

De Palma, Alessandro; Faillo, Marco; Gabriele, Roberto

Working Paper

Decentralized energy: How 100% renewable energy regions affect households' energy saving behavior

DIW Discussion Papers, No. 2055

Provided in Cooperation with:

German Institute for Economic Research (DIW Berlin)

Suggested Citation: De Palma, Alessandro; Faillo, Marco; Gabriele, Roberto (2023) : Decentralized energy: How 100% renewable energy regions affect households' energy saving behavior, DIW Discussion Papers, No. 2055, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin

This Version is available at:

<https://hdl.handle.net/10419/279486>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

2055

Discussion Papers

Deutsches Institut für Wirtschaftsforschung

2023

Decentralized Energy: How 100% Renewable Energy Regions Affect Households' Energy Saving Behavior

Alessandro De Palma, Marco Faillo and Roberto Gabriele

Opinions expressed in this paper are those of the author(s) and do not necessarily reflect views of the institute.

IMPRESSUM

DIW Berlin, 2023

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
<https://www.diw.de>

ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
<https://www.diw.de/discussionpapers>

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
<https://ideas.repec.org/s/diw/diwwpp.html>
<https://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html>

DECENTRALIZED ENERGY: HOW 100% RENEWABLE ENERGY REGIONS AFFECT HOUSEHOLDS' ENERGY SAVING BEHAVIOR

Alessandro De Palma^{a,b}, Marco Faillo^a and Roberto Gabriele^a

a. *Department of Economics and Management, University of Trento, via Inama 5, Trento, Italy*

b. *DIW Berlin*

Abstract

This paper focuses on decentralized energy in Germany and how households' environmental behavior in terms of energy consumption is shaped in these contexts. It sets out to gain a more precise understanding of whether decentralized energy initiatives are a good tool to promote the adoption of renewable energies and engagement in other sustainable behaviors to mitigate global warming.

This study would be one of the first to investigate the effect of living in *100% Renewable Energy Regions*, i.e., regions committed to achieving the status of 100% renewable, on households' behavior using a large-scale dataset, with a quasi-experimental setting.

The analysis, indeed, combines micro-level data from the German Socio-Economic Panel (SOEP) with information on the *Landkreis* (districts) that took part in a regional energy project aimed at supporting regions to achieve 100% neutrality of energy production: Project 100% Erneuerbare-Energie-Regionen (100ee-Region).

The findings show that German households living in these districts have considerably increased their energy consumption through the years with respect to untreated households. Moreover, results report that the adoption of renewable energies mediates the effect of the treatment on energy usage, outlining a concave parabolic relationship between the mediator and the outcome. These findings, based on real-world evidence, provide powerful information that should be considered by policymakers when promoting the decentralization of energy. Moreover, this study fits into the literature on the determinants of pro-environmental behavior, showing that contextual factors are crucial drivers of it.

Keywords: Decentralized energy; energy behavior; rebound effects; Germany; policy evaluation

JEL Classification: C22, D19, Q40, Q48, Q28

1. Introduction

Global warming has become an increasingly concerning issue that needs to be addressed to guarantee a better future for young generations. In December 2015, the nations of UNFCCC (United Nations Framework Convention on Climate Change) signed the Paris agreement, which was committed to adopting policies for reducing greenhouse gas emissions over the long period. There are many strategies that have been developed to achieve this goal. Some of the most important involve the reduction of energy consumption and investments in energy efficiency. Others propose a massive shift in demand from carbon-intensive energy (mainly coal and oil) to “green,” i.e., environmentally friendly, renewable, carbon-free energy sources.

In this sense, Germany has always been considered a leading country in implementing policy measures intended to reduce greenhouse gas emissions to mitigate climate change. This status has been achieved thanks to the successful energy transition process that is known as *Energiewende*.

The goal of Germany is to reach 100% neutrality of energy by 2045. This is an ambitious objective, which requires the participation of many stakeholders. Among them, households play a relevant role. Households, indeed, are attributed the 26% of total electricity consumption in the country (BDEW, 2022).

It is widely accepted that individual action is a key component in climate change mitigation. Therefore, households should be encouraged to engage in pro-environmental behaviors, such as energy conservation, adopting renewable energy technologies, and investing in energy efficiency.

Nevertheless, previous studies have shown that policymakers should be very careful when implementing policies aimed at promoting this kind of pro-environmental behaviors. It may be possible, indeed, to observe counter effects that neutralize their positive outcomes.

For example, regarding energy efficiency, the significant energy savings coming from adopting more efficient technologies may even backfire because of rebound effects (Sorrell, 2007). The explanation of this phenomenon has both economic and behavioral foundations. Following the traditional interpretation, rebounds can be divided into direct and indirect effects (Sorrell, 2007). While the first one implies a higher energy consumption than expected after an energy efficiency investment caused by an increase in real income, the indirect effect happens when cost savings from energy efficiency cause higher spending in goods and services that require themselves energy to be provided (e.g., long distance flights). On the other hand, behavioral forces as moral licensing may intervene as well (Dütschke et al., 2018), especially when it comes to renewable energy technologies. Adopting renewable energies may be perceived as a moral justification for indulgence in behaviors with negative environmental impacts.

Thus, particular attention should be given to how consumer behavior could be shaped and directed towards a “green” energy consumption without observing an increase in total usage. In this sense, bottom-up, rather than top-down initiatives, may be more effective, by fostering individuals’ participation in energy projects. Thus far, indeed, the *Energiewende* has been shaped mainly by federal laws. Nevertheless, since the German energy market was liberalized in 1998, it has been observed a rise of local and regional initiatives going parallel to these policies. Bottom-up initiatives, characterized by citizen-led ideas for policies, may induce strong behavioral changes in citizens, also thanks to the use of new strategies like *thinks* (John et al, 2019), *boosts* (Grüne-Yanoff and Hertwig, 2016) and *nudge plus* (John & Stoker, 2019).

Given that the literature regarding this topic is relatively new, the objective of our research is to understand whether also in these contexts consumers exhibit behaviors that may harm the environment, such as rebounds and negative spillovers. Going into the substance of the issue, as far as we know, this kind of projects and their success are characterized by a high level of heterogeneity (Trutnevyte et al., 2012). Nonetheless, there are some common features that can be identified, such as the centrality of the citizen and a high degree of interactions among the actors. Most of the studies concerning this topic have mainly focused on the outcomes, adopting a macro perspective. Nevertheless, few studies have been conducted on how citizens may be involved in the energy transition on a regional and local scale, showing a substantial diversity in the results obtained. For example, Hatzl et al. (2014) have studied the effect of a regional energy saving program (*e5 program*) on citizens’ behavior and attitudes, reporting no significant effects on citizens’ pro-environmental behavior. One possible explanation is that the implementation of such programs may even backfire by generating a false sense of security among the citizens. In fact, energy efficiency programs may unintentionally convey the message that there is no longer a need for individual effort in terms of energy conservation because so much has already been done. On the other hand, it has been shown by Zwickl-Bernhard & Auer (2021) that the presence of local energy initiatives such as energy communities affect the energy demand of the residential sector on the national level by reducing electricity consumption, increasing the share of renewable energies, and promoting awareness in energy usage, adoption of energy efficient technologies and behavioral changes in the environmental sphere.

The debate regarding how the *Energiewende* should be shaped is extremely relevant and far from a conclusion. Even though some scholars have conducted case studies in Germany to better understand the impact of regional energy transition (e.g., Gailing & Röhring, 2016), the literature lacks quantitative evidence of decentralized initiatives’ effects on micro-level. We aim to fill this gap, providing more knowledge to the present debate.

More specifically, we focus on a decentralized energy project implemented by the German Government called 100% Erneuerbare-Energie-Regionen, 100ee-Region (100% Renewable Energy Region”). The project was initiated in 2007 by the German Federal Ministry of Environment with the aim to support German regions in their path toward a 100% sustainable production of energy.

In this study we ask ourselves the following question: how households living in 100% Renewable Energy Regions have changed their environmental behavior in terms of sustainable energy consumption with respect to households that live in other regions?

The purpose of this study is twofold. First, we assess the effect of living in such committed regions on households’ energy consumption. Second, we try to understand whether the effect of living in 100ee regions on energy consumption is mediated by the adoption of renewable energies or energy efficiency appliances. This allow us to detect how the adoption of renewable energies and investments in energy efficiency influence households’ energy consumption when living in 100ee regions. We use micro-level data from the German Socio-Economic Panel (SOEP) covering private households with information on the regions that joined the project, focusing on the decade 2010-2019. The direct effect of the treatment on energy consumption is measured through a difference-in-difference approach with time varying treatment and multiple periods of time, following the framework of Callaway & Sant’Anna (2021), while the mediation hypothesis is tested with a two-step model, where firstly a random coefficient model (Woolridge, 2010) is estimated to get idiosyncratic average treatment effects for the mediators and then the ATEs obtained are included in a regression where the dependent variable is energy consumption.

We obtained some remarkable results. First, we show that households living in 100ee regions tend to progressively increase their heating consumption with respect to untreated households. Second, we observe that the adoption of renewable energies mediates the effect of the treatment on electricity consumption. Moreover, for a portion of households whose decision to adopt renewable energy technologies is particularly affected by the treatment, the mediation exhibits a negative relationship with energy consumption.

These results certainly carry implications for future intervention analyses in decentralized energy projects and households’ energy consumption domain.

The remainder of the article is organized as follows: in section 2 the 100ee Project will be presented. More specifically, it will be explained how a 100ee region is defined, reporting the advantages that come from having that kind of status and what are the criteria that regions need to satisfy to obtain it; section 3 will review the literature related to the topic; in section 4 two hypotheses will be formulated, based on the pre-existing literature. Then, a brief description of the Data used for the analysis and the

variables that have been constructed will follow. Finally, the models used to test the hypotheses will be presented, reporting the theory of the chosen econometric techniques; section 5 will report the main findings of the analysis; section 6 and 7 will be dedicated respectively to the discussion of the obtained results and some conclusions, highlighting potential policy implications, major contribution to the existing literature, limitations, and cues for future research.

2. Project 100% Erneuerbare-Energie-Regionen (100ee-Region)

100ee-Region project was initiated by the German Federal Ministry for the environment in 2007, seeking to give support to regions intending a 100% switch to renewable energy supply. The project officially started in 2010 and it was ended in 2016. In 2018, the 100ee network was reactivated by Region-N project, which is still operating. The goal of the project was to help regions who had already started an energy transition process, to achieve their goals. 100ee Region is an umbrella term that covers regional and local energy activities linked to the commitment to reaching the goal of a completely renewable energy supply within that region/municipality.

Even though the primary goal of the project was to reach 100% renewable energy production, citizens engagement in energy-saving behaviors (energy sufficiency) and energy efficiency were embedded in it. Energy conservation, indeed, requires the establishment of energy-saving lifestyles and consumption patterns.

From 2011, the regions that wanted to take part in the project had to send a letter of application, containing information that had to satisfy the 33 acceptance criteria covering four areas: defining features; level of objective; action level; status level.

Even though entering the project did not provide the regions a concrete financial support, there were other advantages that came from joining the project that give valuable reasons to study how the environmental behavior of households living in those regions was shaped.

First, once the region entered the project, it obtained the status of a 100ee Region. This resulted in a positive public image, helping the region to obtain funds and investments to achieve the goal of supplying the whole territory with 100% renewable resources energies. Second, the project gave the regions the opportunity to be part of a broad network where they could benefit of knowledge sharing, to fasten the process towards their goal. Third, when a region became a 100ee-Region, it committed to achieve the target stated. This is a crucial aspect, because we may expect a considerable improvement in the involvement of the region to reach the 100%-renewable-resource goal. This allows us to intend the participation to the project as a turning point that causes a change in households' energy consumption from before to after the region joins the project. Finally, the 100ee-

Regionen project, helped regions to set up public campaigns to increase the engagement of private citizens into the energy transition process. This is another major aspect to consider for our analysis. In fact, in every 100ee report the active participation of citizens was highlighted as a crucial element in the regional energy transition process. This means that households' environmental behavior may have changed after the region joined the project.

The concept of region that is used in the project is very broad. The territorial entities taking part to the project were mostly *Landkreis* (districts), but also municipalities and artificial regions were included. As shown in Figure 1, in 2016 the project had reached a high number of regions, exhibiting a heterogeneous distribution on the territory.

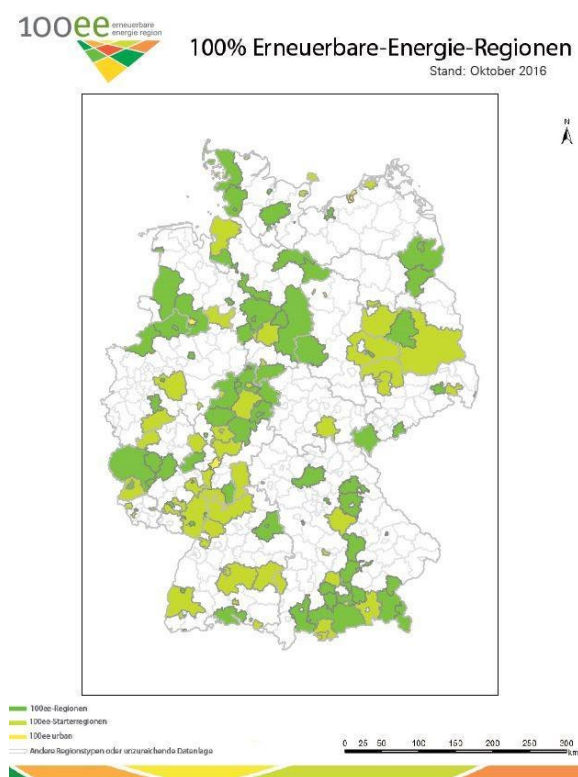


Figure 1: geographical distribution of the 100ee Regions in Germany in 2016. Regions are divided into Starter-Regions (light green) and 100%-EE-Regions (dark green). Regions that are already considered as pioneers of the energy transition process are classified as 100%-EE-Regions, while Starter-Regions are considered to be a stage preliminary to 100%-EE-Regions. Source: Report 100% Erneuerbare-Energie-Regionen (2016)

Given that the dataset regarding the regions that joined the 100ee project has been manually constructed, it was impossible to merge the identification code regarding the municipalities (*Gemeinde* and *Stadt*) with the SOEP. Thus, only *Landkreis* (districts) are considered for our study. The dataset containing 100ee regions and their entry year in the project has been manually created, according to annual reports which listed the new districts that entered the project every year.

As far as we know, no studies have been conducted to measure the effects of this project on a regional or micro level. Therefore, the present analysis would be the first study to understand how the

environmental behavior (to the energy consumption extent) of households living in 100ee Regions is shaped.

Even though the regions participating in the project implemented different plans to reach the goal, there are several common features among 100ee Regions that provide external validity to the results of the present analysis, if the right set of variables is controlled. In fact, all the regions commit to involving the citizens in the energy transition process, creating a higher sense of awareness, not only towards renewable energies but also towards a broader set of pro-environmental behaviors like energy saving habits.

3. Related literature

Households are attributed the 26% of total electricity consumption in Germany (BDEW, 2022) and are accountable for nearly three-quarters of global carbon emissions (Clift & Druckman, 2015), therefore having a considerable impact on the country's footprint. Thus, the study of the determinants of household energy consumption is imperative for the design of sound energy-saving policy.

Regarding this topic, sociodemographic and socioeconomic features have been widely analyzed as drivers of energy consumption and consequent energy saving behaviors. Among them, income has been the most inspected, usually showing a positive correlation with environmental impact of households (e.g., Poortinga et al., 2004; Ivanova et al., 2016; Druckman & Jackson, 2008; Diekmann & Jann, 2000; Lenzen et al., 2006). Gender has brought to contradictory results, sometimes expressing no correlation at all with energy usage (Wilson et al., 2013), and others showing that female-headed households are positively correlated with higher energy consumption (Büchs & Schnepf, 2013). Same happens for age. For example, while Büchs & Schnepf (2013) report no correlation with energy use, according to Pachauri (2004), energy consumption increases as the household head is older. Regarding education, this has been found to be positively correlated with PEBs. More specifically, Poortinga et al. (2004) show that people with higher education are more likely to engage in positive energy-saving behaviors. On the household level, two well-investigated determinants are household size and composition of the household (e.g., O'Neill & Chen 2002; Van Raaij & Verhallen 1983), showing the existence of substantial economies of scale in energy use at the household level.

Attitudinal factors play a relevant role as well (Stern, 2000). For example, general concern for the environment seems to increase the probability that someone engages in pro-environmental actions

(Meloni et al., 2019; Ehrhardt-Martinez & Laitner, 2010). However, there is also considerable evidence that people manifest inconsistency between their internal motivations to protect the environment and concrete actions (Li et al., 2019).

A growing body of literature has focused on the relevance of contextual factors in influencing people's pro-environmental behavior (therefore also energy saving behaviors).

Context covers a wide range of factors that include interpersonal influences, constraints and capabilities provided by the technology of the built environment, policies to support the behavior and other features that constitute the socioeconomic and political context of a given area.

Even though many studies have analyzed the role of macro-contextual features to explain cross-national variation in associations between motivations and PEB, of particular interest for our study is the more recent stream of the literature focusing on the local level. Ling & Xu (2019) found that micro-contextual factors, like community environmental initiatives, have a strong influence on individuals' PEB. Following this line, Cho & Kang (2017) have reported that social capital on the community level, intended as shared understandings, rules, and norms of community members' interaction patterns (Ostrom, 2000) has a significant impact on community members' environmental behavior. Also, Kahn (2007) highlights the importance of living in environmentalist communities, reporting a higher likelihood to use public transport, purchase green vehicles and use less gasoline.

Another stream of literature which is particularly relevant for our analysis is that on rebound effects (Sorrell, 2007), focusing on the cases in which the actual reduction of energy is lower than expected after energy efficiency investments or adoption of renewable energies. Rebounds have been explained using standard microeconomic theory: "an increase in real income thanks to energy efficiency improvements of a specific end use may provoke an increase in demand for the service provided by this end use, thus reducing the expected energy savings" (Yu et al., 2013, p.441). Many studies have proven the presence of rebound effects in residential energy consumption (e.g., Mizobuchi & Takeuchi, 2016). Particularly interesting is the study of Madlener & Hauertmann (2011) who have used the German Socio-Economic Panel (SOEP), to study rebound effects of residential heating in German households. The results provide evidence of positive rebound effects, which are four times bigger for tenants rather than owners.

Rebounds have been studied also using a behavioral perspective, with a growing body of literature explaining this phenomenon referring to *moral licensing*¹, which "occurs when past moral behavior makes people more likely to do potentially immoral things without worrying about feeling or appearing immoral." (Monin & Miller, 2001, p.344). This form of "non-monetary" rebound may be

¹ Sorrell et al. (2020) associate this behavior to negative spillovers. Nevertheless, negative spillovers and indirect rebound effects are conceptually similar (Nash et al., 2017).

higher than monetary rebounds. Following this line, Schleich et al. (2022) have conducted a quasi-experimental analysis to isolate the magnitude of the non-monetary rebound (renewable rebound) when people switch to a green tariff. The results highlighted the presence of a positive rebound effect. Similar results have been found also with the installation of PV systems, labeling the effect as *solar rebound* (Spiller et al., 2017).

To conclude, to drastically reduce the environmental impact, renewable energy adoptions and energy efficiency improvements should be complemented by reduced consumption of energy services and other sustainable behaviors (Sorrell et al., 2020). According to some scholars, indeed, energy efficiency policies need to be supported by energy-sufficiency behaviors², to reduce total energy consumption both on the households and macro levels (Thomas et al., 2015; Spangenberg & Lorek, 2019).

Other authors addressed the problem of how to promote energy-sufficiency habits, by focusing on decentralized energy policies. These, indeed, differently from traditional policies, are people-centered and may produce more beneficial effects for many reasons. First, citizens' behavioral determinants of energy consumption are better addressed. Second, people gain more energy awareness, switching from being simple energy consumers to potential energy producers. Third, the focus of decentralized energy projects is not uniquely on energy efficiency, but also on energy sufficiency and sustainability (Ehrhardt-Martinez & Laitner, 2010). According to this approach small-scale initiatives, like energy regions may reduce households' overall energy consumption and mitigate the counter effect of rebound effects or renewable rebounds.

² "With energy sufficiency, energy consumption is reduced while the utility/technical service changes in quantity or quality" (Thomas et al., 2015, p.60)

4. Hypotheses, Data and Methodology

4.1. Hypotheses

Living in 100ee regions may itself produce a mechanism of self-licensing (Coleman, 2014), where citizens perceive as a moral action the mere aspect of living there and feel free to behave less moral in other domains, such as energy consumption. Nevertheless, decentralized energy governance fosters knowledge regarding environmental issues (Fischer, 2000). Individuals living in these areas may increase their environmental beliefs and engage in more sustainable behaviors. Moreover, people are keener to adopt PEBs when living in areas where local environmental policy is well established (Smiley et al., 2022). Finally, living in 100ee regions should encourage households not only to adopt renewable energy technologies and invest in energy efficiency improvements, but also to engage in other energy conservation behaviors aimed at reducing energy consumption, which are goals that 100ee regions are committed to achieving once they join the project.

If controlling for energy efficiency improvements made by households and adoption of renewable energy technologies, one should be able to detect the direct effect of the treatment on energy consumption. Thus, our first hypothesis is the following:

Hypothesis 1: *living in 100ee regions causally affects households' energy consumption, making treated units use less energy than untreated ones.*

On the other hand, 100ee project should also encourage households to adopt renewable energies and make energy-efficient renovations within their dwelling. It has been shown that engaging in this kind of behaviors may even backfire resulting in higher consumption of energy, because of rebound effects and renewable rebounds (Schleich et al., 2022). Therefore, living in these regions may also have an indirect effect on energy consumption through energy efficiency improvements and the adoption of renewable energies. In this case, the traditional notion of moral licensing could be a valuable explanation: households that make energy efficiency renovations and adopt renewable energy technologies will perceive this choice as moral and consume more electricity than expected.

Given what has been reported, an additional specification will be implemented for the present analysis, testing the following hypothesis:

Hypothesis 2: *living in 100ee regions has an indirect negative effect on households' energy savings through the mediation of energy efficiency improvements and adoption of renewable energies.*

Thus, the treatment (living in 100ee regions) is supposed to have a double effect on energy consumption, which is displayed by figure 2.

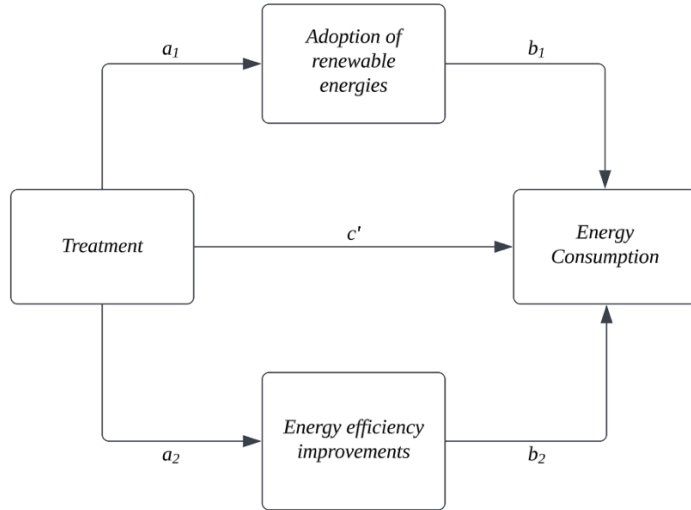


Figure 2: Path diagram of the hypotheses.

Note: c' represents the direct effect of the living in 100ee regions on the outcome, while a_1 , a_2 , b_1 , b_2 show the path of the indirect effect of T on Y.

4.2. Data

To test our two hypotheses, we combine micro-level data from the German Socio-Economic Panel (SOEP) and the 100ee project dataset. The SOEP is an annual household survey program conducted by the German Economic Research Institute (DIW Berlin) since 1984, containing information on approximately 14,000 German households and 30,000 individuals. This panel is almost unique in its genre and covers a wide range of topics. In our analysis we include variables that encompass diverse socio-demographic features, individual attitudes, environmental behavior, and characteristics of households and dwellings. The SOEP respondents' anonymized residence information was linked with a specific dataset (*regionl.dta*) containing regional indicators ranging from federal state level to household postal codes. Household data at the Landkreis level are merged with heating and cooling degree days data from EUROSTAT at the NUTS 3 level. The data³ used in this study cover the period from 2010 to 2019, focusing on household heads as representatives and excluding households that moved after 2010 to ensure treatment randomness.

³ The panel data on household and individual characteristics used in the modeling are unbalanced.

4.3. Variables of interest and descriptive statistics

Treatment

The treatment (T) of the analysis expresses whether a household lives or not in a 100ee region. So, T will assume value 1 when the *Landkreis* where the household lives, joins the project. The treatment is designed to be non-reversible. Therefore, once the household joins the project, T assumes value 1 for the following years.

Dependent variables

Our dependent variable is energy consumption. Two metrics of energy usage were utilized: electricity consumption and heating consumption. Both these metrics are not present in the SOEP and were manually constructed.

Electricity consumption was obtained by dividing the electricity costs by average electricity yearly prices in €/kWh⁴ and then adjusting for the Consumer Price Index (CPI). Thus, if electricity costs (in € per annum) are divided by the electricity price (€ per kWh), we obtain the electricity consumption per household expressed in kWh per year.

Heating consumption was obtained by dividing the heating costs by a weighted average of fuel prices and then adjusting for the CPI. The fuel price is a weighted average of the prices for the three most used fuels in German households. These are: natural gas (56%); heating oil (28%); district heating (16%). (BDEW, 2019). The present metric is expressed in kWh. On both variables was then computed a logarithmic transformation. As shown in table 2, treated households on average have consumed more energy than untreated households, both for heating and electricity.

Mediators

Two variables were created to measure energy efficiency investments and the adoption of renewable energies. Energy efficiency was assessed based on the installation of double-glazed windows and thermal insulation, while the adoption of renewable energies was determined by whether households installed photovoltaic systems. As shown in table 2, the share of households making energy efficiency improvements was higher in 100ee regions (28%) compared to non-100ee regions (22%). The installation of photovoltaic systems was less common overall, but slightly higher in treated units (100ee regions) than in non-treated units (non-100ee regions).

⁴ Prices were collected from the German Federal Office of Statistics (“Statistisches Bundesamt”).

Controls

As shown in table 2, sociodemographic features include: age; gender; German nationality; marital status; household size; household composition.

Regarding socio-economic characteristics, we included the household post-government income.

Given that the income reported referred to the previous year, the values were imputed backward and expressed in logarithmic form. Education level, employment status, which has been shown to be positively correlated to electricity consumption (Kostakis, 2020), and ownership have been also included. For what concerns ownership, more than 60% of household heads living in 100ee regions are owners of the dwelling, while the share for untreated units is more than 10% lower (49%). Ownership is an important determinant of energy usage. Tenants, indeed, have been proven to behave less carefully when consuming energy, with respect to owners (Madlener & Hauertmann, 2011). Also, the characteristics of the dwelling are drivers of domestic energy use (Yohanis et al., 2008). The SOEP provides information on the size of the dwelling, from which the number of rooms and living space per person⁵ have been included in the model. Furthermore, a variable that indicates the time range when the dwelling was constructed is used as a proxy for the condition of the dwelling, which may influence both decisions to make energy-efficiency renovations and energy consumption. As stated before, SOEP provides useful information on the environmental attitudes of individuals. Kaiser et al. (2020), conducting an analysis with SOEP data, have used for their model the same behavioral attitudes that will be included in our analysis, i.e., interest in politics, climate change concerns and environmental concerns. We include interest in politics to control for the potential involvement of households in politics, which may reflect into active participation in the *100ee project*. Finally, heating and electricity consumption may be influenced by the climate of the region. Therefore, to control for this phenomenon, heating and cooling degree days have been merged to the dataset from EUROSTAT.

Finally, to obtain a valid causal relation, also prices for electricity and heating have been controlled for.

⁵ this variable has been constructed dividing the dwelling's total floor area in m² by the number of people in the household

Table 1: Descriptive statistics of treated and untreated households

	(1)		(2)	
	Untreated		Treated	
	mean	sd	mean	sd
<i>Energy Consumption</i>				
Electricity Consumption (log)	7.811999	.5184094	7.913304	.4925641
Heating Consumption (log)	9.724104	.5743049	9.836487	.5575149
<i>Mediators</i>				
Energy efficiency	.2222403	.4157551	.2862096	.4520059
Renewable energies (PV)	.0376761	.1904132	.0636711	.2441754
<i>Sociodemographic</i>				
Age	3.747291	.9000282	3.830168	.8839399
Gender	.5408819	.4983298	.5621879	.4961366
German	.8968711	.3041295	.8979666	.3027038
Marital Status	.4590822	.4983269	.5301598	.4991087
Household Size	1.905194	1.050661	2.025174	1.063035
Household Composition	2.186536	1.514451	2.328074	1.550744
<i>Socioeconomic</i>				
Net Income (log)	10.20281	.6443987	10.33038	.6356621
Ownership	.4922761	.4999443	.6246815	.4842236
Education Level	2.205366	.613505	2.194066	.6067908
Employment Status	.5310741	.4990374	.5243781	.4994245
<i>Dwelling characteristics</i>				
Construction Year	3.491621	1.656164	3.685086	1.711094
Rooms	3.758445	1.661084	4.326544	1.787976
Living Space per Person	58.37997	30.75637	64.76272	35.37495
<i>Attitudinal factors</i>				
Environmental Concerns	1.796628	.6216807	1.82819	.6283088
Climate Concerns	1.837783	.672275	1.838526	.6755974
Interest in Politics	2.537167	.8255813	2.469209	.8167797
<i>Macro</i>				
CDD	33.44948	27.34795	27.82951	23.50223
HDD	2923.144	375.0528	2924.41	324.0008
Heating price	.0652063	.0047467	.064578	.0047418
Electricity price	.2933349	.0166228	.2971008	.0149404
Observations	93045		19543	

Note: this table includes the full 10 years (2010-2019) dataset; Source: SOEP V.37

4.4. Methodology

To test the first hypothesis (whether living in 100ee regions makes households decrease their energy consumption), we implemented a Difference-in-Differences with time-varying treatment.

Then, to test whether the treatment has an indirect effect through energy efficiency improvements or adoption of renewable energies (hypothesis 1b) we used a two-step model inspired by Cerulli et al. (2016), where the relation between the treatment and the mediators will be imputed through a *treatment random coefficient model* (see Woolridge, 2010) and the output variable will be regressed on the ATEs(x_i) obtained from the previous step.

4.4.1. Difference-in-Differences with time-varying treatment and multiple periods of time

As said before, the first hypothesis has been tested with a time-varying Difference-in-Differences, which is an expansion of the difference-in-differences (DID) approach when the binary treatment varies over time. The case of the present analysis differs from the canonical setting of a DID in two ways: it has multiple periods of time, and the treatment varies over time. Therefore, in our analysis we refer to the framework of Callaway & Sant'Anna (2021) (CS), which considers a natural generalization of the ATT that is suitable to setups with multiple treatment groups and multiple time periods. The key concept of CS' framework is the *group-time* ATT, i.e., “the average treatment effect for group g at time t , where a “group” is defined by the time period when units are first treated” (Callaway & Sant'Anna, 2021, p. 201). The group-time ATT is denoted as follows:

$$ATT(g, t) = E[Y_t(g) - Y_t(0) | G_g = 1] \quad (1)$$

CS is implemented through STATA 17 using the command CSDID by Rios-Avila et al. (2022). The parallel trend assumption when the treatment is time varying can be tested indirectly by testing whether all the aggregated pre-treatment ATEs are jointly equal to 0. If H_0 is accepted, then the parallel trend assumption holds, thus validating the causal interpretation of the estimates (Cerulli, 2015).

The model for the present analysis is specified as follows:

$$\log(Y)_{i,t} = \alpha_i + \lambda_t + \sum_{k=-L}^L \beta_k \cdot T_{i,t} + \sum_{j=-L}^L \beta_j \cdot X_{i,t} + \epsilon_{i,t} \quad (2)$$

In equation 2, Y is the outcome (heating and electricity consumption) expressed in logarithm; α_i and λ_t are unit and time fixed effects, respectively; $T_{i,t}$ is the non-reversible treatment variable; $\{\beta_k\}$ for $k < 0$ correspond to the pre-trends and $\{\beta_k\}$ for $k > 0$ measures the project's dynamic effects. Same is for $\{\beta_j\}$, where $X_{i,t}$ is the set of covariates used as controls (including energy efficiency and renewable energies); $\epsilon_{i,t}$ is an idiosyncratic error.

4.4.2. Two-step 'mediating effect' model

With the present model, the aim is to estimate the indirect effect of living in a 100ee region on energy consumption through the mediation of energy efficiency improvements and adoption of renewable energy technologies (a and b in figure 2). The model consists of two steps. First, the effect of the treatment on the two mediators will be estimated. In this phase, a random coefficient model will be used, thus allowing to estimate idiosyncratic effects for each household (Average Treatment Effects conditional on a set of covariates X). The estimation will be computed following the STATA routine IVTREATREG by Cerulli (2012) assuming a heterogeneous response to treatment.

Second, the obtained ATEs from the first step will be included in a linear regression where the outcome is energy consumption (heating and electricity consumption).

Therefore, the function would be defined as follows:

$$\begin{aligned} \log(Y) = & a + \sum_{p=1}^P b_p \cdot [ATE_{PV}(x)]^p + \sum_{q=1}^Q c_q \cdot [ATE_{Energy\ Efficiency}(x)]^q \\ & + d \cdot ATE_{PV}(x) \cdot ATE_{Energy\ Efficiency}(x) + eX + \epsilon \end{aligned} \quad (3)$$

In equation 3, the index i is omitted for the sake of simplicity; Y is the energy consumption outcome (electricity and heating consumption); X is the set of covariates that may influence the outcomes. As the reader may notice, equation 6 also displays the interaction between the ATEs of the two mediators, allowing to capture potential altering effects of combined mediators on energy consumption.

Moreover, also polynomial orders have been added to the equation, to test whether the relationship between the mediators and the outcome is linear or not. P and Q are the maximum polynomial orders considered in the regression respectively for $ATE_{PV}(x)$ and $ATE_{Energy\ Efficiency}(x)$.

To exploit the panel dimension, the variables will be taken in different periods of time. Mediation, indeed, is a process that develops over time (MacKinnon, 2008), and using a cross-sectional

structure often leads to biased results. Therefore, the treatment variable will be measured in the year 2012, the mediators in the year 2014 and the outcome in the year 2016. To avoid that the treatment could influence the controls, the covariates are taken from the same year of T, i.e., 2012.

5. Results

5.1. Difference-in-Differences with time-varying treatment and multiple periods of time

All the units that have always been treated (from 2010) are excluded from the model. Moreover, given that the panel is unbalanced, only paired couple between two periods of time are considered. In this case, the control group is composed by the households that have never been treated.

To understand how the average treatment effects vary by length of exposure to the treatment, event study dynamic effects have been estimated. As shown in table 3, aggregated post-treatment ATTs both for electricity and heating consumption are positive and significant.

A χ^2 test has been conducted to prove the parallel trend assumption. The null hypothesis states that all the aggregated pre-treatments ATTs are equal to 0. For both heating and electricity consumption, the test fails to reject the null hypothesis (prob > $\chi^2 = 0.5718$ for electricity usage; prob > $\chi^2 = 0.9337$ for heating usage), thus validating the parallel trend assumption.

Surprisingly, households living in *Landkreis* that obtain the status of 100ee region, show growing significant ATTs for heating consumption (Table 3). This means that once the households get treated, even though their heating consumption may follow a downward trend through the years, they tend to consume progressively more than untreated households as the length of exposure increases.

The gap of consumption is around 3.5% the first year of the treatment and it gets to be almost half more (47.4%) than never treated households 8 years after their *Landkreis* became a 100ee region.

On the other hand, the only significant effect for the project on households' electricity consumption is eight years after the treatment. One should be careful to interpret these results on such a long period. In fact, the 8 years lag is referred only to the time-group 2011, because it is the only one to display such a long time span after the treatment.

The aggregate dynamic effects draw only a general picture of the treatment's impact on energy consumption. Figure 3 displays the dynamic effects of the single time-groups for heating consumption. The first three groups clearly exhibit that the households treated in 2011, 2012 and 2013 have increased the consumption gap through the years relatively to households that didn't live in regions committed to achieve renewable energy, energy efficiency and energy savings goals.

Table 3: Aggregated dynamic ATTs for electricity and heating consumption

	(1) Electricity	(2) Heating
ATT pre-treatment	-0.006 (0.020)	0.006 (0.015)
ATT post-treatment	0.048* (0.025)	0.108*** (0.031)
T-5	-0.020 (0.092)	0.005 (0.072)
T-4	-0.047 (0.039)	0.012 (0.037)
T-3	0.032 (0.026)	0.022 (0.028)
T-2	0.017 (0.021)	-0.003 (0.020)
T-1	-0.012 (0.017)	-0.007 (0.020)
T0	-0.003 (0.015)	0.035* (0.019)
T+1	0.006 (0.019)	0.001 (0.026)
T+2	0.005 (0.020)	0.054** (0.026)
T+3	-0.025 (0.021)	0.048* (0.028)
T+4	0.023 (0.022)	0.069** (0.030)
T+5	0.023 (0.023)	0.091*** (0.031)
T+6	0.040 (0.029)	0.096** (0.038)
T+7	0.074 (0.055)	0.191*** (0.062)
T+8	0.287* (0.167)	0.388** (0.193)
Observations	64,097	63,543

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the first two lines display the average ATT for all pre and post treatment periods. The leads go from T-1 to T-5, while the lags go from T+1 to T+8.

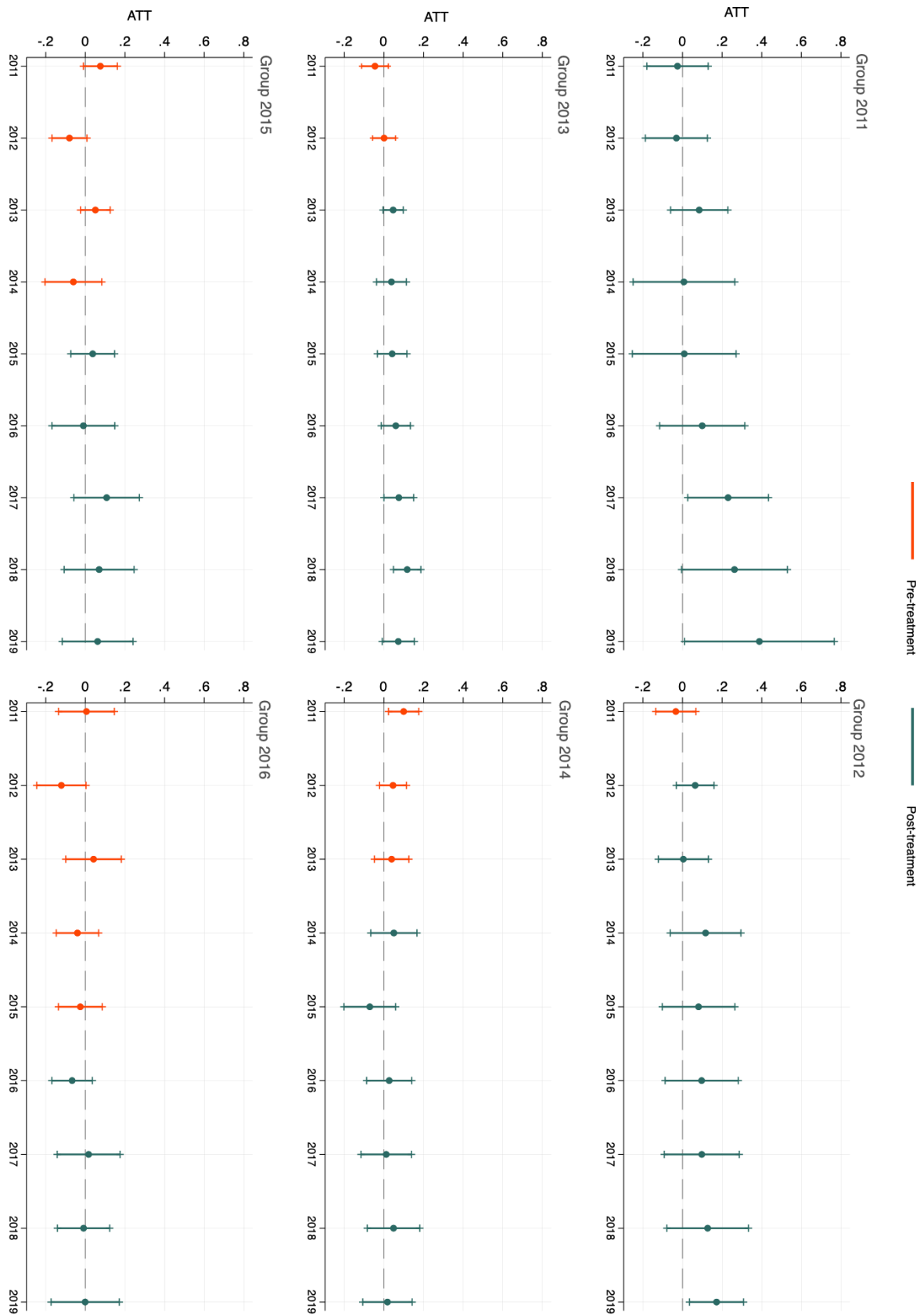


Figure 3: Dynamic ATTs of the single time-groups for heating consumption.
Note: 95% confidence interval bands are displayed.

For example, for household treated in 2013, while their heating consumption was lower than untreated households in 2011 and 2012, after their *Landkreis* joined the project, their usage started to rise showing significant effects 4, 5 and 6 years after the treatment. On the other hand, the groups for the years 2014, 2015, and 2016 show no significant effects of the treatment on treated. It is difficult to tell whether this difference between the first three years and the lasts is due to potential problems with the estimation method chosen, or to some event that may have occurred in the meantime. For the time being, the results obtained for the years 2011, 2012, and 2013 will be prioritized in the discussion of the potential explanations of the findings. Nevertheless, a more detailed analysis should inspect the reasons for such divergent outcomes.

5.2. Two-Step mediating effect model

The following describes the results obtained to test whether energy efficiency improvements and adoption of renewable energies mediates the effect of the treatment on energy consumption. For the present model the sample has been restricted to household heads who are owners of the dwelling. Indeed, the aim is to measure whether the treatment influences the decision to either make energy efficiency renovations or install photovoltaic systems. Generally, who decides to make renovations that require structural changes within the dwelling is the owner. It may be possible to observe this kind of changes also with tenants, but logically the decision would be taken by the owner. Therefore, keeping tenants in the sample would jeopardize the estimations of this analysis, because it would be impossible to measure the actual choice to either adopt renewable energies or invest in energy efficiency.

Moreover, beyond the controls that has been previously described in the descriptive statistics, the model includes also two other independent variables on *Landkreis* level⁶ that may influence the mediators. These are *population density* (expressed in people per km²), which affects the possibility to install photovoltaic systems and *unemployment rate*.

It is important to remind that this model is used to test a specification hypothesis to understand whether adopting renewable energies or making energy efficiency improvements may act as a mediator for households that live in 100ee regions. This mediation analysis does not take into consideration the whole panel, but only three waves: 2012, 2014, 2016. Due to this aspect and the high presence of missing values, the sample size was considerably reduced, counting 4,353

⁶ These have not been included in previous estimations because their values are missing for years 2018 and 2019. Given that this analysis covers only the years 2012, 2014 and 2016, they have been used.

households. Table 5 shows the results of the treatment on the two mediators. The entire table including the effect of the covariates on the mediators has been stored in appendix B.

Table 5: Average treatment effect on renewable energies and energy efficiency

	(1)	(2)
	Renewable Energies	Energy Efficiency
T	0.020*	0.018
	(0.012)	(0.017)
Adj. R ²	0.023	0.055
Observation	4,353	4,353

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table displays a 10% significant positive effect of living in a 100ee region on the decision to install a solar system (around 0.020). This confirms the idea that when regions obtain the status of 100% renewable, citizens are incentivized to adopt renewable energies. On the other hand, the treatment seems to have no significant effect on energy efficiency improvements, even though the energy efficiency goal is considered an important target for 100ee regions.

Given that the treatment has no effect on energy efficiency improvements, only adoption of renewable energies will be considered as potential mediator for energy consumption. Moreover, to have a clearer understanding of the results, PV will be assumed to have an effect only on electricity consumption, given that heating consumption does not derive from electricity sources.

Thus, Equation 3 will be rewritten as follows:

$$\log(Y) = a + \sum_{p=1}^P b_p \cdot [ATE_{PV}(x)]^p + cX + \epsilon \quad (5)$$

Differently from equation 3, $ATE_{Energy\ Efficiency}(x)$ and their interaction have been excluded from the model. Y in this case reflects just one of the two outcomes, i.e., electricity consumption. X is the set of covariates and p represents the number of polynomial degrees included in the model, where the maximum is $P = 3$. Table 6 displays the results of the relationship of $ATE_{PV}(x)$ on electricity consumption. The entire table including the effects of the set of covariates X can be consulted in appendix B. Various polynomial specifications have been included (up to the third degree) to

understand whether the two variables have a linear relationship or not. As displayed in specification 3, where the full model is displayed, no cubic significant effects have been found to shape the relationship between the two variables. The results, though, stress a significant effect of the quadratic form of adoption of renewable energies on electricity consumption (specification 1 in table 6). More precisely, the effect of $[ATE_{PV}(x)]^2$ on electricity usage is negative. Thus, the relationship between adoption of renewable energies and the outcome follows a concave parabola. This means that, if $ATE_{PV}(x)$ reflects a higher probability for treated units to install a solar system within their dwelling, when the probability associated to a household is low, this corresponds to a higher consumption of electricity. But, when $ATE_{PV}(x)$ grows after a certain point on the x axis, then the electricity consumption tends to decrease.

Table 6: Estimation of equation (5)

	(1) Electricity Consumption 2 nd Degree	(2) Electricity Consumption Linear	(3) Electricity Consumption Full Model
$ATE_{PV}(x)$	0.647** (0.252)	0.221 (0.162)	0.649** (0.252)
$[ATE_{PV}(x)]^2$	-3.924** (1.779)	-	-4.997 (4.191)
$[ATE_{PV}(x)]^3$	-	-	5.716 (20.213)
Constant	5.672*** (0.187)	5.606*** (0.185)	5.674*** (0.187)
Adj. R ²	0.157	0.156	0.157
Observation	3,167	3,167	3,167

Standard errors in parentheses
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: three specifications of the model: the first one is the full model, which includes up to the third polynomial degree for $ATE_{PV}(x)$. Then the second one, includes the quadratic form of $ATE_{PV}(x)$. The last one includes only a linear relationship between the mediator and the outcome. The set of covariates used is the same for each model.

More precisely, figure 4 displays the scatterplot of the relationship between electricity consumption and $ATE_{PV}(x)$. As stated in the previous chapter, it has been possible to include $ATE_{PV}(x)$ in the present regression due to the estimation of idiosyncratic effects for each household from the random coefficient model. Estimating an average treatment effect for each unit allows to identify the households for which the decision to adopt renewable energies causes a reduction of electricity usage. This distinction is done by calculating the axis of the parabola in figure 4, i.e., the point at which electricity consumption changes from increasing to decreasing. It is set at $ATE_{PV}(x) = 0.0824945$.

This means that when the treatment decreases or slightly increases the probability to adopt renewable energy technologies, electricity consumption tends to increase. Nevertheless, when $ATE_{PV}(x)$ exceeds the threshold of 0.082, then households who are associated a higher $ATE(x)$, which are around the 10% of the sample, tend to decrease their electricity consumption. Therefore, when the treatment has a high impact on the households' probability to install a solar system, this reflects to a decreasing consumption of electricity.

Another interesting aspect is that there are many ATEs that are lower than 0. If focusing only on the linear relationship between the mediator and the outcome, one would have thought that adopting renewable energies causes an increase in electricity consumption. Nevertheless, most of the households for which this is true have a negative ATE, meaning that the effect of living in 100ee regions tends to decrease the probability to install a photovoltaic panel, which then reflects in increasing usage of electricity.

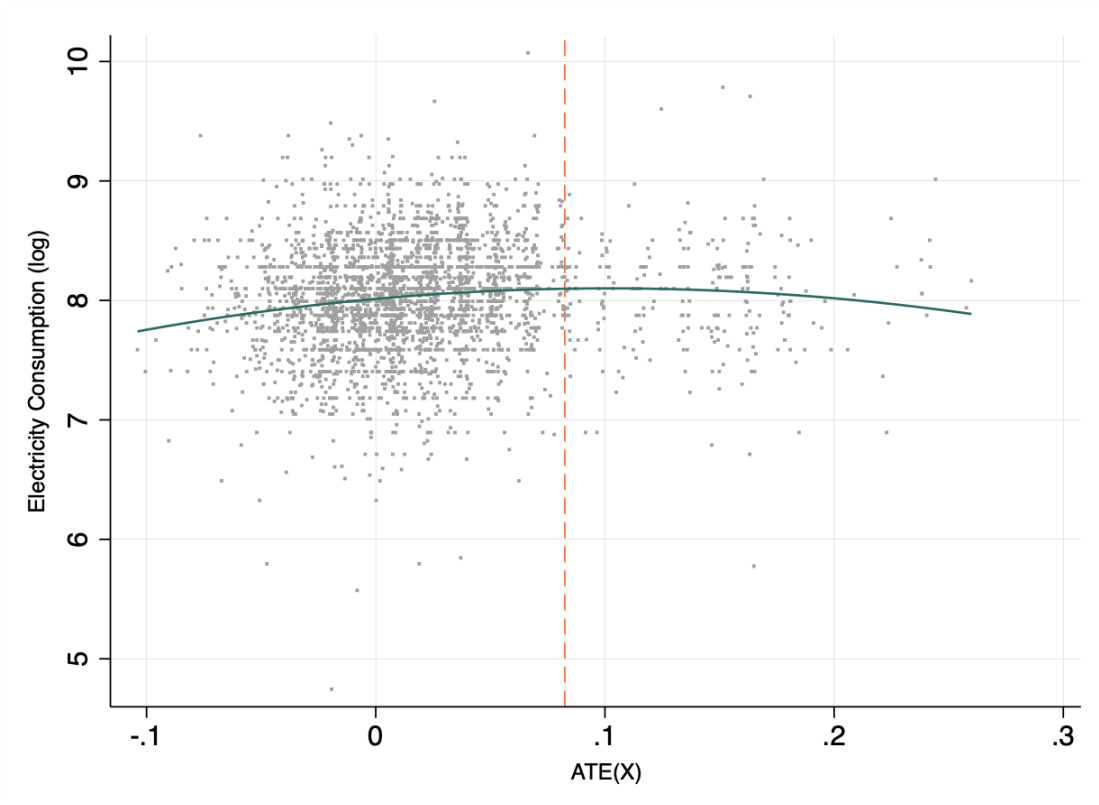


Figure 4: Scatter plot

Note: This graph displays the quadratic relationship between $ATE_{PV}(x)$ and Electricity consumption. The orange line is the axis of symmetry of the parabola, where $x=0.0824945$. The households that exceed this threshold are around 10% of the sample.

6. Discussion

Overall, the findings have partly confirmed the hypotheses that we have formulated, even though with some divergences from the main literature. First, the treatment has a direct effect on energy usage when controlling for the potential mediators and a large set of covariates. Second, living in 100ee regions affects energy consumption indirectly, through the mediation of the choice to install photovoltaic panels. More specifically, the first part of the present analysis has shown that households living in regions committed to achieve renewable energy, energy efficiency and energy saving goals, tend to worsen their pro-environmental behaviors (in terms of energy saving) with respect to households living in areas that do not have this kind of characteristics, thus disproving our first hypothesis. In fact, while for electricity consumption there are no significant aggregated dynamic effects, households tend to progressively increase their relative heating consumption, using almost half kWh more than untreated households 8 years after the region has achieved the status of 100ee region. Even when the length of exposure is reduced to only three years after the treatment, the effect of the treatment on heating consumption is still positive and significant, albeit more restrained.

The model uses a large set of controls to exclude potential explanation of these effects. For example, controlling for energy prices and heating/cooling degree days, exclude the possibility that the results may be driven by economic fluctuation of the energy market and differences of the climatic circumstances in German districts. Even though it is difficult to find a unique explanation of the phenomenon, one reasonable justification is that the effect is explained by a declination of moral licensing in context-based circumstances. In the case of the present analysis, households compare themselves with the whole context they live in. To be more precise, households living in 100ee regions benefit from the perceived morality of living in such an environmentally committed district. Thus, the mere aspect of living there, make the household more relieved in engaging in less moral environmental behaviors, i.e., consuming more energy.

The second part of the analysis has shown that the treatment has a positive impact on the decision to install photovoltaic panels within the dwelling, but not on the choice to make energy efficiency renovations. Moreover, it has also been proved that the treatment has an indirect effect on electricity consumption through the mediation of adoption of renewable energies. Some considerations can be derived from these results. First, living in 100ee regions incentivize households to participate to the energy transition process of the *Landkreis*, with respect to households that do not live in this kind of regions, proving that decentralized initiatives foster people's willingness to participate to energy transition projects. This may be due to the higher centrality of the citizen, encouraged to actively participate within the energy transition process of his/her own region, becoming a prosumer and not a simple passive consumer. The reason of a stronger engagement may be due to a higher sense of

local community, which enhances the activation of positive social norms (Kalkbrenner & Roosen, 2016). Second, even though energy efficiency improvements do not mediate the indirect effect of the treatment on energy consumption, the adoption of renewable energies does. Furthermore, we have shown that the mediation is not linear. In fact, when the effect that the treatment has on the decision to install photovoltaic panels exceeds a certain threshold, households tend to reduce their electricity consumption. Therefore, when living in 100ee regions strongly influences households' decision to participate to the energy transition progress (adopting renewable energies), this results also in the reduction of electricity consumption. The treatment is not completely able to mitigate the counter effect of adopting renewable energies on energy consumption, but for some households that exceeds a specific threshold, the choice to install a PV system driven by the treatment make them reduce their electricity usage. This is an extremely important finding that partially disproves *hypothesis 2*. In fact, the idiosyncratic effects estimated for each household in the random coefficient model, allows to identify a group of households for which the mediating effect of PV causes a significant reduction of electricity usage, thus neutralizing potential rebounds and moral licensing behaviors.

7. Conclusion

We have conducted a quasi-experiment on German private households that lived in districts which were committed to achieving the goal of 100% neutrality in energy production. The project focus of the study was initiated by the German Federal Ministry of Environment to support selected regions in successfully completing the energy transition process. Understanding how households' behavior may be shaped in this kind of context is crucial, given that decentralized projects strongly rely on the active participation of citizens and global warming mitigation necessitates individual action in addition to national policy measures.

The analysis has reported some remarkable results. Overall, the findings have demonstrated that living in 100ee regions has a direct impact on households' energy consumption behavior when a large set of controls and the two potential mediators are taken into account. Furthermore, it has been proven to exist a non-linear mediating effect of the adoption of renewable energies, i.e., installing photovoltaic panels, on energy usage.

These findings undoubtedly have repercussions for future intervention studies in the area of households' energy usage and decentralized energy initiatives. In fact, the war and the consequent unprecedented increase in energy prices have further shed light on the need for the European Union to weaken its systemic dependence on fossil gas in favor of renewable energies. Along with it, EU needs to promote energy saving measures and redesign the energy market to strengthen self-consumerism and decentralized energy production (CAN, 2023). In this sense, understanding how

projects aimed at reaching the aforementioned objectives shape households' environmental behavior becomes crucial for future policy implications. The results suggest that households are incentivized to accept and adopt renewable energies when their own *Landkreis* is committed to achieving 100% renewable energy production. Nevertheless, when it comes to broader outcomes, such as energy conservation behaviors, living in these regions legitimates households to even act in contradiction to the energy saving goals of their district. Therefore, the single districts should foster all the mechanisms that enhance the environmental responsibility of the citizen. In this sense, behavioral interventions may help. For example, information-based campaigns or feedback comparing households' consumption to the community norm could have a positive impact on energy conservation behaviors (Schultz, 2010). On the other hand, demonstrating that a portion of households for whom the treatment provides a strong incentive to install a solar system experience lower electricity consumption, alerts policymakers to the possibility of overcoming the opposing mechanisms of rebound effects and moral licensing behaviors.

Even though the results add valid information to the existing scientific literature, some limitations have been identified and need to be reported, so that future studies could address these issues.

Most of the shortcomings of the present study involve the data and the metrics that have been used to conduct the analysis. First, the dataset containing information on the *Landkreis* that joined the project was self-constructed. In fact, the program was shut down in 2016, continuing as a new project called Region N. Therefore, also the website no longer exists. Even though we have tried to contact multiple times the responsible project members asking whether they could provide us with some sort of official data, we have not received any answer from them. The data were thus constructed relying on official yearly reports found on the internet that listed all the new regions that joined the project each year. Even though we have conducted this task with a very meticulous approach, we cannot exclude the possibility that there may be some regions which joined the project in different years with respect to what has been reported. Second, the SOEP does not provide actual information on households' energy consumption. The variables were constructed based on the self-reported cost of heating and electricity divided by yearly average energy prices in Germany. Moreover, in the questionnaires households who weren't owners of the dwelling were required to report an estimation of the average monthly costs of energy. Thus, it may be possible that the constructed consumption variables differ from the real consumption of energy by households. Finally, in this study we focus on the energy consumption behaviors of households. The SOEP provides information on other environmental behaviors. Nevertheless, the major part of this information was missing for most of the years of the study. A valuable cue for future research would be to further inspect the effect of

living in regions that promote renewable energy production and sustainable consumption on a larger set of environmental domains, such as mobility, food consumption habits, or recycling.

Besides this aspect, other ideas can be developed starting from the present study. For example, decentralized energy projects are characterized by a high level of heterogeneity (Trutnevyte et al., 2012). To better understand the mechanisms underlying the relationship between the explanatory variables, it may be useful to integrate quantitative and qualitative analysis (mixed method approach), carrying out case studies (Weller & Barnes, 2014). Case studies, indeed, have a high level of detail that may help to identify unobserved causal mechanisms between the variables and track potential pathways, that are crucial for a more precise interpretation of the results.

In conclusion, the findings, based on real-world rather than experimental evidence, albeit the listed limitations, warn about the problem that policymakers may encounter when promoting decentralized energy projects, contributing to two relevant streams of literature: the determinants of pro-environmental behaviors and the debate on the energy transition governance in Germany.

Bibliography

- BDEW (2022). Energieverbrauch in Deutschland 2020. Accessed at <https://www.bdew.de/energie/energieverbrauch-deutschland-2020>
- Büchs, M., & Schnepf, S. V. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO₂ emissions. *Ecological Economics*, 90, 114-123.
- Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230.
- Climate Action Network (2023) ENERGY SYSTEM OF TOMORROW: Reconsidering the European Electricity Market for a Flexible, Resilient, People-centred and Efficient System with 100% Renewables, [online], 15th February 2023. Available from: <https://caneurope.org/energy-system-of-tomorrow-reconsidering-the-european-electricity-market-for-a-flexible-resilient-people-centred-and-efficient-system-with-100-renewables/> (accessed 26th February 2023).
- Cerulli, G. (2012). ivtreatreg: a new STATA routine for estimating binary treatment models with heterogeneous response to treatment under observable and unobservable selection. *CNR-Ceris Working Papers*, 3, 12.
- Cerulli, G. (2015). *Econometric evaluation of socio-economic programs Theory and applications*. Springer.
- Cerulli, G., Gabriele, R., & Poti, B. (2016). The role of firm R&D effort and collaboration as mediating drivers of innovation policy effectiveness. *Industry and Innovation*, 23(5), 426-447.
- Cho, S., & Kang, H. (2017). Putting behavior into context: Exploring the contours of social capital influences on environmental behavior. *Environment and Behavior*, 49(3), 283-313.
- Clift, R., & Druckman, A. (2015). Taking stock of industrial ecology (Chapter 9). *Springer Nature*.
- Coleman, E. A. (2014). Behavioral determinants of citizen involvement: Evidence from natural resource decentralization policy. *Public Administration Review*, 74(5), 642-654.
- Ding, Z., Wang, G., Liu, Z., & Long, R. (2017). Research on differences in the factors influencing the energy-saving behavior of urban and rural residents in China—A case study of Jiangsu Province. *Energy policy*, 100, 252-259.
- Diekmann, A., & Jann, B. (2000). Sind die empirischen Ergebnisse zum Umweltverhalten Artefakt? Ein Beitrag zum Problem der Messung von Umweltverhalten [Are the empirical results regarding environmental behavior artefacts? A contribution to the problem of measuring environmental behavior]. *Umweltpsychologie*, 4(1), 64-75.
- Druckman, A., & Jackson, T. (2008). Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy*, 36(8), 3177-3192.
- Dütschke, E., Frondel, M., Schleich, J., & Vance, C. (2018). Moral licensing—another source of rebound?. *Frontiers in Energy Research*, 6, 38.
- Ehrhardt-Martinez, K., and Laitner, J A “Rebound, Technology and People: Mitigating the Rebound Effect with Energy-Resource Management and People-Centered Initiatives” in *The ACEEE Summer Study on Energy Efficiency In Buildings* 2010, pp 7-76.
- Eurostat (2023) Heating and cooling degree days – statistics [online], May 2022. Available from: [https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Heating_and_cooling_degree_days_statistics#:~:text=Heating%20degree%20days%20\(HDD\)%20index,%20conditioning\)%20requirements%20of%20buildings](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Heating_and_cooling_degree_days_statistics#:~:text=Heating%20degree%20days%20(HDD)%20index,%20conditioning)%20requirements%20of%20buildings). (accessed 13th February 2023).
- Fischer, F. (2000). *Citizens, experts, and the environment: The politics of local knowledge*. Duke University Press.
- Gailing, L. (2018). Die räumliche Governance der Energiewende: Eine Systematisierung der relevanten Governance-Formen. In O. Kühne & F. Weber (Eds.), *Bausteine der Energiewende* (pp. 75–90). Wiesbaden: Springer Fachmedien Wiesbaden.
- Gailing, L., & Röhring, A. (2016). Germany's Energiewende and the spatial reconfiguration of an energy system. *Conceptualizing Germany's energy transition: Institutions, materiality, power, Space*, 11-20.
- Grüne-Yanoff, T., & Hertwig, R. (2016). Nudge versus boost: {How} coherent are policy and theory? *Minds and Machines*, 26(1–2), 149–183.
- Hatzl, S., Brudermann, T., Reinsberger, K., & Posch, A. (2014). Do public programs in ‘energy regions’ affect citizen attitudes and behavior?. *Energy Policy*, 69, 425-429.

- IEA/IRENA (2018) *Tracking gender and clean energy transition*. Available from: <https://www.iea.org/articles/tracking-gender-and-the-clean-energy-transition> [accessed 12th February 2023]
- Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., & Hertwich, E. G. (2016). Environmental impact assessment of household consumption. *Journal of Industrial Ecology*, 20(3), 526-536.
- John, P., Cotterill, S., Richardson, L., Moseley, A., Smith, G., Stoker, G., ... & Nomura, H. (2013). *Nudge, nudge, think, think: Experimenting with ways to change civic behaviour*. A&C Black.
- John, P., & Stoker, G. (2019). Rethinking the role of experts and expertise in behavioural public policy. *Policy & Politics*, 47(2), 209-226.
- Kahn, M. E. (2007). Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice. *Journal of Environmental Economics and Management*, 54(2), 129-145.
- Kaiser, M., Bernauer, M., Sunstein, C. R., & Reisch, L. A. (2020). The power of green defaults: the impact of regional variation of opt-out tariffs on green energy demand in Germany. *Ecological Economics*, 174, 106685.
- Kalkbrenner, B. J., & Roosen, J. (2016). Citizens' willingness to participate in local renewable energy projects: The role of community and trust in Germany. *Energy Research & Social Science*, 13, 60-70.
- Kostakis, I. (2020). Socio-demographic determinants of household electricity consumption: Evidence from Greece using quantile regression analysis. *Current Research in Environmental Sustainability*, 1, 23-30.
- Lenzen, M., Wier, M., Cohen, C., Hayami, H., Pachauri, S., & Schaeffer, R. (2006). A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. *Energy*, 31(2-3), 181-207.
- Li, D., Zhao, L., Ma, S., Shao, S., & Zhang, L. (2019). What influences an individual's pro-environmental behavior? A literature review. *Resources, Conservation and Recycling*, 146, 28-34.
- Ling, M., & Xu, L. (2020). Relationships between personal values, micro-contextual factors and residents' pro-environmental behaviors: An explorative study. *Resources, Conservation and Recycling*, 156, 104697.
- MacKinnon, D. P. (2012). *Introduction to statistical mediation analysis*. Routledge.
- Madlener, R., & Hauertmann, M. (2011). Rebound effects in German residential heating: Do ownership and income matter?.
- Meloni, A., Fornara, F., & Carrus, G. (2019). Predicting pro-environmental behaviors in the urban context: The direct or moderated effect of urban stress, city identity, and worldviews. *Cities*, 88, 83-90.
- Mizobuchi, K., & Takeuchi, K. (2016). The rebound effect in residential electricity use: Evidence from a propensity score matching estimator (No. 1639).
- Monin, B., & Miller, D. T. (2001). Moral credentials and the expression of prejudice. *Journal of personality and social psychology*, 81(1), 33.
- Nash, N., Whitmarsh, L., Capstick, S., Hargreaves, T., Poortinga, W., Thomas, G., ... & Xenias, D. (2017). Climate-relevant behavioral spillover and the potential contribution of social practice theory. *Wiley Interdisciplinary Reviews: Climate Change*, 8(6), e481.
- O'Neill, B. C., & Chen, B. S. (2002). Demographic determinants of household energy use in the United States. *Population and development review*, 28, 53-88.
- Ostrom, E. (2000). Social capital: a fad or a fundamental concept. *Social capital: A multifaceted perspective*, 172(173), 195-198.
- Pachauri, S. (2004). An analysis of cross-sectional variations in total household energy requirements in India using micro survey data. *Energy policy*, 32(15), 1723-1735.
- Poortinga, W., Steg, L., & Vlek, C. (2004). Values, environmental concern, and environmental behavior: A study into household energy use. *Environment and behavior*, 36(1), 70-93.
- Schleich, J., Schuler, J., Pfaff, M., & Frank, R. (2022). Do green electricity tariffs increase household electricity consumption?. *Applied Economics*, 1-12.
- Schultz, P. W. (2010). Making energy conservation the norm. *People-centered initiatives for increasing energy savings*, 251-262.
- Smiley, K. T., Chen, Y. A., & Shao, W. (2022). Being green in a green capital: Assessing drivers of pro-environmental behaviors in Copenhagen. *Cities*, 122, 103538.
- SOEP (Sozio.-onomisches Panel) (2009). Deutsches Institut für Wirtschaftsforschung (DIW 24 Berlin), URL: www.diw.de/de/soep.

- Sorrell, S. (2007). The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency.
- Sorrell, S., Gatersleben, B., & Druckman, A. (2020). The limits of energy sufficiency: A review of the evidence for rebound effects and negative spillovers from behavioural change. *Energy Research & Social Science*, 64, 101439.
- Spangenberg, J. H., & Lorek, S. (2019). Sufficiency and consumer behaviour: From theory to policy. *Energy Policy*, 129, 1070-1079.
- Spiller, E., Sopher, P., Martin, N., Mirzatury, M., & Zhang, X. (2017). The environmental impacts of green technologies in TX. *Energy Economics*, 68, 199-214.
- Stern, P. C. (2000). New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of social issues*, 56(3), 407-424.
- Thomas, S., Brischke, L. A., Thema, J., & Kopatz, M. (2015). Energy sufficiency policy: an evolution of energy efficiency policy or radically new approaches?
- Trutnevyte, E., Stauffacher, M., Schlegel, M., & Scholz, R. W. (2012). Context-specific energy strategies: coupling energy system visions with feasible implementation scenarios. *Environmental Science & Technology*, 46(17), 9240-9248.
- Van Raaij, W. F., and Verhallen, T. M. M., 1983, "A Behavioral Model of Residential Energy Use," *Journal of Economic Psychology*, 3(1), pp. 39-63.
- Weller, N., & Barnes, J. (2014). Finding pathways: Mixed-method research for studying causal mechanisms. Cambridge University Press.
- Wilson, J., Tyedmers, P., & Spinney, J. E. L. (2013). An Exploration of the Relationship between Socioeconomic and Well-Being Variables and Household Greenhouse Gas Emissions. [Article]. *Journal of Industrial Ecology*, 17(6), 880-891.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.
- Yohanis, Y. G., Mondol, J. D., Wright, A., & Norton, B. (2008). Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. *Energy and buildings*, 40(6), 1053-1059.
- Yu, B., Zhang, J., & Fujiwara, A. (2013). Evaluating the direct and indirect rebound effects in household energy consumption behavior: a case study of Beijing. *Energy Policy*, 57, 441-453.
- Zwickl-Bernhard, S., & Auer, H. (2021). Citizen Participation in Low-Carbon Energy Systems: Energy Communities and Its Impact on the Electricity Demand on Neighborhood and National Level. *Energies*, 14(2), 305.

Appendix A

Table A1: variables description

Variable definition	Unit	Variable name	Type	Coding
<i>Energy Consumption</i>				
Electricity Consumption (log)	kWh	log_electr_cons	Numeric	-
Heating Consumption (log)	kWh	log_heat_cons	Numeric	-
<i>Mediators</i>				
Energy efficiency	-	eneff_meas	Binary	1 = yes; 0 = no
Renewable energies (PV)	-	PV	Binary	1 = yes; 0 = no
<i>Sociodemographic</i>				
Age	-	age	Categorical	1= GenZ; 2= Millenials; 3= GenX; 4= Baby boomers; 5= Silent generation; 6= Greatest generation
Gender	-	gender	Binary	1= male; 0= female
German	-	german	Binary	1= German; 0= not German
Marital Status	-	married	Binary	1= married; 0= not married
Household Size	-	p_hh	Numeric	-
Household Composition	-	hh_type	Categorical	1= 1-person hh; 2= couple without children; 3= single parent; 4= couple with children <= 16; 5= couple with children > 16; 6= couple with children < and > 16; 7= multiple generation hh; 8= other combinations
<i>Socioeconomic</i>				
Net Income (log)	€	log_net_income	Numeric	-
Ownership	-	owner	Binary	1= owner; 0= tenant
Education Level	-	education	Categorical	1= low; 2= medium; 3= high
Employment Status	-	employed	Binary	1= employed; 0= unemployed
<i>Dwelling characteristics</i>				
Construction Year	-	constr_yr	Categorical	1= before 1919; 2= 1919-1948; 3= 1949-1971; 4= 1972-1980; 5= 1981-1990; 6= 1991-2000; 7= 2001-2010; 8= 2011-2020
Rooms	-	rooms	Numeric	-
Living Space per Person	m ²	living_space_person	Numeric	-

Variable definition	Unit	Variable name	Type	Coding
Environmental Concerns	-	environment	Categorical	1= <i>highly worried</i> ; 2= <i>worried enough</i> ; 3= <i>no worries</i>
Climate Concerns	-	climate	Categorical	.1= <i>highly worried</i> ; 2= <i>worried enough</i> ; 3= <i>no worries</i>
Interest in Politics	-	politics	Categorical	1= <i>very strong</i> ; 2= <i>strong</i> ; 3= <i>not so strong</i> ; 4= <i>not at all</i>
<i>Macro</i>				
CDD	°K days/year	cdd	Numeric	-
HDD	°K days/year	hdd	Numeric	-
Heating price	€	heat_price	Numeric	-
Electricity price	€	electricity_price	Numeric	-

Table A1: continued
Source: SOEP v.37

Appendix B

Table B1: Fixed effects regression model

	(1) Electricity Consumption (log)	(2) Heating Consumption (log)
T	-0.009 (0.009)	0.028** (0.011)
PV	-0.026*** (0.009)	-0.021* (0.012)
EF	-0.001 (0.004)	-0.011** (0.005)
Net Income (log)	0.010** (0.005)	0.024*** (0.006)
Ownership	-0.017 (0.012)	0.033** (0.015)
<i>Age</i>		
Millenials	0.001 (0.030)	0.040 (0.038)
Gen X	0.036 (0.031)	0.062 (0.039)
Baby boomers	0.014 (0.032)	0.052 (0.040)
Silent generation	-0.003 (0.033)	0.037 (0.041)
Greatest	0.071 (0.044)	-0.023 (0.055)
Gender	-0.012 (0.011)	-0.025* (0.014)
German	0.017 (0.032)	0.078** (0.040)
<i>Education level</i>		
Medium education	0.070*** (0.020)	-0.038 (0.025)
High education	0.082*** (0.025)	-0.014 (0.032)
<i>Interest in politics</i>		
Strong	-0.007 (0.005)	0.002 (0.006)
Not so strong	-0.014** (0.006)	-0.008 (0.007)
Not at all	-0.002 (0.007)	-0.008 (0.009)

Table B1: continued

	(1) Electricity Consumption (log)	(2) Heating Consumption (log)
<i>Environmental Concerns</i>		
Worried enough	-0.006* (0.004)	0.001 (0.005)
No worries	-0.012* (0.006)	0.011 (0.008)
<i>Climate concerns</i>		
Worried enough	0.002 (0.004)	0.000 (0.005)
No worries	0.002 (0.006)	0.002 (0.007)
Marital Status	0.023** (0.009)	0.030** (0.012)
Employment Status	-0.001 (0.005)	-0.006 (0.007)
Number of Persons in HH	0.092*** (0.017)	0.043** (0.021)
[Number of Persons in HH] ²	-0.004** (0.002)	-0.002 (0.002)
Rooms	0.012*** (0.003)	0.005* (0.003)
Living space per person	0.001*** (0.000)	0.000* (0.000)
<i>Household Composition</i>		
Couple without children	0.067*** (0.015)	0.019 (0.019)
Single parent	0.076*** (0.018)	0.040* (0.022)
Couple with children ≤ 16	0.083*** (0.023)	0.042 (0.029)
Couple with children > 16	0.099*** (0.023)	0.032 (0.029)
Couple with children ≤ & > 16	0.090*** (0.024)	0.040 (0.031)
Multiple generation hh	0.082*** (0.031)	0.022 (0.039)
Other combination	0.058** (0.026)	0.042 (0.033)

Table B1: continued

	(1) Electricity Consumption (log)	(2) Heating Consumption (log)
CDD	0.000 (0.000)	-0.000 (0.000)
HDD	-0.000 (0.000)	-0.000 (0.000)
Electricity Prices	-2.752*** (0.433)	-
Heating Prices	-	121.749*** (20.511)
<i>Years</i>		
Survey Year = 2011	0.029*** (0.011)	-0.854*** (0.145)
Survey Year = 2012	0.044*** (0.006)	-1.358*** (0.217)
Survey Year = 2013	0.051*** (0.012)	-1.157*** (0.183)
Survey Year = 2014	0.092*** (0.007)	-0.970*** (0.159)
Survey Year = 2015	0.018*** (0.005)	-0.337*** (0.046)
Survey Year = 2016	0.036*** (0.007)	0.284*** (0.045)
Survey Year = 2017	0.026*** (0.008)	0.406*** (0.061)
Survey Year = 2018	0.016*** (0.005)	0.080*** (0.011)
Constant	8.221*** (0.195)	1.901 (1.202)
R ²	0.043	0.025
Observation	78,332	77,669

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robustness check

Even though the results report significant effects of the treatment on heating consumption over the long period, such a long time span may be misleading for the interpretation of the ATTs. Indeed, in that time frame, other events may have happened that could bias the results obtained. Moreover, such high ATTs are likely caused by the low number of units with lags that far ahead. Finally, when computing the aggregate dynamic effects for the periods $t+7$ and $t+8$, these are calculated by the average of only two groups. In fact, only for time-groups 2011 and 2012 it can be estimated the effect of the treatment on energy consumption up to 7 and 8 years. Reducing the length of exposure to three periods after the treatment may lead to more valid results, because the dynamic ATTs computed will be the average of all the time-groups in the model.

All the households treated, indeed, have at least a three-year period to estimate energy consumption after the first time that they have been treated.

Furthermore, the dynamic average treatment effects for the households treated in 2011 seem to significantly influence the aggregate dynamic effects, both for heating and electricity consumption.

Thus, to obtain more robust estimates of the ATTs, the length of exposure has been reduced to three years after the treatment and the household treated in 2011 have been excluded from the model, which is expressed as follows:

$$\log(Y)_{i,t} = \alpha_i + \lambda_t + \sum_{k=-3}^3 \beta_k \cdot T_{i,t} + \sum_{j=-3}^3 \beta_j \cdot X_{i,t} + \epsilon_{i,t} \quad 2012 \leq t \leq 2019 \quad (4)$$

Table 4 add validity to the results obtained from the present analysis.

Even with a shorter length of exposure to the treatment and excluding households treated in 2011 from the model, living in 100ee regions discourages energy sufficiency behaviors in terms of heating consumption. On average, the same year that the *Landkreis* join the project, the households living there tend to consume about 4% more kWh than untreated units. Moreover, the treatment confirms to have statistically significant dynamic effects on heating consumption, increasing the usage by 5% both two and three years the *Landkreis* has entered the program. When taking a shorter length of exposure, though, the effects tend to be more limited and stable with respect to a larger timeframe. On the other hand, no significant effects have been found for electricity consumption.

Table 4: Aggregated dynamic ATTs for electricity and heating consumption

	(1)	(2)
	Electricity	Heating
ATT pre-treatment	0.004 (0.013)	-0.001 (0.014)
ATT post-treatment	-0.010 (0.015)	0.036* (0.020)
T-3	0.022 (0.034)	-0.035 (0.039)
T-2	-0.001 (0.021)	0.033 (0.023)
T-1	-0.008 (0.018)	-0.003 (0.022)
T0	-0.004 (0.015)	0.038** (0.019)
T+1	-0.0003 (0.020)	0.003 (0.027)
T+2	-0.005 (0.020)	0.053* (0.027)
T+3	-0.032 (0.021)	0.050* (0.029)
Observation	57,157	56,635

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: the length of exposure considered is 3 years. The number of observations has decreased because year 2011 has been excluded from the model.