309.83	8084.29	8758.87

Note: the values in parentheses are standard errors

*** Significance level at 1%.

** Significance level at 5%

* Significance level at 10%

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