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Is green always better? The effect of renewables on the energy consumption of German households

Supervisor: Bruhan Konda

Candidate: Emanuel Mahrholdt

Student-Nr.: 0577707

e.s.p.mahrholdt@students.uu.nl

Abstract

The adoption of green electricity tariffs is seen as one of the approaches to support the energy transition away from conventional to renewable energy sources. The anticipated environmental benefits of the tariff switch might nonetheless be mitigated by behavioral biases and counteracting effects, such as moral licensing and the renewable rebound effect. Using micro-data for 2020 from the German Socioeconomic Panel, this study explores the drivers behind the green tariff adoption by households and analyzes their resulting electricity consumption with an endogenous switching regression model. Our findings suggest that socioeconomic and attitudinal factors are mostly responsible for the adoption of green tariffs. The treatment effects for both adopters and non-adopters based on counterfactuals indicated higher consumption of electricity. Thus, the renewable rebound effect found support in this study and has to be accounted for when planning interventions in the field of energy policy.

Table of contents

List of figures

List of tables

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1. Introduction

Germany is often called a first-mover regarding policy measures intended to support the reduction of greenhouse gas emissions to combat global warming. This predicate is earned due to the ambitious but successful German energy transition project called *Energiewende* (Govorukha, Mayer & Rübbelke, 2021). The first policy measures started in 1991 with guaranteed feed-in-tariffs (FIT) for renewable energy sources which expanded further with the liberalization of the energy market in 1998 and the renewable energy sources act (EEG), introduced in 2000 (Böhringer et al., 2017). In the upcoming years, the EEG got adapted several times, i.e., in light of the 2011 Fukushima nuclear disaster when German politics decided to phase out the national nuclear energy production until 2023. Energy production using any form of coal will be abolished no later than 2038, while the achievement of 100% energy neutrality is anticipated by the year 2045 (BMWi, 2021). These national goals are even more ambitious than the European Green Deal, approved in 2020, which includes the goal of energy neutrality by 2050 (European Commission, 2019). If the above mentioned goals were to be accomplished by then, various stakeholders have to contribute by reducing their energy consumption.

One-fifth of the final energy consumption in Germany can be attributed to households, making them the single biggest energy consumer in the energy market (BDEW, 2022). The crucial role of households in the *Energiewende*, especially in the electricity market, can directly be attributed to factors such as their electricity consumption, the choice of green tariffs, and the adoption of innovative technologies (e.g., smart home; Jahn et al., 2010), the small-scale production of energy with photovoltaics (PV) or solar thermal (ST) systems, as well as the use of energy-saving methods. A comparably humble approach for the residential sector to support the transition from conventional to renewable energy sources is through the adoption of green electricity tariffs. In recent years, more than 80% of the 1400 energy suppliers offered at least one green tariff (UBA, 2019) which is based on 100% renewable energy sources, while 30% of German households have adopted one (Federal Network Agency, 2021).

Behavioral issues are often found in the field of energy policy, these include moral licensing behavior and the renewable rebound effect. Moral licensing defines a cognitive process by which individuals justify immoral behavior by having previously engaged in moral behavior (Dütschke et al., 2018) while the renewable rebound effect describes a higher demand or lower

than anticipated reduction for energy after an increase in energy efficiency (Schleich et al., 2021). These effects hint to unintended consequences of households switching to renewable energy sources which might offset the intended environmental impact.

So, what are the main drivers of the green tariff adoption and do German households alter their electricity consumption after switching to a green tariff – or do behavioral issues counteract the intended effects? Evidence on the causal effects of a green tariff adoption on the electricity consumption of German households is scant. The focus of this study is therefore set on households, their adoption of green electricity tariffs, and subsequent electricity consumption.

Households that adopt a green tariff might be different from non-adopter households which could lead to heterogeneous group effects. Endogeneity concerns due to self-selection issues regarding the survey data on the green tariff adoption arose as well. To account for those heterogeneous group effects and the potentially endogenous selection variable, we applied an endogenous switching regression model with full information maximum likelihood following Lokshin & Sajaia (2004). Two different regimes, green tariff adoption or non-adoption, were formed with a selection equation determining which regime is observed. Instrumental variables were used for the dependent variable in the selection equation, which thereby indicates what the drivers of the green tariff adoption are. Afterward, the electricity consumption of green tariff adopting households was compared to non-adopter households. The average treatment effect for the treated, here adopters, and the untreated, here non-adopters, was calculated using the counterfactual. The counterfactual describes the state that would have occurred without the adoption of a green tariff for adopters and conversely the adoption effects for non-adopters.

Based on the existing literature on this topic, three hypotheses were formed and empirically assessed. The underlying dataset for the empirical analysis is the German Socioeconomic Panel (SOEP, 2022)[1], a representative panel dataset conducted annually since 1984 (Schröder et al., 2020). This study used solely the newest available survey year of 2020.

The selection equation for the green tariff adoption likelihood highlights the importance of socioeconomic status and attitudinal drivers for the household decision. The expected average electricity consumption of households as the dependent variable in the endogenous switching regression model indicates that a range of factors play a significant role. The analysis of the treatment effects in the actual and the counterfactual case reveals some remarkable results:

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[1] We would like to appreciate and thank the German Institute for Economic Research (DIW, Berlin) for providing us the research data of the German Socioeconomic Panel (SOEP, 2022) immediately after version 37 was published in April this year. The data distribution contract for the underlying datasets can be found in the appendix.

while green tariff adopters and non-adopters consume similar amounts of electricity in the factual case, adopters would consume considerably less in the counterfactual case of non-adoption. Non-adopting households would consume comparably more in the counterfactual case of adoption. These results certainly carry implications for future intervention analyses in the field of households' energy consumption, where factors such as moral licensing behavior and the renewable rebound effect certainly have to be accounted for.

The subsequent part is dedicated to the critical review of relevant literature and presents the resultant hypotheses. This is followed by the methodology section, before the discussion of the empirical results, a succinct summary, and suitable policy recommendations complete this study.

2. Literature review

Exploring household behavior, especially regarding the impact of policy measures and (behavioral) interventions, can give valuable insights into the actual state and the future progress of the German *Energiewende*. Various recent studies analyzed the factors and drivers that influence household energy consumption (Li et al., 2020; Groh & Ziegler, 2022), the occurrence of (renewable) rebound effects (Dütschke et al., 2018; Frondel et al. 2020; Gillingham, Rapson & Wagner, 2020; Schleich et al., 2021; Schultz et al., 2007), the likelihood of choosing a green energy provider through defaults (Ebeling & Lotz, 2015; Kaiser et al., 2020; Neumann & Mehlkop, 2020; Vetter & Kutzner, 2016), the drivers of investment in small-scale household technologies (Jacksohn et al., 2019; Kastner & Stern, 2015) and their interrelation with the demand for green energy (Dato, 2018). In what follows, the relevant findings of those papers are presented and their relevance in light of this analysis will be discussed.

One of the main targets of the *Energiewende* was to reduce primary energy consumption in various sectors, but while most sectors achieved their goals, the residential sector today lies fairly above the anticipated consumption targets (UBA, 2022 I). While an increased share of energy-efficient household technology led to a 10% decline in households' electricity consumption from 2010 to 2020 (Destatis, 2021), overall energy consumption is expected to rise soon. This development is driven by societal long-term developments such as the ongoing digitalization, and the increasing use of electric vehicles and heating systems, in combination with smaller average household sizes. Furthermore, behavioral issues arise that could have a negative impact on energy consumption and therefore the anticipated success of the *Energiewende*. These obstacles, some of which will be further explained in this part of the study, include i.e., perception biases, moral licensing behavior (Dütschke et al., 2018), the

rebound effect (e.g., Schleich et al., 2021), and the NIMBY (not-in-my-backyard) syndrome (Wexler, 1996).

Fundamental factors of the long-run relationship among variables affecting energy consumption and its determinants include income, human capital, energy productivity, energy prices, and eco-innovation (Li et al., 2020). Groh & Ziegler (2022) found that housing and dwelling characteristics, as well as sociodemographic factors, determine green electricity consumption in Germany, while values and norms were insignificant. The latter is an interesting result since 87% of Germans support the faster and stronger expansion of renewable energy sources (ARD, 2022). This could hint at behavioral issues counteracting economic incentives. According to Dato (2018), the decision to invest in energy efficiency is interrelated to the demand for clean energy while environmental consumer motivation is found to be a principal factor. International studies focusing on energy-relevant investment decisions of households show that energy consulting and financial incentives are crucial aspects (Kastner & Stern, 2015), while the investment of the German household sector in PV or ST systems is foremost driven by economic factors (Jacksohn et al., 2019).

The interdependence of socioeconomic circumstances and economic development regarding environmental pollution was first postulated with the influential *Environmental Kuznets Curve* (EKC) hypothesis by Grossman & Krueger (1995). The hypothesis describes an inverted U-shape relationship between per capita income and the grade of environmental pollution. This means that environmental pressure increases faster than income in the initial stages of economic development before it reaches a turning point after which it slows down relative to GDP. This phenomenon is often explained by macro- together with micro-effects, where macro-effects describe the societal change from a developing over an industrial to a service economy, and micro-effects include the tendency of people with an elevated socioeconomic status to have higher preferences for the quality of the environment (Dinda, 2004). The socioeconomic status of households could not only affect the level of environmental pollution but also the adoption of green tariffs and technologies. Furthermore, distributional aspects could arise that affect the public support and the anticipated success of the *Energiewende*.

The FIT for renewable energy sources, i.e., is found to have distributed income from poorer to richer households, leading to rising income inequality and a transfer from the East to the West of Germany (Winter & Schlesewsky, 2019). Another phenomenon affecting public support is energy poverty, momentarily very topical due to fast-rising energy prices (European Commission, 2020), describing a situation where households spend a significant amount of

their available income on energy sources (Neuhoff et al., 2013). On the one hand, this might cause households with a low socioeconomic status to be less motivated in adopting a green tariff since environmental concerns and subsequent action are prevented by more urgent socioeconomic issues. Households with a higher socioeconomic status, on the other hand, might suffer from moral licensing, a cognitive process by which individuals justify immoral behavior (e.g., consuming more energy) by having previously engaged in moral behavior (e.g., adopting a green tariff) (Dütschke et al., 2018). This leads us directly to the rebound effect.

The rebound effect explains a higher demand or lower than anticipated reduction for products or services after an increase in their efficiency and is mostly found in the field of energy policy and behavioral economics. Figure 1 depicts the rebound effect and its underlying mechanisms. It shows how potential energy savings are cut off by the rebound effect, resulting in lower actual energy savings. The total rebound can be divided into three separate rebound effects, called actual effects. The underlying mechanisms of the effect can be of monetary as well as non-monetary nature, sparked by economic, psychological, and other mechanisms (Dütschke et al., 2018).
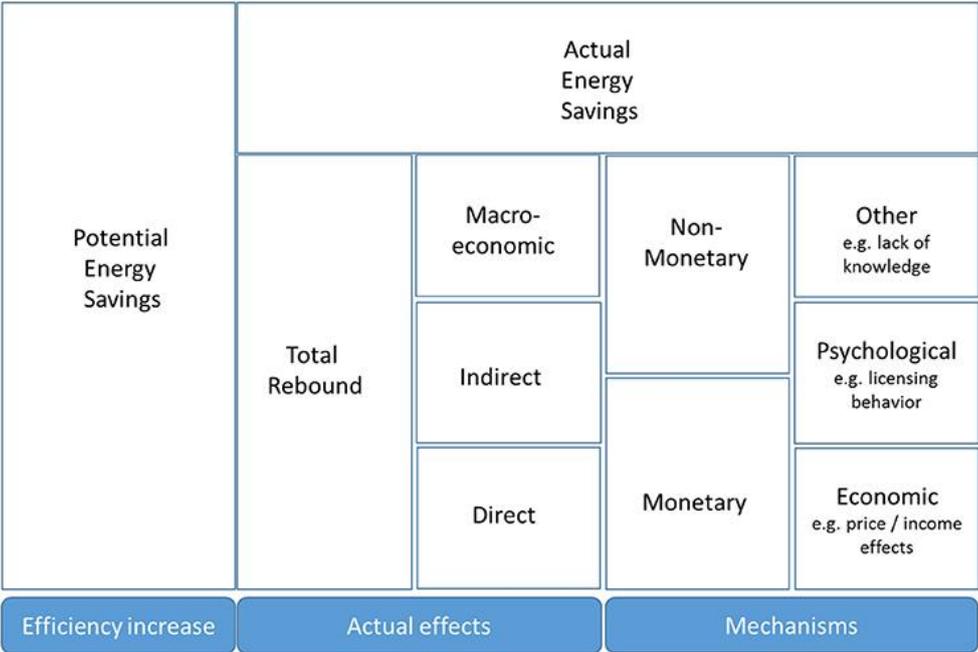
Fig. 1: The rebound effect and its underlying mechanisms. Source: Dütschke et al. (2018, p. 17)

The well-known effect repeatedly served as one major explanation for unexpected behavioral intervention outcomes. It can be divided into three parts: Direct, indirect, and macroeconomic rebound effects (BMWi, 2016). A direct rebound effect found in this study is an increase in electricity consumption after the adoption of a green tariff. Using data provided by an electricity provider, Schleich et al. (2021) similarly studied German households before and after they switched to a green tariff. Their findings suggest a renewable rebound effect of about 8.5 %

which is persistent over at least four years and even higher rebound effects (>11%) for households with a low socioeconomic status. Another recent study found substantial increases in electricity consumption after the installation of a PV module through the so-called solar rebound (Frondel et al., 2021). While the direct rebound effect is frequently triggered by moral licensing behavior, the solar rebound might be explained by economic incentives due to zero marginal costs of household PV electricity generation (Oliver et al., 2019).

Indirect rebound effects are mostly caused by the income and substitution effect and describe increased good efficiency leading to lower running costs and substitution towards the more energy-efficient good (e.g., driving more with an electric car). The increased purchasing power of the consumer then results in a higher demand for energy-inefficient products or services (e.g., traveling by plane). Macroeconomic rebound effects describe a societal change in demand, production, and distribution structures because of technological efficiency improvements, such as more cost-efficient cars leading to lower demand for public transportation (BMWi, 2016). A recent overview of studies with a focus on macroeconomic rebound effects found little support for the 'backfire' hypothesis in the international literature (Gillingham, Rapson & Wagner, 2020) – although the difficulties of precisely measuring, interpreting, and understanding the macroeconomic rebound effect were highlighted. Overall, the missed opportunities for energy saving demonstrate why the rebound effect stands in line with the goal of improving energy efficiency.

The question arises of what policymakers can do to support such energy transition projects while limiting negative (financial) externalities. Numerous studies explore the effects of green defaults as demand-size policies in Germany (Kaiser et al., 2020; Ebeling & Lotz, 2015; Neumann & Mehlkop, 2020; Vetter & Kutzner, 2016) and Switzerland (Liebe, Gewinner & Diekmann, 2021). According to Ebeling & Lotz (2015), an opt-out default increased the choice of green electricity by 59.64% with stronger effects than motivational factors. When comparing opt-out with opt-in default rules, green opt-outs are found to quadruple the choice of green energy (Vetter & Kutzner, 2016). Accordingly, a recently conducted field study in Switzerland found that green defaults led to 80% of households and businesses staying in the tariff, and women were more likely to choose green energy plans than men (Liebe, Gewinner & Diekmann, 2021). Using macro-level information combined with micro-level data retrieved from the SOEP, Kaiser et al. (2020) conducted a field experiment in Germany. They analyzed basic energy providers and their green opt-out tariffs. This is due to the reason that two-thirds of the population hold an electricity contract with their basic provider. One half uses the basic tariff, and the other half is distributed over the remaining tariffs. 17% of basic providers offer

a green opt-out tariff which subsequently led to a significant increase in customers adopting green energy, even among those who are not too concerned about climate change (Kaiser et al., 2020).

Other studies regarded behavioral interventions intending to reduce households' energy consumption and overcome possible rebound effects. Andor & Fels (2018) analyzed four nudge-like non-price interventions (social comparison, commitment devices, goal setting, and labeling) in forty-four international studies comprising 105 treatments and found that all those four interventions have the potential to significantly reduce the energy consumption of private households. Schultz et al. (2007) showed UK households normative messages, comparing their energy consumption to the average consumption of their neighbors, which led to subsequent energy savings in households with a higher-than-average consumption level. The rebound effect raised the energy consumption of households that had a lower-than-average consumption level, thereby counteracting the intended outcome of this behavioral intervention. Adding a simple injunctive message to the letter, showing social approval or disapproval, led to the elimination of the rebound effect and an ongoing energy saving of higher-than-average consumption households (Schultz et al., 2007). The results highlight the role and importance of behavioral factors in household energy plan decisions and how interventions in this field should be tackled by policymakers with appropriate methods.

Based on the existing literature in the field, we form the following three hypotheses that will be evaluated throughout the empirical part of this study:

H1: A higher socioeconomic status (e.g., income, education, dwelling characteristics) positively influences household demand for green electricity.

H2: Relevant attitudinal factors (environmental concerns, interest in politics) positively affect the demand for green electricity.

H3: Households that adopted a green tariff consume more electricity than non-adopter households, leading to a measurable renewable rebound effect.

3. Methodology

The methodology section describes the underlying dataset and its limitations, before presenting the empirical strategy for the analysis of the green tariff adoption and its effects on households' electricity consumption.

3.1 Data

The data of this study was retrieved by version 37 of the German Socio-Economic Panel (SOEP, 2022; Schröder et al., 2020) conducted by the DIW Berlin. The SOEP is an annual representative household survey program initiated in 1984 consisting of more than 19.000 households and 32.000 individuals living in Germany. The dataset contains a wide range of sociodemographic and socioeconomic characteristics, as well as the attitudes and interests of participants. Questions regarding the electricity consumption patterns are included, such as the money the household spends on electricity, the adoption of green energy technologies and green tariffs, or whether the household changed its electricity provider during the past five years. This variety of data allows researchers to tackle important economic and behavioral issues affecting household energy consumption.

After merging different panel datasets from the SOEP for the survey year 2020, extreme or unplausible values regarding age, income, and the electricity price were excluded. This analysis will focus on the household level. The dataset now includes more than 15,000 household observations (12,575 in the main analysis) which can be grouped into sociodemographic, socioeconomic, as well as 'green' and attitudinal factors. Table 1 below summarizes the key variables and offers descriptive statistics.

Limitations of the dataset result from the privacy restriction of the SOEP data; it cannot be analyzed on lower regional levels than the German federal states without an expanded data distribution contract and an expanded data protection concept. The vote share of the German party Alliance 90/The Greens (Greens) in the 2017 federal election, which will be used as an instrumental variable in the main analysis, was therefore built on their respective federal state results. Since electricity consumption statistics were not part of the original SOEP dataset, consumption was imputed using the average price households paid for electricity.

The average price households spent annually on electricity was 909.62€, which results in an imputed yearly consumption level of 3,008 kWh, similar to the 3,148 kWh a comparison portal for electricity analysis found for 2020 (Check24, 2021). About 24% of households adopted a green tariff and 26.5% changed their electricity provider during the past five years, while only 1% of households used an electric car as their first vehicle. Environmental concerns are high when compared to the general interest in politics, which is unsurprising since 65% of Germans reported that environmental protection and climate action are especially important challenges (German Environment Agency, 2022). The Greens vote share results in an average of 8.57% (the actual result was 8.9%; Federal Returning Officer, 2017). This lower share might be

explained by some smaller federal states with an unrepresentative number of survey participants.

Table 1. Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
Age	19,917	48.57	16.95	18	99
Male	19,911	.55	.50	0	1
German	19,917	.68	.47	0	1
Education	18,794	12.00	3.10	7	18
Children	19,916	.79	1.22	0	10
Employment	19,917	.63	.48	0	1
HH net income	17,100	3217.76	1930.93	900	13000
HH size	19,917	2.53	1.54	1	13
Rooms	19,233	3.79	1.85	1	25
Owner	19,445	.36	.48	0	1
Electricity price	17,136	909.62	441.13	240	2916
Electricity consumption	17,136	3007.51	1458.54	793.52	9641.26
Green tariff	15,936	.24	.43	0	1
Provider change	16,249	.27	.44	0	1
Electric car	19,916	.01	.09	0	1
Environmental concerns	16,488	1.24	.65	0	2
Interest in politics	18,741	1.31	.91	0	3
Greens vote share	19,916	8.57	2.88	3.7	13.9

Note: Table A1 in the appendix contains the description of the variables

Overall, after successfully merging various datasets and adjusting them for analysis purposes, the data is adequate for the anticipated endogenous regression model. The following part describes the empirical framework and estimation techniques for the analysis – conducted with STATA IC 16.1 as a statistical software package.

3.2 Empirical framework

3.2.1 Endogenous switching regression

The decision to adopt a green tariff is voluntary and may be based on individual self-selection since households that adopted a green tariff may have systematically distinct characteristics from the households that did not adopt it (see Table A2 in the appendix for a comparison of the adopter and non-adopter households). Two main problems arise, namely confounding factors that influence dependent and independent variables, as well as self-selection biases. To evaluate

assumptions about the exogeneity of treatment effects from survey data (Powers, 1993) and thereby account for the endogeneity of the green tariff adoption, an endogenous switching regression (ESR) model using full information maximum likelihood (FIML) was applied (Lokshin & Sajaia, 2004, 2011). This method estimates simultaneous equations to fit binary and continuous parts of the model, an approach that relies on joint normality of the error terms in both equations. For the model to be identified it is important to use variables that directly affect the selection variable but not the outcome variable as selection instruments, together with those automatically generated by the nonlinearity of the selection model. The calculation of the average treatment effects for the treated and the untreated was conducted by answering the counterfactual question. The counterfactual describes what would have happened to adopter households without the adoption of a green tariff and conversely to non-adopter households in case of adoption.

As selection instruments for the green tariff variable, we use the Greens vote share in the 2017 federal election and an electricity provider change during the past five years. The Greens election result is used to instrument the green tariff adoption as the party has a distinct focus on protecting the environment and supporting the *Energiewende*. By achieving a comparably low election result in 2017, they were foremost strong in traditionally green voting districts. Households in those regions, mostly cities and their surroundings in Western Germany, often have an elevated socioeconomic status paired with high grades of environmental awareness. These values are often found to be significant contributing factors to the willingness to pay for green tariffs (Danne, Meier-Sauthoff & Musshoff, 2021; Kowalska-Pyzalska, 2019). Therefore, a distinct local demand for green electricity tariffs can be assumed.
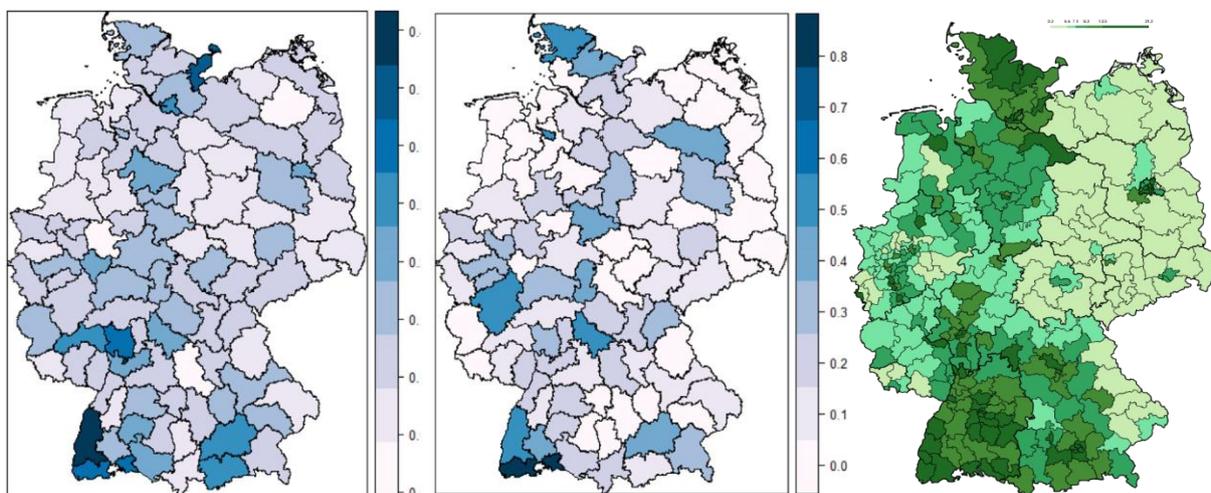

Fig. 2: Green electricity demand (left) and share of green opt-out tariffs (right) across regional policy levels. Source: Kaiser et al. (2020, p.6)

Fig 3. Greens 2017 federal election results Source: Federal Returning Officer (2018)

Figures 2 and 3 show the idea and relevance of using Green's vote share as an instrumental variable for the green tariff adoption. Figure 2 shows the green electricity demand and the share of green opt-out tariffs across regional policy levels while figure 3 depicts the Greens vote share across the election districts for the 2017 federal election. It is visible that clusters of a high Greens vote share are mostly accompanied by elevated local demand for green tariffs. Energy providers might consider this local demand for green energy as an incentive to offer (more) green tariffs in this region or even make use of green opt-out tariffs. Numerous studies show that the latter tend to stick to consumer households (e.g., Liebe, Gewinner & Diekmann, 2021), regardless of consumer attitudes towards climate change (Kaiser et al., 2020).

The second selection instrument is an electricity provider change during the past five years. In light of competitive market prices for electricity produced by renewable energy sources, a growing number of energy providers now offer green tariffs. 2020 was an unprecedented record year for provider changes – with 5.4 million changes in the residential sector alone (Federal Network Agency, 2021). This demonstrates that consumers are increasingly taking advantage of the opportunities to save, while energy providers face increased (green) market competition. The rising number of households changing their provider paired with a steadily growing demand for green tariffs leads to the assumption that the provider change variable might have a direct effect on the green tariff adoption whereas a direct effect on electricity consumption seems unlikely.

The admissibility of these instruments is verified by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the adoption decision (relevance), but it will not affect the electricity consumption of households that did not adopt (exclusion restriction). Table A3 in the appendix shows that one of the two variables has some issues regarding the latter. Nevertheless, they might be considered valid selection instruments since they are jointly statistically significant drivers of the decision to adopt a green tariff (Model 1, F-stat.=594.95; $p=0.00$). For the joint effect of the variables on electricity consumed by non-adopter households the results turned out to be significant but less relevant (Model 2, F-stat.=49.53, $p=0.00$). According to the relevance test, the Greens share does not influence electricity consumption. The effect can be traced back to the provider change that individually affects both variables, the green tariff choice by households (F-stat.=1006.57, $p=0.00$) as well as the electricity consumption of non-adopters (F-stat.= 81.71, $p=0.00$). Households with a high electricity consumption might change their energy provider more often than their peers. This is

due to exclusive offers by providers that are more lucrative for households with an elevated level of electricity consumption.

Nevertheless, since an exclusion of the variable would cost too much predictive power and other explanatory variables for the selection equation are automatically generated by the nonlinearity of the model as well, the provider change is jointly used with the Greens vote share to instrument the green tariff adoption in the selection model. The parameter values of the model, therefore, have to be interpreted with caution, but the detected trend should not be affected significantly.

The following part is based on the empirical analysis of Di Falco, Veronesi & Yesuf (2011). The two regimes that households face (1) to adopt, and (2) not to adopt are defined as follows:

(1) Regime 1: $y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i}$ *if* $G_i = 1$
(2) Regime 2: $y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i}$ *if* $G_i = 0$

where y_i is the electricity consumed by households in regimes 1 and 2, X_i represents the input vectors (e.g., age, education, income), ε_i describes the error term, and G_i *is* the selection variable (green tariff adoption).

The ESR model can be used to compare the expected electricity consumption of households that adopted a green tariff (a) to the households that did not adopt (b), and to investigate the expected electricity consumption in the counterfactual hypothetical cases (c) that the adopting households did not adopt, and (d) that the non-adopter households adopted. The conditional expectations for electricity consumption in the four cases are presented in table 2 and are defined as follows:

(3a) $E(y_{1i}|G_i=1) = X_{1i}\beta_1 + \sigma_1\eta\lambda_{1i}$

(3b) $E(y_{2i}|G_i=0) = X_{2i}\beta_2 + \sigma_2\eta\lambda_{2i}$

(3c) $E(y_{2i}|G_i=1) = X_{1i}\beta_2 + \sigma_2\eta\lambda_{1i}$

(3d) $E(y_{1i}|G_i=0) = X_{2i}\beta_1 + \sigma_1\eta\lambda_{2i}$.

Cases (a) and (b) of table 2 represent the actual expectations observed in the sample (c) and (d) represent the counterfactual expected outcomes.

Table 2. Conditional Expectations, Treatment, and Heterogeneity Effects

Subsamples	Decision stage		Treatment effects
	To adopt	Not to adopt	
Households adopted	(a) E($y1i$/Gi=1)	(c) E($y2i$/Gi=1)	TT
Households did not adopt	(d) E($y1i$/Gi=0)	(b) E($y2i$/Gi=0)	TU
Heterogeneity effects	BH1	BH2	TH

Note: (a) and (b) represent observed expected electricity consumption of households; (c) and (d) represent counterfactual expected electricity consumption.
Gi= 1 if households adopted a green tariff; Gi= 0 if households did not adopt
$Y1i$: electricity consumption if households adopted
$Y2i$: electricity consumption if households did not adopt
TT: the effect of the treatment (i.e., adoption) on the treated (i.e., households that adopted)
TU: the effect of the treatment (i.e., adoption) on the untreated (i.e., non-adopter households)
BHi: the effect of base heterogeneity for households that adopted (i =1), and did not adopt (i =2)
TH= (TT - TU), i.e., transitional heterogeneity.

Following Heckman, Tobias & Vytlacil (2001), we calculate the effect of the treatment "to adopt" on the treated (TT) as the difference between (a) and (c),

$$(4)\ TT = E(y1i|Gi =1) − E(y2i|Gi =1) = \mathbf{X1i}(\mathbf{\beta 1} − \mathbf{\beta 2}) + (\sigma 1\eta − \sigma 2\eta)\lambda 1i$$

which represents the effect of adopting a green tariff on the electricity consumption of the households that actually adopted it. Similarly, we calculate the effect of the treatment on the untreated (TU) for the households that actually did not adopt as the difference between (d) and (b),

$$(5)\ TU = E(y1i|Gi =0) − E(y2i|Gi=0) = \mathbf{X2i}(\mathbf{\beta 1} − \mathbf{\beta 2}) + (\sigma 1\eta − \sigma 2\eta)\lambda 2i.$$

We can use the expected outcomes described in equations (3a)–(3d) to also calculate the heterogeneity effects. Households that adopted may have a higher consumption level than households that did not adopt, regardless of the fact that they decided to adopt but because of unobservable characteristics. The effect of base heterogeneity for the group of adopter households is defined as the difference between (a) and (d),

$$(6)\ BH1 = E(y1i|Gi =1) − E(y1i|Gi=0) = (\mathbf{X1i} − \mathbf{X2i})\mathbf{\beta 1i} + \sigma 1\eta(\lambda 1i − \lambda 2i).$$

Similarly for the households that did not adopt, the effect of base heterogeneity is the difference between (c) and (b),

$$(7)\ BH2 = E(y2i|Gi =1) − E(y2i|Gi=0) = (\mathbf{X1i} − \mathbf{X2i})\mathbf{\beta 2i} + \sigma 2\eta(\lambda 1i − \lambda 2i).$$

Finally, we investigate the transitional heterogeneity (TH), that is whether the effect of adopting a green tariff is larger or smaller for households that adopted a green tariff or for households

that did not adopt in the counterfactual case that they did adopt, that is the difference between equations (5) and (6) (i.e., TT and TU).

4. Results

Table 3 below presents the results of the selection equation (1) as well as the ESR results for the electricity consumption of green tariff adopters (2) and non-adopter households (3). The selection equation for the green tariff adoption shows highly significant results for most variables, besides gender and being the owner of the dwelling. The respondents' age, household size as well as the number of rooms of the current dwelling all have significant, negative effects on the likelihood of a green tariff adoption. A higher household income positively influences the adoption likelihood, as well as the German citizenship, the years of education or training, being fully employed, the number of children, and using an electric car as the first vehicle.

Relevant attitudinal factors, measured by the grade of environmental concerns and general interest in politics, positively affect the demand for green tariffs as well. Additionally, as expected, both IVs are significant drivers of the green tariff adoption.

The presented results above are mostly in line with prior literature studying the adoption of green tariffs and help to determine the most crucial factors relevant for the households' tariff adoption. The findings highlight the importance of socioeconomic as well as attitudinal factors affecting the adoption decision. When turning to households' expected electricity consumption, and especially the expected treatment effects, remarkable results can be presented.

The ESR results for the electricity consumption of adopter (2) and non-adopter (3) households show that age positively and significantly contributes to the electricity consumption in both regimes. The same can be said about dwelling characteristics such as the household size, the number of rooms, and being the owner of the dwelling. It seems unsurprising that a larger dwelling increases electricity consumption, nevertheless, having (more) children is negatively affecting the electricity consumption of households. Every additional year of education or training reduces electricity consumption as well as higher grades of environmental concerns. Some variables need some further investigation and explanation since they change their sign depending on the observed regime or are significant only for one regime. Namely, these variables include the household net income, interest in politics, using an electric car, and German nationality.

The net household income affects the green tariff adoption as well as the consumption level of adopter households, while it is positive but insignificant regarding non-adopters.

Table 3. Endogenous Switching Regression Model

Model	(1)	(2)	(3)
Variables	Selection equation (Green tariff)	Electricity consumption, adoption (=1)	Electricity consumption, adoption (=0)
Age	-0.00343***	9.676***	8.620***
	(0.000937)	(1.961)	(1.278)
Male	0.0168	40.39	-11.93
	(0.0244)	(45.59)	(30.74)
Education	0.0667***	-60.91***	-97.65***
	(0.00629)	(9.377)	(11.59)
Employment	0.0640*	-29.24	-14.83
	(0.0352)	(65.22)	(38.01)
Children	0.0501**	-141.4***	-146.3***
	(0.0239)	(46.67)	(32.57)
HH net income	3.25e-05**	0.0656***	0.0123
	(1.41e-05)	(0.0151)	(0.0209)
HH size	-0.0904***	385.6***	448.0***
	(0.0240)	(42.61)	(25.08)
Rooms	-0.0399**	202.6***	181.4***
	(0.0179)	(19.73)	(13.91)
Interest in politics	0.111***	-10.85	-103.3***
	(0.0245)	(30.54)	(26.99)
Electric car	0.521***	35.70	-595.7**
	(0.124)	(173.3)	(245.8)
Owner	-0.00993	116.8**	122.5***
	(0.0381)	(58.89)	(39.35)
Environmental concerns	0.200***	-231.4***	-148.5***
	(0.0256)	(40.51)	(37.51)
German	0.200***	213.0**	-75.93*
	(0.0547)	(90.52)	(45.87)
Greens vote share	0.0188**		
	(0.00948)		
Provider change	0.331***		
	(0.126)		
Constant	-2.003***	1,538***	1,859***
	(0.451)	(265.4)	(206.4)

Note: Table A4 in the appendix summarizes the test statistics of the regression. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The insignificance for non-adopters could be due to factors such as more energy-efficient technology used in high-income households or the heterogeneous group constellations, where adopters have a significantly higher income than non-adopters (see Table A2 in the appendix).

The general interest in politics and using an electric car as the first vehicle are both insignificant regarding adopter households, but significant and contributing factors for non-adopters. While both variables have a significant impact on the green tariff adoption likelihood, the values for non-adopters might be explained by the variables catching attitudinal drivers of households that save electricity without having adopted a green tariff. Additionally, electric car ownership in the group of non-adopters is exceedingly rare, and subsidies, as well as free recharging stations, could influence the electricity consumption of electric car users in the sample.

Finally, being German positively affects the green tariff adoption and the electricity consumption of adopters, but it turns out to be a negative factor for the group of non-adopters. We explain this counterintuitive outcome with the historical differences between Eastern and Western Germany. Western Germany tends to be richer; the share of immigrants is elevated; electricity consumption is higher (Check24, 2021), and the green tariff adoption likelihood is by far larger (see Fig. 2). This indicates that the elevated consumption level of Germans in the group of adopter households (92.6% German adopters vs. 80.5% German non-adopters, Table A2) represents the outcomes of an elevated socioeconomic status. The converse holds for non-adopters from Eastern Germany, where the German nationality more often indicates an inferior socioeconomic status, therefore resulting in lower expected electricity consumption. Overall, the ESR results seem to be plausible and widely as expected. The next part is dedicated to the treatment effects of the green tariff adoption on electricity consumption.

Table 4 presents the expected yearly electricity consumption under actual and counterfactual conditions. Cells (a) and (b) represent the expected quantity of kWh annually consumed per household observed in the sample. The expected electricity consumption by households that adopted a green tariff is about 3,047 kWh, the same as the 3,049 kWh consumed by non-adopter households. The last column presents the treatment effects of the green tariff adoption on electricity consumption.

In the counterfactual case (c), households who actually adopted would have consumed about 2,181 kWh (~71.6%) less if they did not adopt a green tariff. In the counterfactual case (d), where non-adopter households adopt, they would have consumed about 60 kWh (~2%) more if they had adopted. These results imply that a green tariff adoption significantly increases electricity consumption while the transitional heterogeneity effect is large and positive;

demonstrating that the effect is substantially larger for the households that adopted relative to the non-adopters.

Table 4. Average Expected Electricity Consumption, Treatment, and Heterogeneity Effects

Subsamples	Decision stage		Treatment effects
	To adopt	Not to adopt	
Households adopted	(a) 3046.638	(c) 865.532	TT= 2181.106***
	(13.712)	(11.569)	(17.94)
Households did not adopt	(d) 3109.214	(b) 3049.135	TU= 60.079***
	(7.525)	(6.588)	(10.002)
Heterogeneity effects	BH_1= −62.577***	BH_2= −2183.603***	TH= 2121.027***
	(15.303)	(13.271)	(5.045)

See note of table 2. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The last row of the table, which adjusts for the potential heterogeneity in the sample, shows that non-adopter households would have consumed significantly more than the households not adopting in the counterfactual case (c). This finding indicates that there are some relevant sources of heterogeneity in the sample. In the counterfactual case (d), where the non-adopter households had adopted, they would also have consumed significantly more electricity. Consequently, both groups of households are better off not adopting than adopting a green tariff.

5. Discussion and conclusions

The objectives of this paper were to analyze the driving forces behind the household decision to adopt a green tariff and to investigate the implications of this decision on households' electricity consumption. To conduct the empirical analysis, we used the newly available and representative SOEP dataset, which includes the survey year 2020 and various relevant explanatory variables. To account for unobservable factors and to estimate the parameters that influence the green tariff adoption and the subsequent electricity consumption, an endogenous switching regression model was applied. For the selection equation that determines which regime is observed, two instrumental variables, namely the Greens vote share and a provider change during the past five years, were used. The following analysis of the treatment effects, here the adoption of a green tariff, was conducted by using the actual and counterfactual cases.

While dwelling characteristics were found to be insignificant or negatively contributing factors for the adoption of a green tariff – income, education, employment, and being German – all had significant, positive effects. These empirical findings speak in favor of the first hypothesis of a higher socioeconomic status resulting in a higher demand for green electricity tariffs (H1).

Environmental concerns as well as the participants' general interest in politics were found to have highly significant effects on the likelihood of a green tariff adoption. The grade of environmental concerns then also reduced the expected electricity consumption by households in both regimes. The obtained results, therefore, support the second hypothesis of relevant attitudinal factors positively influencing the demand for green electricity tariffs (H2).

The main part of the analysis focused on households' electricity consumption in case of green tariff adoption, compared to non-adopters and the counterfactual cases for both groups. The results of the treatment effects suggest the occurrence of a significant renewable rebound effect which is in line with prior literature studying this effect (e.g., Schleich et al., 2021). The actual size of the rebound effect is hard to measure but the counterfactual cases suggest that households who actually adopted a green tariff would consume significantly less electricity in case of non-adoption whereas non-adopter households would consume more electricity in case of adoption. Moral licensing behavior of households could be one major explanation for these counterintuitive results (Dütschke et al., 2018). These findings can be interpreted as dedicated support for the third hypothesis of higher electricity consumption for households that adopted a green tariff, leading to a measurable renewable rebound effect (H3).

To sum up, the empirical analysis included the selection equation, the ESR model for electricity consumption, and the treatment effects in the factual and counterfactual cases. The obtained results stated support for all of the three hypotheses. Although the detected effects seem to be large and clear, some data limitations prevented us from digging deeper into the topic. First of all, the panel dataset was used but with a cross-sectional approach since some important variables (e.g., green tariff adoption) were not part of prior SOEP versions. Secondly, the analysis of regional differences was restricted to the level of the federal states because data protection regulations prohibited otherwise. Lastly, some assumptions were made regarding the imputed level of electricity consumption and the instrumental variables used to instrument the green tariff adoption. Overall, we were able to account for the most severe issues regarding heterogeneous group effects and the endogenous nature of the main variable in the dataset.

In light of the fast-rising energy prices due to the heavier regulation of the energy market, geopolitical instability, and the international efforts for the energy transition – energy consumption, the drivers behind and suitable policy interventions, remain a highly topical debate. The conclusion we draw is that policymakers when targeting policies at energy consumption, have to take the rebound effect and moral licensing behavior into consideration.

This is surely warranted for judging the efficacy of those policies and thereby helps design better future policies.

Since Germany mostly tried to support the *Energiewende* by direct prohibitions (e.g., the shutdown of nuclear energy plants) and market price interventions (e.g., FIT for renewables and emission pricing), this study presented literature that accounted for behavioral biases and offered suitable non-price solutions in support of the energy transition. These solutions include increasing the regional share of green opt-out tariffs (Kaiser et al., 2020), making use of good fitting feedback mechanisms (Schultz et al., 2007), and nudge-like non-price interventions such as social comparison and commitment devices (Andor & Fels, 2018). Further empirical research into this relevant topic, covering the hard-to-measure behavioral issues such as moral licensing behavior and the renewable rebound effect, is suggested.

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Appendix

Table A1. Variables Definition

Variable name	Definition
Age	Age of the respondent
Male	Dummy variable: 1= male, 0= female
Education	Amount of education or training in years
Employment	Dummy variable: 1= fully employed, 0= otherwise
Children	Number of children
HH net income	Monthly net household income
HH size	Number of persons in HH
Rooms	Number of rooms of the dwelling
Electricity price	Electricity costs (€) previous year
Electricity consumption	Imputed for consumption in kWh: Electricity costs/0.30245 (avg. electricity price for German households in 2020)
Provider change	Dummy variable: Changed electricity provider in the past 5 years. 1= yes, 0= no
Green tariff	Dummy variable: Green electricity tariff. 1= yes, 0= no
Interest in politics	Political interests (Likert-scale: 0= no interest, 3= extremely interested)
Environmental concerns	Worried about the environment (Likert-scale: 0= no concerns, 2= extremely worried)
German	Dummy variable: Citizenship. 1= German, 0= non-German
Greens vote share	The vote share of the green party in the 2017 federal election per federal state
Owner	Dummy variable: 1= owner of the dwelling, 0= tenant
Electric car	Dummy variable: 1. vehicle: electricity. 1= yes, 0= no

Table A2. Summary Statistics for Adopters and Non-adopters

Variable	Mean (GT=0)		Mean (GT=1)	Min	Max
Age	**51.56**	>	**51.25**	18	99
Men	**50.9%**	<	**54.1%**	0	1
German	**80.5%**	<	**92.6%**	0	1
Education	**12.197**	<	**13.969**	7	18
Employment	**65.6%**	<	**74.8%**	0	1
Children	**.634**	<	**.772**	0	8
HH net income	**3223.75€**	<	**4141.50€**	900	13000
HH size	**2.324**	<	**2.487**	1	12
Rooms	**3.875**	<	**4.371**	1	20
Owner	**40.12%**	<	**51.77%**	0	1
Electricity price	**903.95€**	<	**911.59€**	240	2916
Electricity consumption	**2988.77**	<	**3014.02**	793.52	9641.26
Provider change	**20.6%**	<	**45.9%**	0	1
Electric car	**0.6%**	<	**2.4%**	0	1
Environmental concerns	**1.192**	<	**1.386**	0	2
Interest in politics	**1.324**	<	**1.686**	0	3
Greens vote share	**8.35%**	<	**9.06%**	3.7	13.9
Observations	**10,736**	>	**3,494**	3494	12133

Note: GT stands for green tariff, GT=0 for non-adopters, GT=1 for adopters. The value of dummy variables was adjusted to a percentage share of respondents for better readability.

Table A3. Relevance of Instrumental Variables

```
. test greenshare changein5

( 1)  greenshare = 0
( 2)  changein5 = 0

      F(  2, 15832) =  594.95
          Prob > F =    0.0000
```
Model 1 (green tariff)

```
. test greenshare changein5

( 1)  greenshare = 0
( 2)  changein5 = 0

      F(  2, 10826) =   49.53
          Prob > F =    0.0000
```
Model 2 (electricity consumption)

Table A4. Test statistics for the ESR

/lns1	7.105091	.0036509	1946.14	0.000	7.097936	7.112247
/lns2	7.286389	.0863758	84.36	0.000	7.117095	7.455682
/r1	-.0666328	.0821133	-0.81	0.417	-.2275719	.0943063
/r2	-1.73831	.7116638	-2.44	0.015	-3.133146	-.3434748
sigma_1	1218.153	4.447302			1209.468	1226.901
sigma_2	1460.287	126.1335			1232.864	1729.663
rho_1	-.0665344	.0817498			-.223723	.0940277
rho_2	-.9400304	.082797			-.9962087	-.330576

Wald test of indep. eqns. :   chi2(1) =   6.77   Prob > chi2 = 0.0093

Datenweitergabevertrag **6067**

Zwischen dem

DIW Berlin
Deutsches Institut für
Wirtschaftsforschung
Mohrenstraße 58
10117 Berlin

einerseits

und

Utrecht University

3584EC Utrecht

andererseits
-nachstehend Datenempfänger genannt-

wird folgender Vertrag geschlossen:

1 Das DIW Berlin räumt dem Datenempfänger das einfache Nutzungsrecht an den Mikrodaten (im Folgenden SO EP-Daten genannt) des Sozio-oekonomischen Pa- nels (SO EP) ein.

2 Umfang und Inhalt des Nutzungsrechts sind an folgende Bedingungen geknüpft:

2.1 Der Datenempfänger verpflichtet sich, die Daten nicht an andere Personen - au- ßer den unter 2.3 genannten datenschutzrechtlich verpflichteten Mitarbeitern am Forschungsvorhaben - oder an andere Einrichtungen weiterzugeben oder sie ihnen zugänglich zu machen. Dies gilt auch für modifizierte Daten.

2.2 Die Daten dürfen nur in der eigenen wissenschaftlichen Forschung der Datenemp- fänger eingesetzt werden. Eine Nutzung für gewerbliche oder sonstige wirtschaft- liche Zwecke ist nicht gestattet; hierüber muss gegebenenfalls eine gesonderte Vereinbarung getroffen werden. Nicht gestattet ist auch die Nutzung des vollstän- digen Datensatzes für die Lehre. Für diesen Zweck dürfen ausschließlich SO EP- Daten aus der um 50% der Fälle reduzierten Lehrversion des Datensatzes genutzt werden. Die Lehrversion des Datensatzes übermittelt das DIW Berlin dem Daten- empfänger auf gesonderte Anfrage.

2.3 Die SO EP-Daten dürfen ausschließlich in folgendem Forschungsvorhaben einge- setzt werden:

Is green always better? The impact of renewables on the energy consumption of German households

Sie dürfen zu keinem anderen als dem angegebenen Zweck eingesetzt werden.

Die Datennutzung erfolgt ausschließlich durch die beim Datenempfänger tätigen Personen, die mit der Bearbeitung des o.g. Forschungsvorhabens betraut sind. Dies sind:

Prof Bruhan Konda (Projektleitung)

sowie Emanuel Mahrholdt

Der Datenempfänger stellt sicher, dass die oben genannten zur Datennutzung be- rechtigten Personen die Vorgaben einhalten zu deren Erfüllung er auf Grund die- ses Vertrages verpflichtet ist und dass sie die SO EP-Daten in gleicher Weise be- handeln, wie nach den gesetzlichen Bestimmungen personenbezogene Daten zu behandeln sind.

2.4 Es dürfen keine Re-Anonymisierungsmaßnahmen durchgeführt und keine Einzel- datensätze veröffentlicht werden. Eine Zusammenführung mit nicht-anonymisier- ten SO EP-Daten ist nicht gestattet. Verknüpfungen mit anderen personen- bzw.

27

haushaltsbezogenen Daten (zum Beispiel Verfahren des Statistical Matchings) be- dürfen der schriftlichen Zustimmung durch das Forschungsdatenzentrum des SOEP.

1.1 Der Datenempfänger stellt für die Daten die vom Bundesdatenschutzgesetz oder dem jeweiligen Landesdatenschutzgesetz geforderten technisch-organisatorischen Maßnah- men zum Schutz personenbezogener Daten sicher. Das DIW Berlin stellt dazu eine Über- sicht zur Verfügung. Im Übrigen gelten die gesetzlichen Bestimmungen zum Daten- schutz in Deutschland.

1.2 Nach Abschluss des in Ziffer 2.3 genannten Forschungsprojekts sind die übermittelten SOEP-Daten, evtl. Sicherungskopien, Auszugsdateien und Hilfsdateien zu löschen. Dem DIW Berlin sind die Beendigung der Arbeiten sowie das Datum und die Art und Weise der Löschung schriftlich mitzuteilen.

1.3 Die mit SOEP-Daten erzielten veröffentlichten Ergebnisse und darauf Bezug nehmende Veröffentlichungen werden dem DIW Berlin zum Zwecke der Aufnahme in die SOEPlit Datenbank kostenlos zur Verfügung gestellt.

1.4 Bei der Veröffentlichung Ihrer Forschungsergebnisse haben der Datenempfänger sowie die in Ziffer 2.3 benannten Personen streng darauf zu achten, dass keine Rückschlüsse auf einzelne Personen möglich sind. Sollten Verleger/Zeitschriften die Veröffentlichung des eingereichten Aufsatzes davon abhängig machen, dass die verwendeten SOEP-Daten öffentlich zugänglich sind, ist zu beachten, dass die Weitergabe des von uns gelieferten Datensatzes grundsätzlich nicht erlaubt ist. Wir bieten daher allen Nutzern die Möglich- keit, entsprechende Datensätze im SOEP-FDZ-Archiv für Re-Analysen zu speichern.

1.5 Der Datenempfänger versichert, dass er das Einverständnis der/des unter 2.3 genannten Projektleiterin/Projektleiters eingeholt hat, welches das DIW Berlin berechtigt, sie oder ihn in der nächsten Ausgabe des SOEP newsletter namentlich und unter Angabe der Ein- richtung/des Forschungsbereichs sowie des Projekttitels in der Rubrik „Neue Datennut- zer/-innen" zu erwähnen.

1.6 Der Datenempfänger verpflichtet sich, Veröffentlichungen, in die SOEP-Daten eingehen, immer mit der entsprechenden Quellenangabe „SOEP" und der entsprechenden DOI zu versehen.

2 Für die Überlassung der Daten wird keine Vergütung vereinbart. Für die Datenübermitt- lung und die Dokumentation entstehen keine Kosten.

3 Bei Meinungsverschiedenheiten über Inhalt und Umfang des Nutzungsrechtes entschei- det das DIW Berlin.

4 Die Berechtigung der in 2.3 genannten Personen zur Nutzung der Daten endet mit ihrem Ausscheiden aus der Institution des Datenempfängers bzw. mit ihrer Auflösung, Über- nahme oder Neugründung. Dies gilt ausdrücklich auch dann, wenn die Personen das For- schungsvorhaben an einer anderen Einrichtung weiterführen. Die Personen sind in die- sem Fall zur weiteren Nutzung der SOEP-Daten nur auf Grundlage eines Datennutzungs- vertrages zwischen der neuen Einrichtung und dem DIW-Berlin berechtigt. Auch in den genannten Situationen sind die SOEP-Daten und evtl. Sicherungskopien, Auszugsdateien und Hilfsdateien vom Datenempfänger zu löschen. Alle Änderungen im Sinne dieses Pa- ragraphen sind dem DIW Berlin unaufgefordert mitzuteilen. Im Übrigen ist das DIW Berlin berechtigt, das Nutzungsrecht jederzeit zurückzunehmen. Auch dann sind die übermittelten SOEP- Daten durch den Datenempfänger zu löschen. Die nach diesem Ab- satz von den Datenempfängern vorgenommenen Löschungen sind dem DIW Berlin ent- sprechend Ziffer 2.6 mitzuteilen.

5 Änderungen oder Ergänzungen des Vertrages bedürfen zu ihrer Wirksamkeit der Schrift- form.

Berlin, den   30.03.2022   Utrecht, den

Dr. Jan Goebel   Prof Bruhan Konda
Leiter des Forschungsdatenzentrums der   Utrecht University
Infrastruktureinrichtung Längsschnittstudie
Sozio-oekonomisches Panel (SOEP)