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Are Prosumer Households That Much Different? Evidence from Stated Residential Energy Consumption in Germany

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Abstract

This paper discusses the effect of residential energy prosuming on households’ energy consumption behavior with the objective to find evidence for a “prosumer rebound effect” on energy consumption. Prosuming is the partial self-consumption of distributed energy production. We hypothesize that prosumer households are systematically different from consumer households regarding their housing situation and socio-economic characteristics. We address sample selection bias by using a quasi-experimental technique called propensity score matching as our identification strategy. We employ data from a nationwide online survey among homeowners in Germany. While the data shows a correlation of lower energy consumption and prosumer households, we find no significant difference of energy consumption behavior between prosumers and non-prosumers when controlling for sample selection bias. Instead, the lower energy consumption of prosumer households is attributed to more energy-efficient technical equipment and thus to purchasing behavior. Our results show neither evidence for negative nor positive externalities of prosuming on residential energy consumption behavior and therefore we conclude that there is no need for additional governmental measures in the form of taxation or subsidies to address behavioral changes of energy prosuming.

Keywords: Prosumer Households, Rebound, Propensity Score Matching, Residential Energy Consumption, Energy Efficiency, Renewable Energies

JEL Classification Codes: C14, D12, O33, Q42
1. Introduction

The main objectives of the energy transition in Germany are increasing energy efficiency, deployment of renewable energy, and most importantly, the reduction of greenhouse gas (GHG) emissions. For the promotion of a decentralized sustainable energy system, prosumer households can play a key role as investors in renewable energy technologies and partially or completely self-supplying themselves with renewable energies from distributed micro-generation technologies (MGT). The term ‘prosumer’ (first introduced by Toffler 1981) is used in the debate on the energy transition to discuss the new dual role of private households as consumers and producers in the energy market (see for example IEA 2014, Flaute et al. 2017, May and Neuhoff 2016). The main reason for the rapidly increasing importance of prosumer households, and prosuming potential in general, is the successful market diffusion of MGT for producing and storing electricity and heat. Since energy prosumer households are a relatively recent phenomenon, there is no universally accepted definition or official statistics yet. In the strictest sense, prosumers fulfil parts of their energy needs through self-produced energy. The crucial variable to define prosuming in the narrow sense is the degree of self-supplied energy, which can be increased through installing a storage device, implementing advanced energy management measures, and changes in consumption behavior. More broadly, any household producing electricity in their own home with MGT might be considered a prosumer household, regardless of how and by who that electricity is ultimately used. This broad definition of prosumer households comprises all three types of prosumers as defined by IEA (2014)1:

(a) prosumers commercially selling “a large share of the power generated into the grid, while continuing to purchase electricity from the utility as well”,

(b) prosumers self-consuming, by continuing “to purchase power from the grid, but reducing the amount purchased by using their PV [Photovoltaic System] to supply a portion of their own electricity needs (and potentially get remunerated for any surplus generation that they may inject into the grid)”, and

(c) self-providers (or off-grid prosumers) that “supply 100% of their own electricity needs with PV, storage, and other technologies”.

We use this broader definition of prosumers in the present article due to limitations of the data set. While there are no comprehensive statistics publicly available on residential prosumer households’ electricity supply and self-consumption for the case of Germany (cf. Flaute et al. 2017, Bardt et al. 2014), it is reasonable to assume that the group of commercially selling prosumers is predominant, mainly with the feed-in in accordance with the Renewable Energy Sources Act (EEG). The second group of primarily

1 Slightly adapted from the case of PV as reported in IEA 2014 to the more general case of MGT.
self-consuming producers is assumed to be relatively small, but has been gaining relevance since 2012, due to decreasing guaranteed rates in the feed-in scheme. These changes make it financially beneficial for households to self-consume instead of feeding power into the grid (Flaute et al. 2017, Oberst and Madlener 2014). The last group of self-providers can be assumed to be negligibly small for main residences in Germany.

Prosumer households can play a crucial part in a socio-ecological transformation of the energy system towards a more decentralized energy system based predominantly on renewable energies. How the general prosumer potential is used depends on a number of factors including market conditions, regulation, and preferences. Prosumer households have the potential to disrupt energy markets in a variety of ways (Gährs et al. 2016). Firstly, prosumer households can change the load curve by using micro-generation and storage technologies, particularly by shaving and reducing peak loads, which might reduce the need for (transport) grid expansion (Bost et al. 2016). In the future, prosumer households might even (cooperatively) provide flexibility to the grid, e.g. by supply network and systems services with interconnected smart controllable demand response and distributed energy storage and generation. Whether prosuming contributes to grid stability or causes additional expenses due to increasing volatility and complexity in local grids depends on the type of prosuming patterns and local technology concentration, which in turn depend heavily on legal framework and market conditions. Secondly, prosumer households have the potential to exert competitive pressure on traditional energy providers, diversify the technology mix and promote the democratization of the energy sector due to the increase of distributed energy generation and ownership. Other possible benefits include the advancement of sector coupling, e.g. the interconnection with the heat sector via power-to-heat applications, or with the transport sector and the possible mutually beneficial co-evolution of prosuming and electric vehicles. A potential drawback of prosuming is (potential) loss of system-wide efficiency (Schill et al. 2017). Further, there is a risk of technological path dependency in inferior technology options in case of a strong governmental promotion prior to technological maturity. The social objective associated with energy prosuming is an efficient development of renewable energies that decarbonizes, decentralizes and diversifies the technology mix in the energy system. In particular, for a decentralized energy system, prosumer households have to be taken into account and their potential and behavior must be investigated. Possible positive or negative market externalities are decisive for an economic policy evaluation.

The direct effects of the diffusion of prosumer households that change the process of energy production and consumption from the technical aspects related to the emergence of MGT. Focusing purely on these technical aspects neglects the possibility of behavioral changes resulting from prosuming. Technical innovations often trigger unanticipated behavioral responses of adopters regarding the consumption of goods and services related to that innovation. For example, energy rebound effects reduce the effectiveness of efficiency-increasing measures, because consumer demand for an energy service that
has become more efficient and therefore cheaper to use will typically increase (see e.g. Sorrell and Dimitropoulos 2008).

Recent research has explored the role of behavioral mechanisms in energy decision making, such as exogenous and endogenous inattention or biased beliefs (see e.g. Allcott 2016). This could also be the case when private households become prosumers by adopting MGT. Through prosuming, households might develop changing attitudes that would result in increasing energy consumption. Households could consider prosuming as a sufficient contribution to sustainability and allow themselves to use more energy, a phenomenon that is known as ‘moral licensing’ (see e.g. Brown et al. 2011). While this has been examined in the field of energy use (see e.g. Tiefenbeck et al. 2013), there is no clear evidence specific to energy prosumers yet. Prosumer households might consider their self-produced energy to be free, neglecting the opportunity cost of selling it to the grid. The lower cost of self-produced electricity could therefore lead to a rebound effect caused by prosuming (Schill et al. 2017). However, prosuming might also induce households to be more aware (informed) of their energy usage, which could result in lower energy consumption. If there is evidence that prosumer households change their consumption behavior so that they use less energy compared to comparable non-prosuming households, this would indicate social benefits that go beyond the mere substitution of non-renewable energy for (decentralized) renewable energy produced by prosumers. So far, there is little empirical evidence on the existence and magnitude of prosumer rebound effects (Schill et al. 2017). More generally, Luthander et al. (2015) reviews the literature on behavioral changes following the installation of a PV system. As the authors point out, “From these previous studies, it is not possible to draw any general conclusions on the responses to PV installations. Many results have been based on self-reported data through questionnaires and interviews.” (Luthander et al. 2015). In contrast to this primarily qualitative approach, we apply a quantitative framework.

In this paper, we focus on providing evidence for an overall effect of prosuming on households’ energy consumption and providing insights on the role of behavioral aspects. Specifically, the objective of this paper is to quantify differences in energy usage between prosumer and comparable consumer households. Therefore, our contribution to the existing literature is at least twofold: Firstly, we empirically investigate the overall effect of prosuming on energy consumption behavior. Secondly, we aim to lay the groundwork for further research to derive implications for designing experimental settings in the field. Our findings have implications for energy policy: given the increasing presence of prosumer households in Germany, an effect of prosuming on individual energy use would have to be taken into account when projecting future aggregate energy demand and supply. Furthermore, a prosumer rebound effect would shift the optimal scheme of subsidization (or taxation) of micro-generation technologies in relation to alternative generation technologies of renewables. Ceteris paribus, a substantial rebound effect resulting from prosuming would make the subsidization of prosuming less attractive. In the case of a negative rebound effect of prosuming, the opposite would be the case justifying support measures. In this way, a behavioral prosuming effect should change how governments support prosuming and the
market diffusion of prosuming technologies. This is similar to other areas of energy use: for example, rebound effects for a particular energy service reduce the usefulness of energy efficiency standards for achieving the policy goal of reducing energy consumption. When assessing the effectiveness of a policy measure, it is therefore important that behavioral effects be taken into account adequately.

In our study, we employ data from an online survey among homeowners in Germany from Oberst and Madlener (2014). The sample consists of homeowners living in detached and semi-detached owner-occupied residences. The case of Germany is particularly interesting, because the diffusion process of electricity generation based on renewable energy sources has long been encouraged by a range of political measures and subsidies. In particular, these incentives encompass a relatively stable support system with guaranteed feed-in tariffs, preferential dispatch, and grid connection requirements. In addition, the country pursues a nuclear phase-out in combination with ambitious goals for the reduction of GHG emissions until 2050 (Brunekreeft et al. 2016), which increases the importance of the energy transition process. We use self-reported revealed preference data on energy consumption as well as building and household characteristics. We define our treatment group (prosumers) based on the ownership of a MGT to produce electricity. We apply Propensity Score Matching (PSM) to mitigate sample selection bias and ensure comparability between the treatment and control groups with regard to socio-economic and housing characteristics, given that we cannot assume random selection into the treatment group of being a prosumer. Since many respondents are unaware of their electricity consumption in kWh, we use monetary values in the form of energy expenditures instead. Following from this, we focus on heating expenditures as the dependent variable instead of electricity expenditures to avoid endogeneity problems and statistically control for heating generation technology and other relevant aspects.

The remainder of this paper has the following structure. Section 2 describes the data set. Section 3 discusses the methods we employ for the matching procedure and presents the results from the matching. In section 4, we then investigate the relationship between energy consumption, being a prosumer and further explanatory variables (socio-demographics, energy, home and preference characteristics) with a comprehensive estimation approach. We compare estimation results for the full data set and two matching data sets and subsequently discuss our results. Section 5 concludes.

2. Data and descriptive statistics

For our analysis, we use data from a demographically representative stratified internet-based survey among German homeowners, carried out in November 2014 with 1030 interviews. The data provides cross-sectional information on a variety of variables reflecting socio-demographic and technical

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2 Stratification variables are ‘Age’ and ‘Gender’. More information on the survey can be found in Oberst and Madlener (2014).
characteristics of the participating households, including data on the specific technology used for heating and hot water. Prosuming is mainly relevant for households that (a) live in 1- and 2-family houses, as opposed to apartments, and (b) own their homes (Oberst and Madlener 2014). Therefore, the dataset only consists of respondents who live in owner-occupied houses. We eliminate incomplete observations and extreme outliers, which reduces our sample to 849 observations.³ For information on the geographical location of the homeowners, the dataset is conjoined with spatial information obtained from BBSR Bonn (2016) via zip and district codes.

As dependent variable in our analysis, we use households’ yearly heating expenditures, which serves as a proxy variable for household energy consumption. Note that using electricity expenditures would not be feasible since we cannot control for self-consumption by prosumers. This means that if prosumers were to spend less on electricity, we would be unable to distinguish how much of this is due to electricity-saving behavior or due to self-consumption. When controlling for differences in technology, being a prosumer should not influence heating expenditures from a technical point of view. Therefore, if we do find differences between the two groups, this would provide evidence for a behavioral effect, provided that the two groups are similar in all other covariates besides ownership of a micro-generation system. In line with related research on heating demand (e.g. Rehdanz 2007, Schmitz and Madlener 2016) we consider heating expenditures in Euros per square meter of living space.

Table 1 shows descriptive statistics for selected variables, both for the full sample and divided by treatment group. The observational unit in our analysis is the household, and only the variables ‘Age’ and ‘Gender’ refer specifically to the individual answering the survey. Figure 1 shows the distribution of heating costs across the two groups, with prosumers in green and consumers in yellow. The figure shows that the density is skewed slightly to the left for prosumers indicating lower heating expenditures. The less peaked distribution of prosumers indicates a more heterogeneous group. The binary treatment variable of being a prosumer is negatively correlated with heating expenditures suggesting a possible negative prosumer rebound effect. A means comparison of yearly heating costs between prosumers and consumers reveals a difference of € 120.75; however, a t-test rejects that this difference is statistically significant. The proportion of prosumers who have an ecofriendly (“green”) electricity tariff is 46% compared to 27% of consumers. Prosumers commonly live in newer buildings and it is more common for prosumers to own a solar thermal system, heat pump, combined heat and power (CHP) or an electric heating system. Prosumers are associated with higher incomes and household members are more likely to be in full-time employment, while those variables are in turn correlated with lower heating expenditures in Euros per m². The comparison of means and correlations supports the hypothesis that prosumer households are systematically different from consumer households, which reveals the need

³ Specifically, we remove observations where the heating expenditures were not reported (173 obs.) and those where heating expenditures deviate from the mean by more than five standard deviations (8 obs.).
for a matching analysis to control for sample selection bias and an unbiased comparison of energy consumption between consumers and producers.

Table 1: Descriptive statistics of selected variables

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Full sample</th>
<th>Prosumers</th>
<th>Consumers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating Costs in Euros</td>
<td>1,459.177</td>
<td>1,357.205</td>
<td>1,477.950</td>
</tr>
<tr>
<td>Heating Costs in Euros / m²</td>
<td>10.790</td>
<td>9.518</td>
<td>11.029</td>
</tr>
<tr>
<td>Prosumer</td>
<td>0.155</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>E-Tariff: Ecofriendly (“green”)</td>
<td>0.302</td>
<td>0.455</td>
<td>0.500</td>
</tr>
<tr>
<td>E-Tariff: Standard</td>
<td>0.570</td>
<td>0.455</td>
<td>0.591</td>
</tr>
<tr>
<td>E-Tariff: Unknown</td>
<td>0.128</td>
<td>0.091</td>
<td>0.135</td>
</tr>
<tr>
<td>Respondent’s Age in years</td>
<td>50.823</td>
<td>47.174</td>
<td>51.495</td>
</tr>
<tr>
<td>Household size in no. of people</td>
<td>2.800</td>
<td>2.864</td>
<td>2.788</td>
</tr>
<tr>
<td>Living Space in m²</td>
<td>146.323</td>
<td>160.742</td>
<td>143.668</td>
</tr>
<tr>
<td>Respondent Gender: Male</td>
<td>0.584</td>
<td>0.356</td>
<td>0.573</td>
</tr>
<tr>
<td>Respondent Gender: Female</td>
<td>0.416</td>
<td>0.356</td>
<td>0.427</td>
</tr>
<tr>
<td>Building Age: &lt; 1949</td>
<td>0.211</td>
<td>0.114</td>
<td>0.229</td>
</tr>
<tr>
<td>Building Age: 1949 – 1978</td>
<td>0.260</td>
<td>0.189</td>
<td>0.273</td>
</tr>
<tr>
<td>Building Age: 1979 – 1986</td>
<td>0.097</td>
<td>0.106</td>
<td>0.095</td>
</tr>
<tr>
<td>Building Age: 1987 – 1990</td>
<td>0.059</td>
<td>0.061</td>
<td>0.059</td>
</tr>
<tr>
<td>Building Age: 1991 – 2000</td>
<td>0.177</td>
<td>0.197</td>
<td>0.173</td>
</tr>
<tr>
<td>Building Age: 2001 – 2009</td>
<td>0.139</td>
<td>0.242</td>
<td>0.120</td>
</tr>
<tr>
<td>Building Age: &gt; 2009</td>
<td>0.058</td>
<td>0.091</td>
<td>0.052</td>
</tr>
<tr>
<td>Building Type: (Semi-)Detached</td>
<td>0.665</td>
<td>0.780</td>
<td>0.644</td>
</tr>
<tr>
<td>Building Type: Row House</td>
<td>0.296</td>
<td>0.182</td>
<td>0.317</td>
</tr>
<tr>
<td>Building Type: Other</td>
<td>0.039</td>
<td>0.038</td>
<td>0.039</td>
</tr>
<tr>
<td>Region Type: Urban</td>
<td>0.425</td>
<td>0.439</td>
<td>0.423</td>
</tr>
<tr>
<td>Region Type: Mixed</td>
<td>0.327</td>
<td>0.242</td>
<td>0.343</td>
</tr>
<tr>
<td>Region Type: Rural</td>
<td>0.247</td>
<td>0.318</td>
<td>0.234</td>
</tr>
</tbody>
</table>

| N    | 849 | 132 | 717 |

Note: Variables without unit are binary variables (1 or 0).

Figure 1: Distribution of heating costs (density plot)
Note: Prosumers are in green, consumers in yellow.
3. Matching analysis

3.1 Methodology

The starting point of the matching analysis is that random selection of a household into the treatment group “prosumer” cannot be assumed, since a household’s decision in favor of prosuming is likely to be correlated with the dependent variable of energy expenditures, and therefore causing a self-selection bias. Given the amount of monetary and cognitive effort associated with installing and operating prosuming technologies, a random assignment by researchers as part of a field experiment is extremely difficult to implement due to high costs. Therefore, we use propensity score matching (PSM) to address sample selection bias. The concept of PSM for causal effects was originally introduced by Rosenbaum and Rubin (1983) and has seen many adjustments since, spawning numerous empirical applications in a variety of fields including political science and economics.

In matching, an observation in the treatment group is paired with one or more observations from the control group, with the goal of creating two groups that are as similar as possible in the distribution of their covariates, so that any selection bias is eliminated, or at least greatly reduced. The basic idea of matching is that by doing so, the mean difference in the outcome variable between treatment and control group can be attributed solely to the treatment. This simplicity of the matching approach is one of its advantages, since assessing treatment effects can be as simple as the comparison of two means. The straightforward nature of analyzing matched data makes it a suitable option to mimic an experimental setting when experimental data is not available. As in our case, running a randomized controlled trial is not always possible due to monetary, technical, legal, or ethical concerns. For further discussions on matching methods, see e.g. Dehejia and Wahba (2002), Heckman et al. (1997), and Imbens (2004). Imbens and Wooldridge (2009) present an overview of the last three decades of research in this area. For a set of guidelines on the practical implementation of PSM, see Caliendo and Kopeinig (2008).

3.2 Estimation of the propensity score

The observations are matched based on so-called (single) balancing scores, which is a function of the vector of covariates. A variety of methods exists to obtain this score; we use the propensity score, originally introduced by Rosenbaum and Rubin (1983), which is defined as the probability of receiving treatment given the covariates. As we consider a binary treatment, we use a standard logit model to estimate the propensity score. Generally, all variables that simultaneously affect both treatment and outcome should be included in the estimation. The main goal of estimating the propensity score is not to predict the treatment as accurately as possible, but to create a balance in the covariates between the treatment and control groups. However, the variables for which the two groups differ significantly are also the ones that are good predictors for the treatment status. Therefore, a model that proves to be unable to predict the treatment is likely to be misspecified.

Table 2 shows the results of the regression analysis to estimate propensity scores of being a prosumer.
The results of the propensity score estimation reported in Table 2 show that the type of electricity tariff (E-Tariff), respondents’ age, building age, living space and building type are good predictors for being a prosumer, while household size, respondents’ gender, and region type are not. Specifically, households that have an ecofriendly (“green”) electricity tariff or live in newer and larger homes are more likely to be prosumers, while households living in a row house and those who do not know the type of their electricity tariff are less likely to be prosumers. The negative influence of row houses is likely due to technical reasons since detached homes are generally better suited for the installation of PV systems, which account for a large share of micro-generation systems used by private households.

An important condition when using PSM is that of common support. This means that in order to avoid biased estimations, there has to be at least some overlap in the density distribution of the estimated propensity scores between the treatment and control groups. Otherwise, e.g. if the model is able to perfectly predict treatment, the two groups are not comparable anymore (Heckman et al. 1998). Figure 2 shows this distribution of the probability of ownership (being a prosumer) for our matching analysis with the control group (0) on the left and the treatment group (1) on the right. The x-axes show the estimated propensity scores from the logit estimation. As Figure 2 shows, the common support condition is fulfilled. For the control group, the range of the propensity score is given by [0.02, 0.60], whereas for the treated households, the range is [0.03, 0.64]. The overlap between the two groups is evidence that they are indeed comparable for further analysis.

### Table 2: Propensity score estimation results

<table>
<thead>
<tr>
<th></th>
<th>Prosumer</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>E-Tariff: Standard</td>
<td>-0.751*** (0.214)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-Tariff: Unknown</td>
<td>-0.742** (0.354)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Respondents Age</td>
<td>-0.030** (0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household size</td>
<td>-0.061 (0.090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Living Space</td>
<td>0.003 (0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Respondents Gender: Female</td>
<td>-0.195 (0.210)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: &lt;1979</td>
<td>0.363 (0.362)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: 1979 – 1986</td>
<td>0.975*** (0.420)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: 1987 – 1990</td>
<td>0.840** (0.501)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: 1991 – 2000</td>
<td>0.686** (0.367)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: 2001 – 2009</td>
<td>1.215*** (0.366)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Age: &gt; 2009</td>
<td>0.772 (0.465)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Type: Row House</td>
<td>-0.698*** (0.257)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Building Type: Other</td>
<td>0.075 (0.551)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region Type: Mixed</td>
<td>-0.389 (0.249)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region Type: Rural</td>
<td>0.231 (0.244)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.200 (0.752)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
3.3 Matching results

A variety of algorithms exists for conducting matching, each with different strengths and limitations. In many cases, the choice between different options constitutes a tradeoff between creating better, i.e. more accurate, matches and lowering the variance of the estimator (Caliendo and Kopeinig 2008). We use the matching algorithm nearest neighbor, which, for every observation in the treatment group, assigns the control observation that has the lowest difference in propensity score to that of the treatment observation. At first, we match without replacement, meaning that every control observation is matched once, even in the case where it is the nearest neighbor for two (or more) treatment households. Allowing replacement potentially increases the matching quality at the cost of increased variance (Smith and Todd 2005). In an alternative specification, we also allow replacement. For an extensive discussion of other matching algorithms see Caliendo and Kopeinig (2008).

Table 3 depicts the results of the matching by comparing the mean values of relevant variables for the different observation groups, i.e. the treatment group (prosumers), the unmatched control group (all non-prosumers), and the two matched control groups (comparable consumers) for matching with and without replacement. The comparison in Table 3 illustrates that the imbalance between the treatment and control groups is significantly mitigated by matching. The most obvious differences between the treatment and matched control groups towards the unmatched control group are shown for the variables ‘Eco E-Tariff’
and ‘Building Age’. This implies that prosumers and comparable consumers are significantly more likely to have a green electricity tariff and more often live in newly constructed buildings. As Table 3 shows, balance also improves in the other variables. Furthermore, the results between matching with and without replacement are nearly identical.

Table 3: Mean value of relevant variables for treatment and different control groups (before and after matching)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treatment group (prosumers)</th>
<th>Control group unmatched (all consumers)</th>
<th>Control group matching with replacement (comparable consumers)</th>
<th>Control group matching without replacement (comparable consumers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating Costs in Euros</td>
<td>1357.21</td>
<td>1477.95</td>
<td>1390.99</td>
<td>1378.60</td>
</tr>
<tr>
<td>E-Tariff: Ecofriendly (“green”)</td>
<td>0.45</td>
<td>0.27</td>
<td>0.48</td>
<td>0.45</td>
</tr>
<tr>
<td>E-Tariff: Standard</td>
<td>0.45</td>
<td>0.59</td>
<td>0.43</td>
<td>0.43</td>
</tr>
<tr>
<td>E-Tariff: Unknown</td>
<td>0.09</td>
<td>0.14</td>
<td>0.09</td>
<td>0.12</td>
</tr>
<tr>
<td>Respondents Age in years</td>
<td>51.50</td>
<td>47.17</td>
<td>48.70</td>
<td>47.94</td>
</tr>
<tr>
<td>Household Size in no. of persons</td>
<td>2.86</td>
<td>2.79</td>
<td>2.80</td>
<td>2.92</td>
</tr>
<tr>
<td>Living Space in m²</td>
<td>160.74</td>
<td>143.67</td>
<td>155.67</td>
<td>156.95</td>
</tr>
<tr>
<td>Respondents Gender (M=1, F=2)</td>
<td>1.36</td>
<td>1.43</td>
<td>1.30</td>
<td>1.30</td>
</tr>
<tr>
<td>Building Age &lt;1948</td>
<td>0.11</td>
<td>0.23</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td>Building Age 1949 – 1978</td>
<td>0.19</td>
<td>0.27</td>
<td>0.20</td>
<td>0.21</td>
</tr>
<tr>
<td>Building Age 1979 – 1986</td>
<td>0.11</td>
<td>0.09</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td>Building Age 1987 – 1990</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
</tr>
<tr>
<td>Building Age 1991 – 2000</td>
<td>0.20</td>
<td>0.17</td>
<td>0.23</td>
<td>0.23</td>
</tr>
<tr>
<td>Building Age 2001 – 2009</td>
<td>0.24</td>
<td>0.12</td>
<td>0.26</td>
<td>0.23</td>
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<td>Building Age &gt; 2009:</td>
<td>0.09</td>
<td>0.05</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Building Type (Semi) Detached</td>
<td>0.78</td>
<td>0.64</td>
<td>0.79</td>
<td>0.80</td>
</tr>
<tr>
<td>Building Type Row House</td>
<td>0.18</td>
<td>0.32</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td>Building Type Other</td>
<td>0.04</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Region Type Urban</td>
<td>0.44</td>
<td>0.42</td>
<td>0.41</td>
<td>0.44</td>
</tr>
<tr>
<td>Region Type Mixed</td>
<td>0.24</td>
<td>0.25</td>
<td>0.20</td>
<td>0.23</td>
</tr>
<tr>
<td>Region Type Rural</td>
<td>0.32</td>
<td>0.34</td>
<td>0.39</td>
<td>0.34</td>
</tr>
</tbody>
</table>

No. of observations              | 132                         | 717                                    | 108                                                          | 132                                                          |

Note: Variables without unit are binary variables (1 or 0).

Apart from comparing the means of the different covariates between the groups, there are other ways to evaluate the quality of the matching. One of them is to estimate the propensity scores again on the matched data, using the same logit specification as before, and comparing the predictive power of the new model with the original model used for the unmatched data in section 3.2. If the matching works as intended, we can expect the model to be unable to explain treatment given the covariates, because the distribution of covariates should be fairly similar between both groups (Sianesi 2004). In our case, estimating on the matched data results in a McFadden-R² of about 0.01 for matching with replacement and without replacement, compared to 0.10 for the initial estimation (in Table 2). Furthermore, a likelihood ratio test on joint significance is rejected for the matched data with and without replacement, respectively, while it cannot be rejected in the initial propensity score estimation. We take these results as an indication that the matching works as intended.

4. Empirical analysis of energy consumption

Generally, the matched data can be examined in different ways. For the assessment of a prosumer treatment effect, we use a comparison of means, correlation and estimation analysis. Ideally, after performing the matching analysis the difference in means of the variable in question, which in our case
is household heating expenditures, provides an unbiased estimate of the treatment effect. Compared with comparable consumer households in our sample, the average prosumer’s heating expenditures are between 21 and 34 Euros lower. Before the matching, compared to the unmatched control group of all consumers, the difference between prosumer and consumer heating expenditures would be greatly overestimated at about 120 Euros (see Table 3).

Results of a correlation analysis are in line with the means comparison presented above. In the following, we focus on logarithmic values of heating expenditures in Euros per m² of living space and year, $\log(\text{HeatCosts/LivingSpace})$, as our dependent variable which is in line with related research. The correlation coefficient between the binary variable of being a prosumer and $\log(\text{HeatCosts/LivingSpace})$ is reduced by the matching from –0.12 with the unmatched data to –0.04 with the matched data. Note that the correlation coefficient of $\log(\text{HeatCosts/LivingSpace})$ and having an ecofriendly (“green”) electricity tariff ($E$-Tariff: Ecofriendly) remains unchanged at –0.11 and the correlation coefficient of Prosumer and $E$-Tariff: Ecofriendly slightly increases from 0.14 to 0.17 by the matching.

In a more systematic approach, we investigate the relationship between energy consumption and being a prosumer household further with a regression analysis where we control for the type of electricity tariff as well as building, technical, household socio-demographic characteristics, and stated preferences by the respondent. For the estimation, we use standard Ordinary Least Squares (OLS) regression, and use heteroskedasticity-consistent covariance matrix estimation in order to obtain robust standard errors. We develop four models, each of which is estimated with the full sample (without matching) and with both matching samples (with and without replacement) for comparison purposes. The number of attribute levels is reduced for some variables in the regression analysis due to the smaller number of observations in the matching sample. The total number of observations in the full sample is 849, whereas in both matching samples it is 261.

Our approach is to estimate four different models in the following order:

- In the first model specification (M1), we only consider the key variables of this analysis: prosumer and type of electricity tariff (being a consumer household and having a standard electricity tariff are the respective baselines);
- In the second model specification (M2), we additionally include control variables for the home characteristics, socio-demographics of the household, and regional aspects;
- In the third model specification (M3), we further add variables on stated preferences regarding prosuming, as well as the usefulness of participating in the energy transition and expectations on the price development;

---

4 See Zeileis (2006) for implementation details.
In the fourth model specification (M4), we include all variables that were shown before in the estimations on M1 – M3 that have relatively small standard errors (p-value <= 0.2), but are not necessarily significant at the 10% level. Given that a high number of variables in model specifications M2 and M3 are shown to be not significant, the motivation of M4 is to check whether these models may lose efficiency and exhibit biased standard errors, which in turn may wrongly indicate the significance (or insignificance) of a factor.

Table 4 reports the estimation results for model specifications specification M1 and M4 for three different samples (unmatched full sample, \( N = 849 \), and both matching samples, with and without replacement, each with \( N = 261 \)). We find that while being a prosumer is negatively correlated with heating costs (–0.12), there is no statistically significant difference between prosumers and consumers when

(a) controlling for sample selection bias by employing a matching analysis;

(b) controlling for home and socio-demographic characteristics within a standard regression analysis; or

(c) applying both techniques.

Being a prosumer is significantly associated with lower heating expenditures only in model (1), which is the parsimonious model without control variables (M1) and estimated on the unmatched data. In all other estimations, being a prosumer is shown to be an insignificant factor for households’ heating expenditures. This indicates a spurious relationship between being a prosumer and lower heating expenditures, which can be identified by either including the relevant control variables or through matching analysis. The effect of having an eco-friendly electricity tariff on energy expenditures is similar in magnitude to the effect of prosuming. The eco-friendly tariff is negatively correlated with heating costs (–0.11), but generally not statistically significant when controlling for sample selection bias by employing a matching analysis with or without controlling for building and household characteristics. An exception to this is the estimation of M4 on the full sample, where the results show a significant negative relation between having an ecofriendly electricity tariff and heating expenditures. However, this finding is not confirmed by the estimates based on the matching samples. Our interpretation is that the linear regression analysis can fail to identify this potentially spurious relationship. One reason why matching might be more reliable in this case, compared to linear regression analysis, is that the effect could be caused by a nonlinear and unknown functional form.
The results for *E-Tariff unknown* are inconclusive. It is associated with significantly higher heating expenditures in estimations on the unmatched data and for model specification M3 for both matching samples. A reason for the variation in results for *E-Tariff unknown* might be that the number of respondents that could not state their electricity tariff dropped from 109 (12.8%) in the unmatched data to only 35 (13.4%) in the matched data and therefore be explained by the low number of observations. Factors that are uniquely shown in our results to be associated with lower heating expenditures per m² are living space, a lower building year (1990 and newer compared to the base group of 1979 to 1989), and a lower age of the respondent (under 50 years compared to the base group of 50 to 65). The negative estimation coefficient for log(*LivingSpace*) indicates economies of scale. In the same way, associated with higher heating expenditures per m² are low-income households (relatively for homeowners in Germany), and a high education degree at university level (*Education Uni*). The results are broadly in

<table>
<thead>
<tr>
<th>Table 4: Regression results for Models M1–M4, Dependent variable: log(HeatCosts/LivingSpace)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>---------------------------------------------------------</td>
</tr>
<tr>
<td>Prosumer</td>
</tr>
<tr>
<td>E-Tariff: Ecofriendly</td>
</tr>
<tr>
<td>E-Tariff: Unknown</td>
</tr>
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<td>Log(<em>LivingSpace</em>)</td>
</tr>
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<td>Other BuildingType</td>
</tr>
<tr>
<td>Building Year: &lt;1979</td>
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<tr>
<td>Building Year: 1990-2009</td>
</tr>
<tr>
<td>Building Year: &gt; 2010</td>
</tr>
<tr>
<td>Single Store</td>
</tr>
<tr>
<td>Heat Pump</td>
</tr>
<tr>
<td>Household Income: &lt; € 2600</td>
</tr>
<tr>
<td>Log(*Household size)</td>
</tr>
<tr>
<td>Respondent Age: 51-64</td>
</tr>
<tr>
<td>Respondent Age: &gt;= 65</td>
</tr>
<tr>
<td>Female Respondent</td>
</tr>
<tr>
<td>Education: University</td>
</tr>
<tr>
<td>Log(*Land Prices)</td>
</tr>
<tr>
<td>Berlin (Capital)</td>
</tr>
<tr>
<td>East**</td>
</tr>
<tr>
<td>Hotwater Electric</td>
</tr>
<tr>
<td>Stated Preference for Selfsupply</td>
</tr>
<tr>
<td>Stated No Preference for Selfsupply</td>
</tr>
<tr>
<td>Stated No Preference for Climate</td>
</tr>
<tr>
<td>Stated High Relevance Ownership</td>
</tr>
<tr>
<td>Stated High Relevance Battery</td>
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<tr>
<td>Constant</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R²</td>
</tr>
<tr>
<td>Adjusted R²</td>
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<td>Residual Std. Error</td>
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<tr>
<td>F Statistic</td>
</tr>
<tr>
<td>VIF</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
line with current literature (see e.g. Meier and Rehdanz 2010, Longhi 2015, Schmitz and Madlener 2016).

5. Conclusions and outlook

In this paper, we discuss whether being an energy prosumer affects energy-using behavior in ways that are unrelated to technical differences between prosumers and non-prosumers. While we find that prosumer households’ differ significantly in socio-economic, building and other household characteristics, we find no evidence for different energy consumption behavior. Our results show neither evidence for negative nor positive aggregated effects of prosuming on residential energy consumption and therefore no evidence for a prosumer rebound effect. In order to address the selection bias resulting from non-random selection into treatment in our sample, we create a (quasi-)experimental setting by using propensity score matching. Considering the policy relevance and the vested interests of different groups aiming to influence the political debate, it is important to show that overly simplistic statistical comparisons regarding energy behavior may lead to premature or even wrong conclusions.

From a behavioral point of view, our results indicate no need for additional taxation or subsidies that specifically target prosuming. Instead, prosumer households should be treated similarly to other renewable energy technologies. Policy measures might be appropriate for other reasons, for example to address possible externalities on energy grids, which were not part of our investigation. Further, the results show that residential energy use cannot easily be explained by a small number of factors. Instead, both technological and social characteristics of households matter, and they often involve complex processes and interactions that researchers do not yet fully understand. In future research, the increasingly important group of prosumer households, the different types of which were discussed at the beginning of the article, should be studied in more detail and with a larger sample, taking preferences and social groups into account.

A limitation of the present study is the relatively small sample size of the data set. An opportunity for future research is therefore to repeat the analysis with alternative data sets with larger sample sizes and longitudinal data. Ideally, the behavior of prosumers would be examined in a number of carefully designed, large-scale controlled randomized trials. In such analyses, the dependent variable should be the households’ energy consumption level, rather than energy expenditures. This would allow researchers to distinguish clearly between price and consumption effects. However, for this approach to be feasible, researchers would first have to overcome a number of technical, political and legal barriers.

The main contribution of this study is twofold. Firstly, the illustrated methodological framework and research questions paves the way for future studies on this topic. Secondly, our empirical results may serve to alleviate the high expectations that some stakeholders have regarding the future role of prosumer households as part of the energy transition. Still, as the role of prosumers and distributed generation in
energy markets increases, we consider more research on prosumers, across disciplines and methods, to be both necessary and worthwhile.

Acknowledgments

This study was conducted within the project “Private Households as Key Actors of the Energiewende: Recommendations for a Social-Ecological Oriented Policy Approach”, funded by the Federal Ministry of Education and Research (Ref. No.: BMBF01UN1209A) under the umbrella of the socio-ecological research program (SOEF), which is gratefully acknowledged. The authors would like to thank the participants at the 39th IAEE International Conference 2016 in Bergen, Norway, as well as the project partners (in particular Anett Großmann and Swantje Gährs) for their useful comments and suggestions.

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