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Abstract

Recent research suggests that households would increase their electricity consumption in the aftermath of installing photovoltaics (PV) panels, a behavioral change commonly referred to as the solar rebound. Drawing on panel data originating from the German Residential Energy Consumption Survey (GRECS), we employ panel estimation methods and the dynamic system estimator developed by Blundell and Bond (1998) to investigate the solar rebound effect, thereby accounting for simultaneity and endogeneity issues relating to PV installation and the electricity price. Our empirical results suggest that PV panel adoption of households hardly reduces the amount of electricity taken from the grid. As we derive theoretically, this outcome implies that the rebound reaches a maximum that is bounded by about 30% for German households. Yet, we are skeptical of whether there is such a large solar rebound effect given the strong economic incentives to feed solar electricty into the public grid in the past.

JEL Codes: C23, H10, Q41.

Keywords: Feed-in tariffs, GMM system estimator, German Residential Energy Consumption Survey (GRECS).

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1 Introduction

In Germany, electricity generated from renewable energy sources (RES) is promoted via a feed-in-tariff (FiT) system that guarantees technology-specific above-market rates, commonly over about two decades. This promotion scheme has established itself as a global role model and has been adopted by a wide range of countries (CEER, 2013), even some with a high endowment of sun, such as Australia (Nelson et al., 2011).

Since the implementation of Germany's FiT system in 2000, installed capacities of renewable energy technologies have increased more than ten-fold: from 11.8 Gigawatt (GW) in 2000 to 124.4 GW in 2019 (BMWi, 2020). Photovoltaics (PV) and onshore windmills experienced the largest increase, with PV capacities sky-rocketing: While amounting to about 1 GW in 2004, PV capacities increased to 49.0 GW in 2019 (BMWi, 2020), today representing almost a quarter of total electricity production capacities in Germany. More than 1 million rooftop solar installations of private households contributed to this capacity increase (ISE, 2019).

Recent research suggests that such "solar" households would change their behavior due to PV installation by increasing their electricity consumption (see e.g. La Nauze, 2019; Oliver et al., 2019; Qiu et al., 2019; Spiller et al., 2017), thereby undermining the environmental benefits of PV adoption by not fully exploiting the potential of PV in reducing the amount of electricity that households take from the public grid. In analogy to the literature on the rebound effects associated with energy and fuel efficiency improvements (see e.g. Binswanger, 2001; Frondel et al., 2008; Chan and Gillingham, 2015; Frondel et al., 2012; Frondel and Vance, 2013; Frondel et al., 2017; Dütschke et al., 2018), the behavioral response of solar households that adopt a PV panel is commonly referred to as the solar rebound (see e.g. Oliver et al., 2019).

Theory suggests that the solar rebound is due to the fact that solar electricity is generated by PV panels at zero marginal costs (Oliver et al., 2019). As a result, the average price that consumers have to pay for electricity shrinks, thereby potentially triggering a rebound effect in the form of increased electricity consumption. This increase would diminish the potential of PV with respect to a one-for-one reduction of electricity taken from the public grid. Empirical evidence on the magnitude of the solar rebound effect is scant, though, particularly for Germany, a country whose PV capacities are among the highest in the world.

Drawing on household data originating from the German Residential Energy Consumption Survey (GRECS), this paper aims to fill this gap by empirically investigating whether German solar households reduce the amount of electricity taken from the grid in the aftermath of installing a PV panel. Based on a longitudinal data set comprising 7,948 households and spanning the period from 2004 to 2015, we employ panel estimation methods and the dynamic system estimator developed by Blundell and Bond (1998) to estimate the solar rebound effect, thereby accounting for simultaneity and endogeneity issues arising from the possibility that electricity consumption and prices, as well as the decision on PV installation, may be jointly determined by unobserved covariates.

Two instrumental variables are used to this end. First, based on the theory of *peer effects*, we employ the number of installed PV systems per zip code as a candidate instrument for the likely endogenous variable indicating PV ownership.[1] Second, following

[1]Peer effects are a type of social spillover that is based on the assumption that consumers' action indirectly influences other consumers. In the case of PV, the number of installed panels in a neighborhood may affect the likelihood of others to install PV systems as well (see e.g. Bollinger and Gillingham,

Frondel et al. (2019), we employ the sum of regulated electricity price components as an instrumental variable for the potentially endogenous price.

Our empirical results indicate that PV panel adoption of households hardly reduces the amount of electricity that they take from the public grid. As theoretically derived below, this outcome might be an indication that the solar rebound for German households reaches a maximum that is lower than an upper bound θ. In contrast to the rebound due to energy efficiency improvements, where backfire, in other words rebound effects of more than 100%, is possible, we demonstrate that the maximum solar rebound cannot exceed unity. Actually, in practice, θ should be much lower than unity: $\theta \ll 1$. For German households that installed PV systems in the period 2004 to 2015, we derive an upper bound θ for the solar rebound of around 30%. Yet, given the high opportunity cost of self-consumption in terms of forgone remunerations for each kWh solar electricity fed into the grid, it seems likely that the solar rebound is much lower.

This conclusion is corroborated by other empirical research on the recently emerging topic of solar rebound, which has primarily focused on Australia and the United States. Findings from these studies suggest a moderate increase in electricity consumption due to the solar electricity generation of private households (see e.g. Havas et al., 2015; Deng and Newton, 2017; Spiller et al., 2017; McKenna et al., 2018; Sekitou et al., 2018; Qiu et al., 2019; La Nauze, 2019). For the U. S. , for example, Qiu et al. (2019) estimate that an increase in solar electricity generation by 1 kilowatthour (kWh) results in a rise in household electricity consumption by 0.18 kWh, in other words, the solar rebound amounts to 18%.

In the subsequent section, we provide a theoretical derivation of the solar rebound effect and discuss the economic incentives for German households to produce solar electricity. Section 3 describes the data set used for the estimations, while Section 4 presents our methodological approach. The empirical results are discussed in Section

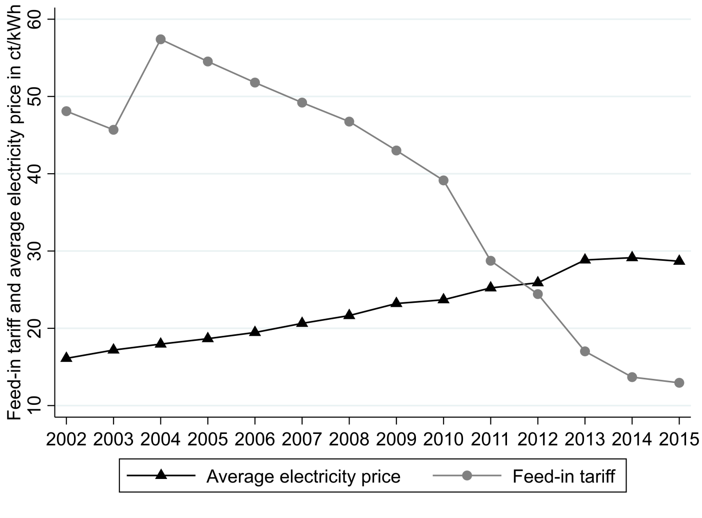
2012). A variety of studies examine the drivers of households' PV adoption, finding that income, homeownership, as well as peer effects, positively affect the likelihood of a household to adopt a PV system (see e.g. Bollinger and Gillingham, 2012; Andor et al., 2015; Jacksohn et al., 2019).

5. The last section summarizes and concludes.

2 Economic Incentives and Theoretical Background

Germany's PV boom was due to generous feed-in tariffs (FiTs) for solar electricity, which are guaranteed for up to 21 years in an intertemporally fixed form, with the level depending on the date of installation. Between 2000 and 2012, solar FiTs were higher than the average electriciy price for households with an annual electricity consumption of 3.500 kWh (see Figure 1). Thus, for households that installed PV panels before 2012, the combination of electricity prices that are much lower than the generous FiTs made the feed-in of solar electricity into the public grid particularly attractive (see e.g. Andor et al., 2015).

Figure 1: Average electricity prices for households with an annual electricity consumption of 3.500 kWh (BDEW, 2016) and feed-in tariffs for solar households with a PV capacity below 10 kW (BNetzA, 2020).



Generous tariffs implied high opportunity cost of self-consuming solar electricity, rather than feeding it into the grid, and, hence, provided strong disincentives for solar households to increase their electricity consumption by overly consuming self-produced solar electricity. This disincentive renders the prevalence of a strong solar rebound rather unlikely for German households, at least for the years before 2011, when FiTs were substantially higher than average electricity prices (see Figure 1). In fact, generous FiTs may have even provided incentives for households to maximize the feed-in of solar electricity into the grid by shifting their demand from times of strong solar electricity production, typically around noon in the summer, to times of zero production at night, thereby exploiting the gap between high FiTs and lower electricity prices.

Alas, given that the amount of solar electricity produced by a household is generally not metered, there is no way to empirically test for such behavior of solar households, as neither data on solar electricity production, nor on the feed-in of solar electricity into the grid is available for individual German households. Hence, the total electricity consumption of a solar household is unknown as well. Without exception, German solar households are net-metered customers whose solar electricity production is first consumed by themselves, while only the excess solar electricity is sold to the grid operator. Thus, German solar households do not export their entire solar electricity production to the public grid.

Taking these circumstances into account, a solar household's electricity balance is now described in formal terms, with its electricity consumption e being given by

$$e = eg(epv) + \theta \cdot epv, \tag{1}$$

where eg denotes the amount of electricity that a solar household gets from the public grid and $0 < \theta < 1$ reflects the fraction of solar electricity production epv that is self-consumed by the household. Accordingly, $(1 - \theta)epv$ is the amount of solar electricity that is fed into the public grid, thereby getting a fixed remuneration for each kWh.

It bears noting that only if $\theta = 1$ would solar electricity be a perfect substitute for grid electricity. Typically, though, θ is far lower than unity: For German households, the share of self-consumed solar electricity lies around 30% if a household has no battery storage capacities (VZ, 2020). But even when a household avails of some storage capacities, these are rather small due to the high cost of batteries and are, hence, commonly insufficient to ensure that $\theta = 1$. Note also that due to the better availability of more economic battery storage systems in recent years, but, more importantly, due to decreasing FiTs in parallel with increasing electricity prices, the incentive to maximize the feed-in of solar electricity into the grid has vanished after 2011 (see Figure 1). Instead, self-consuming solar electricity has become more and more attractive thereafter.

Inspired by the theoretical dicussion by Oliver et al. (2019) on the solar rebound, we now derive the null hypothesis underlying our empirical research. According to Oliver et al. (2019), the solar rebound is defined as the percentage increase in total electricity consumption e due to a percentage increase in solar electricity output epv. Thus, formally, the solar rebound SR is given by the following elasticity:

$$SR := \frac{\partial \ln e}{\partial \ln epv}. \tag{2}$$

Based on equation (1) for electricity consumption e, we can derive an upper bound for the solar rebound by taking the derivative with respect to epv:

$$\frac{\partial e}{\partial epv} = \frac{\partial eg}{\partial epv} + \theta \cdot \frac{\partial epv}{\partial epv} = \frac{\partial eg}{\partial epv} + \theta. \tag{3}$$

From this expression follows that $\partial e/\partial epv = \theta$ if $\partial eg/\partial epv = 0$ and thus:

$$SR = \frac{\partial \ln e}{\partial \ln epv} = \frac{epv}{e}\frac{\partial e}{\partial epv} = \frac{epv}{e}\theta < \theta, \tag{4}$$

as epv is always lower than e. In short, from expression (4) follows that if $\frac{\partial eg}{\partial epv} = 0$, the solar rebound SR is bounded from above by θ. Condition $\frac{\partial eg}{\partial epv} = 0$ implies that the amount of electricity taken from the grid remains unchanged upon PV adoption, because the produced solar electricity epv serves to increase electricity consumption e, rather than reducing the amount of electricity eg taken from the grid.

From expression (3) also follows that the solar rebound equals zero if $\frac{\partial eg}{\partial epv} = -\theta$. In this case, only if $\theta = 1$ would solar electricity generation result in a one-for-one decrease in the consumption of grid electricity. In practice, however, the solar rebound lies between zero and unity: $0 < SR < 1$. In fact, for German housholds that installed PV systems in the period 2000 to 2015, the upper bound θ for the solar rebound should be much lower than unity: $\theta \ll 1$, as the above discussion should have clarified.

In the absence of data on the solar electricity production epv of individual households, as well as their electricity consumption e, we are unable to quantify the solar rebound, but we can preclude the case of a maximum solar rebound by testing the following null hypothesis H_0 against the alternative hypothesis H_1:

$$H_0 : \frac{\partial \ln eg}{\partial PV} = 0 \qquad \text{versus} \qquad H_1 : \frac{\partial \ln eg}{\partial PV} < 0, \tag{5}$$

where PV is an indicator of a household's PV panel ownership.

A necessary, yet not sufficent, condition for the solar rebound SR to reach its maximum is that H_0 holds true, i. e. that the amount of electricity taken from the grid remains unchanged after PV adoption. As a simplified illustration of this circumstance, assume that a household acquires a PV panel, with which it produces some positive amount of solar electricity, $epv > 0$. Recognizing that the self-produced solar electricity is first used to meet the household's own demand, it follows that were eg to remain unchanged upon acquiring the panel, the household's total electricity consumption e would necessarily increase, with the magnitude of the increase representing the solar rebound.

Yet, if the alternative H_1 holds true, it remains unclear whether there is a solar rebound $SR > 0$ or whether solar electricity production leads to a one-for-one reduction in a household's grid electricity demand and, hence, a vanishing solar rebound: $SR = 0$. To empirically investigate these issues, in what follows, we draw on panel data for German households that are described in the subsequent section.

Finally, in the absence of data on the solar electricity production and electricity consumption of individual households, as a robustness check, we attempt to indirectly estimate the solar rebound by estimating the price elasticticity of electricity demand $\xi = \partial \ln e / \partial \ln ap$, where ap denotes the average electricity price, thereby following Qiu et al. (2019), who derive the solar rebound to equal the negative of price elasticticity: $SR = -\xi$. As we cannot observe electricity consumption e, we thereby assume that the average prive elasticity estimate with respect to electricity consumption e equals that with respect to the amount of electricity eg taken from the grid.

3 Data

The data used for this reserach is drawn from the German Residential Energy Consumption Survey (GRECS). Commissioned by the Federal Ministry of Economics and Energy, the GRECS comprises seven surveys that were jointly conducted by *RWI - Leibniz Institute for Economic Research* and the professional survey institute *forsa* (GRECS, 2020). With about 80,000 households, forsa maintains a household panel that is representative for the German population aged 14 and above. Altogether, the seven surveys yield an unbalanced panel of households spanning the period from 2004 to 2015 and including 15,873 observations (see Table A1 in the appendix).

Taking only those households into account for which information on PV ownership, the electricity eg taken from the grid, as well as marginal electricity prices and costs is available, the number of households employed for our empirical analysis amounts to 7,948. Among these are 358 solar households, representing 4.5% of the sample. This share is very close to the overall share of solar households in Germany, which amounted to 4.8% in 2015 (see Table A2 in the appendix). By way of comparison, the share of dwellings with rooftop panels in California was 5%, while in Australia – the world's largest market per capita – the share was even higher at 15% (La Nauze, 2019).

Survey participants, in this case the household heads, were requested to fill out a questionnaire with which data on electricity consumption and cost, socio-economic characteristics, such as household net income, age, gender and education of the household head, as well as PV ownership, are elicited. By definition, household heads are those household members who are responsible for financial decisions at the household level. Households were requested to state whether their dwelling was equipped with a PV system. In the first four surveys, PV households were also asked about the year of installation.

The information on electricity drawn from the grid (eg), marginal prices, and elelctricity costs is drawn from the households' bills that cover the years prior to each survey year. In the best case, a household head reported electricity information for up to $T = 10$ years. While this was the case for only two households, more than half of the respondents reported electricity information at least twice (see Table A1 in the appendix).[2]

About 32% of the household heads of our estimation sample graduated from college (Table 1), but only 30.5% are female, which is due to our choice to focus on household heads. Comparing population data with our sample, we see that our sample is not representative for the German population (see Table A2 in the appendix). For instance, the share of high-income households tends to be higher in our sample than in the German population, whereas the share of single-person households is significantly lower.

Not surprisingly, solar households differ from households without a PV panel in several respects (see Table A3 of the appendix). Most notably, solar households have a significantly higher income than other households. This is in line with the fact that, typically, households with an above-median income live in their own house and, almost exclusively, only such homeowners have the possibility to install a PV system (Jacksohn et al., 2019). This explains why the share of property owners is higher among solar households than in the population.

The overwhelming majority of solar households installed a PV panel before 2012,

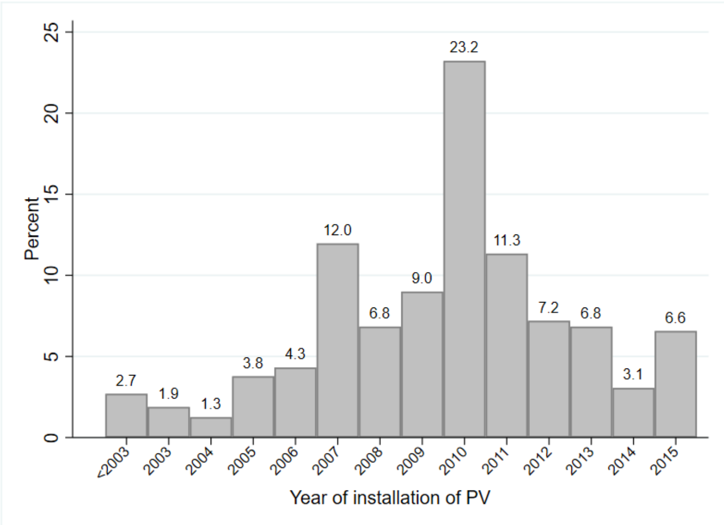
[2]For the common case that an electricity bill did not cover the entire calendar year, the annual consumption was extrapolated based on the average consumption per day of the period for which household heads reported consumption. To exclude seasonal impacts, we only use information from electricity bills covering a time period of more than 180 days for our analysis.

Table 1: Descriptive Statistics for the Estimation Sample.

Variable	Explanation	Mean	Std. Dev.
Age	Age of household head	52.63	12.97
Female	Dummy: 1 if household head is female	0.305	–
College	Dummy: 1 if household head has a college degree	0.317	–
Household size=1	Dummy: 1 if household comprises one member	0.186	–
Household size=2	Dummy: 1 if household comprises two members	0.432	–
Household size=3	Dummy: 1 if household comprises three members	0.171	–
Household size=4	Dummy: 1 if household comprises four members	0.156	–
Household size>4	Dummy: 1 if household comprises five or more members	0.054	–
Homeowner	Dummy: 1 if household resides in an own dwelling	0.722	–
Income	Monthly household net income in €	2,841	1,180
eg	Annual amount of electricity taken from the grid in kWh	3,651	1,676
PV	Dummy: 1 if household owns a PV system	0.045	–
p	Marginal electricity price in cent per kWh	21.06	4.67
ap	Average electricity price in cent per kWh	24.40	5.40
z_p	Sum of fees, taxes, and levies in cent per kWh	12.20	2.35
z_{PV}	Sum of installed PV systems within a zip code as of previous year	131.35	170.54

Notes: Number of observations and households employed for estimations: 11,427 and 5,209, respectively. Income information was provided in €500 intervals, from which a continuous variable has been derived by assigning the mid-point of the interval reported.

Figure 2: Year of PV Installation for Solar Households in the Estimation Sample. Source: German Residential Energy Consumption Survey (GRECS).



with almost a quarter of all installations emerging from the single year 2010 (Figure 2).[3] This mimics the small-scale PV installations in Germany, where the annual number of new installations peaked in 2010 and 2011 (see Figure A1 in the appendix). Given that the majority of sample households installed their PV panels before 2012, these households can be expected to receive FiTs that are substantially higher than average

[3]For about 97% of the solar households in our sample, we know the year of installation.

electricity prices (Figure 1).[4]

Finally, with respect to endogenity issues, as an instrument for the likely endogenous PV variable, we use the number z_{PV} of PV systems within a zip-code area, taken from the four German Transmission System Operators (TSO, 2017). Averaged over all 12 years, z_{PV} amounts to about 131 PV panels per zip-code area (Table 1). Peer effect studies for the U. S. and Germany indicate that households are more likely to install a PV panel the higher is the number of installed PV panels in the neighborhood (Bollinger and Gillingham, 2012).

For the likely endogenous electricity price, which is due to the large variety of electricity suppliers and consumers' possibility to freely choose both suppliers and tariffs, we use the sum of regulated price components as an instrumental variable, thereby following Frondel et al. (2019) and Frondel and Kussel (2019), who provide evidence for the validity and relevance of this instrument. The sum of the regulated price components z_p, including, for instance, the levy with which renewable energy technologies are supported, averages 12.2 cents per kWh over the period from 2004 to 2015 (Table 1).

4 Methodology

To identify the impact of PV ownership on the amount of electricity eg that households take from the public grid, we estimate the following specification:

$$\ln(eg_{it}) = \beta_{PV}\ PV_{it} + \beta_p\ \ln(p_{it}) + \boldsymbol{\beta}_{\boldsymbol{x}}^T \boldsymbol{x}_{it} + \tau_t + \mu_i + \epsilon_{it}, \tag{6}$$

where $\ln(eg_{it})$ is the natural logarithm of the annual amount of electricity that household i takes in year t from the grid and PV is an indicator variable of PV ownership, equalling unity if the household owns a PV system and zero otherwise. $\ln(p)$ denotes the natural logarithm of the marginal electricity price and $\boldsymbol{x}$ is a vector comprising the

[4] Although we do not know the capacity of a household's PV system, we can safely assume that the solar households in our sample own a PV system with a capacity below 10 kW, since this capacity is the most common maximimum size for residential PV systems in Germany (BMWi, 2014).

set of socio-economic variables. τ_t denotes year fixed effects that account for a general trend in the average household electricity consumption, μ_i designates individual-specific fixed effects, capturing unobservable, time-invariant household characteristics, and ϵ is the error term.

By employing fixed-effects methods, we tackle potential problems of omitted variable bias due to time-invariant and individual-specific unobservables, to obtain consistent estimates under the assumption of time-constant unobserved heterogeneity (see e.g. Wooldridge, 2010; Cameron and Trivedi, 2005; Greene, 2012). This feature is especially important, as potential biases due to omitted variables are highly likely. For instance, unobserved individual characteristics, such as a respondent's environmental attitude, may influence the probability of a household to install a PV system and thus may be correlated with the PV indicator. In short, estimating equation (6) using either pooled OLS methods or random-effects estimation methods is unlikely to yield consistent estimates.

The static model given by equation (6) assumes that households instantaneously adjust their appliance stock and thus their consumption behavior as a response to the installation of a PV system and varying electricity prices. To account for sluggish appliance stock adjustments and inflexible utilization behavior in the short run, the lagged value $eg_{i,t-1}$ of the dependent variable is added to static specification (6), leading to a dynamic panel model:

$$\ln(eg_{it}) = \beta_{t-1}\ \ln(eg_{i,t-1}) + \beta_{PV}\ PV_{it} + \beta_p\ \ln(p_{it}) + \boldsymbol{\beta}_{\boldsymbol{x}}^T \boldsymbol{x}_{it} + \tau_t + \mu_i + \nu_{it}, \qquad (7)$$

with ν_{it} denoting another idiosyncratic error term and β_{t-1} being the coefficient on the lagged dependent variable.

Estimating dynamic model (7) on the basis of OLS methods yields inconsistent estimates, as the individual effect μ_i enters all values of the dependent variable, implying that the lagged dependent variable cannot be independent of the composite error process $\mu_i + \nu_{it}$. For the same reason, estimating dynamic model (7) using random-effects estimation methods also yields inconsistent estimates.

Moreover, when equation (7) is estimated using fixed-effects methods, the resulting estimates suffer from the Nickell bias (Nickell, 1981), particularly in panels with small T (see e. g. Baltagi, 2005, p.136f.). As Nickell (1981) demonstrates, this bias arises because the within transformation that is typically employed for fixed-effects estimations creates a correlation between the regressors and the error term.

One alternative to consistently estimate equation (7) involves taking first differences to eliminate the problems arising from the individual effects μ_i:

$$\Delta \ln eg_{it} = \beta_{t-1} \Delta \ln eg_{i,t-1} + + \beta_{PV} \, \Delta PV_{it} + \beta_p \Delta \ln p_{it} + \boldsymbol{\beta}_{\mathbf{x}}^T \Delta \mathbf{x}_{it} + \Delta \tau_t + \Delta \nu_{it}, \quad (8)$$

and to use either $\Delta eg_{i,t-2} := eg_{i,t-2} - eg_{i,t-3}$ or $eg_{i,t-2}$ as an instrument for $\Delta eg_{i,t-1} := eg_{i,t-1} - eg_{i,t-2}$ (Anderson and Hsiao, 1982). These instruments will not be correlated with $\Delta \nu_{it} := \nu_{it} - \nu_{i,t-1}$ as long as the error terms ν_{it} are not serially correlated (Baltagi, 2005, p.136f.).

Yet, Arellano and Bond (1991) argue that, albeit consistent, this estimator is not necessarily efficient, because it does not make use of all available moment conditions. Instead, they advocate for employing what is now frequently called the Arellano-Bond difference GMM estimator, which uses the generalized method of moments (GMM) and exploits all orthogonality conditions between the lagged values of eg_{it} and the error term ν_{it} (Blundell and Bond, 1998, p.118): $E(eg_{i,t-s} \Delta \nu_{it}) = 0$ for $t = 3, \ldots, T$ and $s \geq 2$.

According to Blundell and Bond (1998), however, the Arellano-Bond estimator can have a large finite sample bias and poor precision, because lagged levels of y_{it} are weak instruments for first differences. Building upon Arellano and Bover (1995), Blundell and Bond (1998) develop a system GMM estimator that uses both lagged differences of eg_{it} to instrument for levels and lagged levels of eg_{it} as instruments for differences.

This results in a (stacked) system of $T-2$ equations in first differences as well as $T-2$ equations in levels, as for the periods $3, \ldots T$, valid instruments are available. Hence, the Blundell-Bond estimator, known as system GMM estimator, builds on a system of two sets of equations: the original equation and that in first differences. In short, Blundell and Bond (1998) augment the Arellano-Bond estimator by invoking the additional assumption that the first differences of instrumental variables are uncorrelated with the fixed effects, which allows the introduction of more instruments and can dramatically improve efficiency.

Finally, to cope with the likely endogeneity of electricity prices and PV ownership, in the system GMM estimation, we incorporate the sum of regulated price components as instrumental variable z_p for prices, as well as the number of installed PV systems per zip code as instrument z_{PV} for PV ownership.

5 Empirical Results

Employing both the static and dynamic model specifications (6) and (7) described in the previous section, this section presents the estimation results.

5.1 Results for Static Model (6)

Ignoring issues of endogeneity due to unobserved heterogeneity, as well as reverse causality, pooled OLS estimates are reported in the left panel of Table 2 as a reference case. With 0.021, the OLS estimate on the coefficient of PV ownership is positive. Although this estimate is not different from zero in statistical terms, its positive sign may reflect unobservable heterogeneity across solar and other households and may also be the result of reversed causality: the higher is the electricity consumption of a household, the higher is the likelihood of installing a PV system.

In contrast, the fixed-effects estimate on β_{PV} is negative: -0.096. Testing the hypotheses formulated in Section 2 by employing a one-sided test, we would reject the hypothesis H_0 that households do not change the amount of electricity taken from the grid after installing a PV system, thereby dismissing the hypothesis of a maximum solar rebound effect: $t = |-3.\bar{5}| > t_{1-0.001} = 3.09$.

Table 2: Estimation Results based on Static Model (6) on the Amount of Electricity taken from the Public Grid.

	Without Interaction Terms				With Interaction Terms	
	OLS		Fixed Effects		Fixed Effects	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
ln(p)	-0.108***	(0.020)	-0.038**	(0.016)	-0.036**	(0.017)
PV	0.021	(0.019)	-0.096***	(0.027)	0.016	(0.179)
PV× ln(p)	–	–	–	–	-0.036	(0.058)
ln(Income)	0.091***	(0.010)	0.020	(0.017)	0.020	(0.017)
Household size = 2	0.447***	(0.015)	0.290***	(0.032)	0.290***	(0.032)
Household size = 3	0.692***	(0.017)	0.438***	(0.036)	0.438***	(0.036)
Household size = 4	0.796***	(0.018)	0.515***	(0.036)	0.515***	(0.036)
Household size > 4	0.951***	(0.024)	0.595***	(0.043)	0.595***	(0.043)
College degree	-0.050***	(0.010)	0.017	(0.021)	0.018	(0.021)
Homeowner	0.164***	(0.011)	0.166***	(0.040)	0.166***	(0.040)
Age	0.006***	(0.000)	0.004	(0.003)	0.004	(0.003)
Female	-0.006	(0.010)	–	–	–	–
Constant	6.886***	(0.099)	7.495***	(0.206)	7.490***	(0.206)
Year Dummies	Yes		Yes		Yes	
Number of observations	14,561		14,561		14,561	

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

To explore whether PV ownership alters households' response to electricity prices, which may be part of the explanation for observed differences in electricity consumption of solar and non-solar households, we have additionally estimated a specification that includes the interaction term PV $\times \ln(p)$. The results, reported in the right panel of Table 2, provide no indication of a distinct price responsiveness of solar households. Overall, based on the results presented in Table 2, there is no conclusive evidence for a solar rebound effect.

Static model (6) is predicated on the simplifying assumption that in the short run, households are unlikely to instantaneously adjust their consumption behavior in response to varying electricity prices. Instead accounting for sluggish utilization behavior and potential endogeneity problems, we now present the estimates of dynamic model (7), which are based on the System GMM estimator developed by Blundell and Bond (1998).

5.2 Results for Dynamic Model (7)

The consistency of the GMM estimates hinges on the assumption of no second-order serial correlation $E(\Delta v_{it} \Delta v_{i,t-2}) = 0$ in the idiosyncratic errors of first-differenced model (8). Conducting a test proposed by Arellano and Bond (1991), we can confirm the validity of this assumption: With p values of 0.926 and 0.854, we cannot reject the null hypothesis of no AR(2) process for the two specifications presented in Table 3. Furthermore, since we can clearly reject the null hypothesis of no AR(1) process, it seems appropriate to include the first-order lag of the dependent variable in dynamic model (7). Moreover, the results of the Hansen overidentification test suggest that our instruments z_p and z_{PV}, the sum of the regulated price components and the number of installed PV systems per zip code, are jointly valid (Roodman, 2009a).

To examine the strength of our instruments, we conduct a Wald test (Kleibergen and Paap, 2006) after regressing the instruments on the respective endogenous variables. With an F statistic of $F = 6.12$ for the two instruments, which lies above the critical value of 4.58 given by Stock and Yogo (2005), we can reject the null hypothesis of weak identification at the 5% significance level (see Table A4 of the appendix). In addition, our instruments prove to be relevant as we find that both z_p and z_{PV} are strongly and positively correlated with the electricity price and the PV variable, respectively, as indicated by the positive coefficient estimates of the first-stage estimation of the static 2SLS model presented in Table A4 in the appendix.

Now exploiting the inertia of household electricity consumption by estimating dynamic model (7), the coefficient estimate on the PV variable presented on the left-hand side of Table 3 is again negative, but, with a value of -0.029, is much smaller in magnitude than the fixed-effects estimate of -0.096 resulting from static model (6). Based on the estimate of -0.029 and using again a one-sided t test, even for a significance level of 10%, we cannot reject our null hypothesis H_0 that solar households do not change the amount of electricity taken from the grid: $t = |-0.547| < t_{1-0.1} = 1.282$.

That we cannot reject the null hypothesis suggests that the solar rebound reaches a maximum because solar households' electricity consumption increases by partly self-consuming their solar electricity production, while the amount of electricity taken from the grid remains unchanged. As derived in Section 2, the maximum solar rebound is bounded by θ (see equation (4)), which is on the order of 30% for German households. Yet, given the strong economic incentives to feed solar electricty into the public grid, we are skeptical that there is such a strong solar rebound effect.

Our skepticism that the solar rebound effect is as high as 30% for German households is corroborated by the moderate effects found for the United States and Australia (see e.g. Deng and Newton, 2017; Qiu et al., 2019). For instance, the findings by Havas et al. (2015) indicate a solar rebound of 15% for Australian households. A quite similar magnitude is found for U. S. solar homes in Phoenix, Arizona: Qiu et al. (2019) estimate a solar rebound effect of 18% for the period spanning from 2013 to 2017. Similarly, the results by Oberst et al. (2019), who analyse the existence of a "prosumer rebound effect" for German households that are equipped with micro-generation technologies, such as PV panels, support our caution. Using heating expenditures and matching techniques, the authors do not find any evidence of a rebound effect for these prosumers.

Moreover, as the overwhelming majority of our sample households were guaranteed feed-in tariffs that were much higher than their electricity prices (Figure 1), households faced a strong economic incentive to limit the self-consumption of solar electricity and, hence, we expect the rebound effect to be much lower than 30%. We illustrate our argument of the high opportunity cost of self-consuming solar electricity by the following back-of-the-envelope calculation: Assuming a rebound effect of 30%, an average annual solar production of about $5,500$ kWh, and an average feed-in tariff of 41.5 cents per kWh for a typical sample household with a small-scale PV panel, the foregone annual remuneration of not feeding a share of 30% of the produced solar electricity into the grid may be as high as about 680 euros per year.[5]

[5] According to installation data by the German TSOs, a typical PV system for private households in Germany installed before 2016 had an average installed capacity of 6.12 kW (TSO, 2017). Given 892

For households that enjoy higher feed-in tariffs of 50 cents and more because they were early adopters of PV systems, foregone remunerations due to self-consuming solar electricity are even higher and tend to reach 1,000 euros per year. Therefore, foregone remunerations due to a 30% rebound may be easily in the range of average residential electricity costs per annum, averaging about €890 for our sample households when we multiply their mean annual electricity consumption of $3,651$ kWh with the sample mean electricity price of 24.4 ct/kWh (see Table 1).

Table 3: Estimation Results for Dynamic Model (7) based on the Blundell-Bond GMM System Estimator.

	Without Interaction Terms		With Interaction Terms	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln (eg_{t-1})	0.626***	(0.074)	0.626***	(0.077)
$\widehat{\ln(p)}$	-0.326**	(0.145)	-0.278**	(0.130)
$\widehat{PV}$	-0.029	(0.053)	-0.037	(1.351)
$\widehat{PV} \times \widehat{\ln(p)}$	–	–	0.002	(0.451)
ln (Income)	0.023**	(0.010)	0.023**	(0.010)
Household size = 2	0.180***	(0.034)	0.181***	(0.035)
Household size = 3	0.277***	(0.052)	0.279***	(0.054)
Household size = 4	0.306***	(0.059)	0.307***	(0.061)
Household size > 4	0.375***	(0.070)	0.376***	(0.072)
College degree	-0.012	(0.007)	-0.012	(0.007)
Homeowner	0.047***	(0.015)	0.046***	(0.015)
Age	0.001**	(0.001)	0.001**	(0.001)
Female	-0.001	(0.007)	-0.001	(0.007)
Constant	3.579***	(0.756)	–	–
Year Dummies	Yes		Yes	
Number of observations	4,655		4,655	
Number of instruments	50		57	
Arellano-Bond test for AR(1)	p=0.000		p=0.000	
Arellano-Bond test for AR(2)	p=0.926		p=0.854	
Hansen test of overid. restrictions	p=0.657		p=0.545	
Long-run price elasticity	-0.872**	(0.381)	–	–

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Including again the interaction term PV $\times \ln(p)$, as with static specification (6), we find that neither the PV dummy, nor the interaction term is statistically different from zero, nor are they jointly significant. Hence, these results do not reveal any statistically significant difference in the price responsiveness of solar and other households. These results contrast with findings from Japan, which indicate that households become more interested in energy costs after installing a PV system and therefore improve their energy-saving behavior (see Hondo and Baba, 2010), suggesting that households

full-load hours for rooftop PV panels (TSO, 2019), the average annual solar production thus amounts to $5,459$ kWh.

are also more aware of electricity prices. Yet, our price elasticity estimates are in line with those presented by Nikodinoska and Schröder (2016) and Frondel et al. (2019), who estimate the long-run price elasticity of electricity consumption at -0.811 and -0.663, respectively, while our long-run price elasticity estimate, obtained by dividing the short-run estimate $\widehat{\beta_p}$ by $1 - \widehat{\beta_{t-1}}$, amounts to $-0.326/(1 - 0.626) = -0.872$.

5.3 Robustness Checks

To check the robustness of our results, the outcomes of a suite of additional estimations are now presented. First, employing the sub-sample with which we have estimated dynamic specification (7), we reestimate static specification (6). Applying a one-sided test ($t = |-1.5\bar{7}| > t_{1-0.1} = 1.282$), the estimate of -0.071 for the coefficient on PV reported in Table A5 of the appendix is statistically significant at the 10% significance level and quite close to the estimate of -0.096 originating from of static specification (6) when it is estimated on the basis of the full sample.

Second, we investigate the robustness of our results for dynamic specification (7) by focusing on the years 2004 to 2011, that is, on that time period in which feed-in tariffs were higher than electricity prices (Figure 1). With an estimate of 0.021 for the coefficient on PV that is not statistically significant (see Table A6), as well as for the entire sample period 2004-2015, we are unable to reject the null hypothesis H_0 that solar households do not change the amount of electricity taken from the grid: $t = |0.389| < t_{1-0.1} = 1.282$.

Third, following Frondel et al. (2019), we check whether our results are robust to the use of average, rather than marginal, electricity prices when estimating dynamic specification (7). While the short-run price elasticity estimate of -0.43 is virtually identical to that found by Frondel et al. (2019), the coefficient estimate on PV ownership of -0.02 is vanishing and clearly not statistically significantly different from zero (see Table A7).

Following Qiu et al. (2019), who derive that the solar rebound equals the negative of price elasticticity ξ, we would overestimate the solar rebound for German households on the basis of elasticity estimate -0.43: $SR = -\xi = -\partial \ln e / \partial \ln ap = 0.43$, thereby assuming that the average prive elasticity estimate with respect to the electricity eg taken from the grid equals that with respect to electricity consumption e. A solar rebound of $SR = 0.43$ would be larger than the upper bound of $\theta = 0.3$ derived in Section 2, which might be due to the fact that we estimate the price elasticity with respect to eg: $\partial \ln eg / \partial \ln ap$, rather than that with respect to electricity consumption: $\partial \ln e / \partial \ln ap$.

Fourth, to deal with gaps in unbalanced panels, as suggested by Arellano and Bover (1995), we employ the System GMM estimator using orthogonal deviations, that is, the average of all future available observations of a variable.[6] The results of this exercise, for which we vary the way in which the endogenous lagged variable is instrumented, are presented in Table A8 of the appendix. While the number of instruments varies, in statistical terms, the estimates on the PV variable do not differ across the variants.

Lastly, we employ a matching approach to improve the comparability of solar households and non-solar households (see e.g. Rosenbaum and Rubin, 1983; Heckman et al., 1997). To this end, we use propensity score matching (PSM), as well as a logit model to calculate the propensity scores based on household-level pre-treatment means of all covariates that may impact both electricity consumption and PV adoption.[7] As Ferraro and Miranda (2017) demonstrate, matching approaches combined with panel data estimation methods can bring the accuracy of causal inference based on observational data closer to that of a randomized controlled trial.

The estimation results for dynamic specification (7) based on the matched sample (see Table A9 of the appendix) are quite similar to the unmatched results.[8] Most no-

[6]To this end, the Stata command *xtabond2* written by Roodman (2009b) has been employed.

[7]We have also employed coarsened exact matching (CEM) based on Blackwell et al. (2009) and Iacus et al. (2012). However, this approach left us with an extremely reduced sample size of 193 observations. Since a dynamic estimation based on this sample failed to meet the assumptions of the System GMM estimator (Arellano and Bond, 1991), we refrain from reporting these results.

[8]We choose to report the results from radius matching with a caliper of 0.2 times the standard deviation of the estimated propensity score, which yields the best balance in the covariates after matching (see Table A10). The variance ratio for the marginal price falls outside the allowed intervall [0.64; 1.56], but is very close to 0.5, which is the lower bound for reasonable balancing according to Rubin (2001).

tably, the estimate of -0.088 for the coefficient on PV reported in Table A9 is hardly statistically significant. Based on a one-sided test, it is merely significant at the 10% level ($t = |-1.49| > t_{1-0.1} = 1.282$), while the estimate for the interaction term is again not statistically significant. Not least, it bears noting that the common-support assumption (Smith and Todd, 2005) is fulfilled pretty well, as Figure A2 of the appendix indicates. The graphical analysis confirms the assumption that the probability of a household to install a PV panel conditional on the control variables is positive and that there is some overlap in this conditional probability between solar and non-solar households.

6 Summary and Conclusions

Recent research suggests that the installment of a PV panel encourages households to increase their electricity consumption (see e.g. Spiller et al., 2017; Oliver et al., 2019; Qiu et al., 2019), a behavioral response that is referred to as the solar rebound. This effect undermines the full potential of PV in reducing the amount of electricity that households take from the public grid and, hence, diminishes the environmental benefits of PV adoption. Empirical evidence on the magnitude of the solar rebound is scant, though, and is primarily available for Australia and the United States.

Drawing on the German Residential Energy Consumption Survey (GRECS) and extracting a household panel data set comprising 7,948 households spanning the period 2004-2015, this paper has employed panel estimation methods and the dynamic system estimator developed by Blundell and Bond (1998) to gauge the solar rebound effect, thereby accounting for simultaneity and endogeneity issues arising from the possibility that electricity consumption and prices, as well as the decision on PV installation, may be jointly determined by unobserved covariates.

Our dynamic system estimates indicate that PV panel adoption hardly reduces the amount of electricity that households take from the public grid. As has been theoretically derived here, this outcome suggests that the solar rebound reaches a maximum, which is bounded by about 30% for German households. Yet, we are skeptical that there is such a large rebound effect, given the strong economic incentives to feed solar electricty into the public grid, particularly in the years 2000 to 2012. In fact, as our back-of-the-envelope calculation presented in the previous section has demonstrated, foregone remunerations due to a 30% solar rebound may be easily in the range of average residential electricity costs per annum. Our skepticism about a substantial rebound is further corroborated by empirical studies for Australia and the United States, which estimate the solar rebound effect to be substantially lower than 30% (Havas et al., 2015; Qiu et al., 2019).

Despite the fact that feed-in tariffs were drastically reduced in recent years, it is to be expected that the solar rebound will remain moderate in the German residential sector, as further increasing electricity prices may increase both the incentive to substitute electricity taken from the grid by self-produced solar electricity and the disincentive to overly consume electricity, irrespective of being self-produced or taken from the grid.

Finally, with respect to the environmental benefits of producing solar electricity, it bears noting that, irrespective of the magnitude of a potential solar rebound, at least in the short run, the level of carbon dioxid emissions in the European Union (EU) remains unaffected by the expansion of renewable energy capacities, such as PV panels. This conclusion is due to the so-called waterbed effect that emerges with the prevalence of the European Emissions Trading Scheme (ETS): Assuming that the ETS emissions cap is fixed and unilateral measures do not impact future political cap adjustments, the waterbed phenomenon describes the fact that in the short run emission reductions resulting from additional policies, such as the boost of PV capacities in Germany, will not lead to additional net emission reductions in the EU (see e.g. Perino, 2018; Perino et al., 2019).

Instead, the growing solar electricity production reduces the demand for emissions allowances in Germany, leading to lower certificate prices than otherwise and higher emissions elsewhere in the EU. In the end, ignoring solar rebound effects may thus imply the overestimation of environmental benefits other than diminishing greenhouse gases, such as the reduction of local environmental pollutants, but renders the greenhouse gas balance unaffected.

Appendix A

Table A1: Frequency in the GRECS Participation of Housholds and Number of Observations.

Number of responses	Frequency	Share	Cumulated	Number of observations
1	3,758	47.3%	47.3%	3,758
2	2,328	29.3%	76.6%	4,656
3	936	11.8%	88.4%	2,808
4	440	5.5%	93.9%	1,760
5	239	3.0%	96.9%	1,195
6	107	1.3%	98.2%	642
7	85	1.1%	99.3%	595
8	38	0.5%	99.8%	304
9	15	0.18%	99.98%	135
10	2	0.02%	100.0%	20
Total	7,948	100.0%	–	15,873

Source: GRECS (2020).

Figure A1: Distribution of year of PV installation for households in Germany. Source: BSW-Solar (2019).

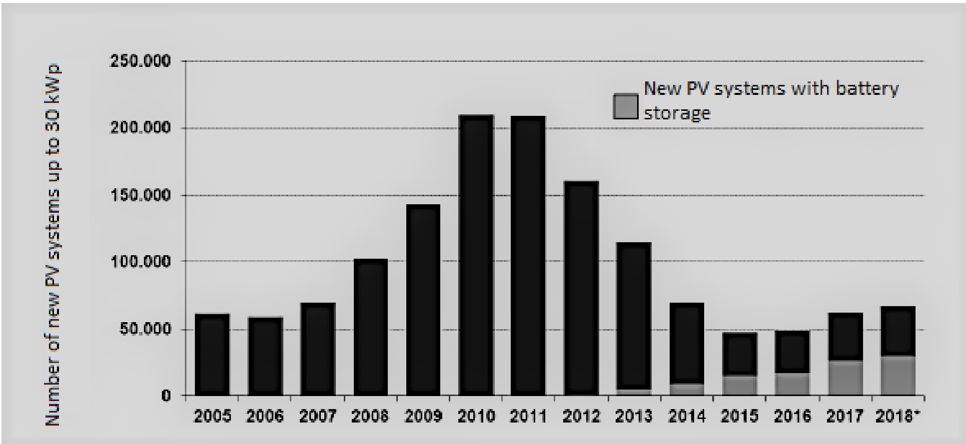


Table A2: Comparison of the Estimation Sample with the Population of German households

	2004			2015		
	Sample	Population	t-Statistic	Sample	Population	t-Statistic
Age< 25 years	2.8%	4.5%	-3.27***	0.0%	4.6%	–
Age 25-64 years	89.1%	67.5%	21.23***	56.7%	67.0%	-6.43***
Age>64 years	8.2%	27.8%	-22.01***	42.7%	28.4%	8.94***
Female	27.9%	31.7%	-2.61***	35.4%	35.5%	-0.06
College	28.5%	11.0%	11.89***	29.0%	20.2%	5.94***
High income	11.4%	5.3%	5.65***	9.2%	11.4%	-2.26**
Household size=1	10.1%	37.2%	-27.66***	30.0%	41.4%	-7.73***
Household size=2	33.4%	34.1%	-0.45	52.8%	34.2%	11.52***
Household size=3	20.9%	13.8%	5.35***	8.7%	12.1%	-3.69***
Householdsize=4	25.5%	10.8%	10.32***	6.0%	9.0%	-3.86
Householdsize>4	10.2%	4.1%	6.17***	2.5%	3.2%	-1.40
PV	1.1%	0.5%	1.56	4.2%	4.8%	-0.97

Note: Population data is drawn from the German TSOs (TSO, 2017) and the German Federal Statistical Office (Destatis, 2005, 2016). This data source asks the main earner to complete the questionnaire, whereas in the sample, the household member who usually makes the financial decisions for the household is asked. Furthermore, the variable High income is top-coded at 4500€, while in the sample the upper threshold is at 5100€. *** and ** denote statistical significance at the 1%- and 5%-level, respectively.

Table A3: Summary Statistics for Solar and Non-solar Households.

Variable	All	No PV	PV	t-Statistic
Age	52.63	52.63	52.61	-0.05
Female	0.305	0.309	0.231	-4.42***
College	0.317	0.317	0.316	-0.08
Household size=1	0.186	0.191	0.078	-7.64***
Household size=2	0.432	0.434	0.393	-2.17**
Household size=3	0.171	0.168	0.232	4.43***
Household size=4	0.156	0.154	0.218	4.66***
Household size>4	0.054	0.053	0.079	3.01***
Homeowner	0.722	0.713	0.915	11.90***
Income	2,841	2,822	3,254	9.29***
eg	3,651	3,629	4,108	7.51***
p	21.06	21.03	21.78	4.22***
ap	24.40	24.38	24.68	1.42
z	12.20	12.20	12.18	-0.198
z_{PV}	131.35	127.17	218.89	14.20***

Note: ***,**, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Table A4: First Stage Estimation Results.

	Standard 2SLS				Fixed Effects 2SLS			
	Price		PV		Price		PV	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
z_{PV}	-0.000	(0.000)	0.0001***	(0.000)	-0.000	(0.000)	0.0001**	(0.000)
z_p	0.279***	(0.032)	-0.088**	(0.044)	0.202***	(0.064)	0.093*	(0.052)
ln(Income)	-0.002	(0.005)	0.011**	(0.005)	0.012	(0.017)	-0.008	(0.012)
Household size = 2	-0.022***	(0.006)	0.007	(0.006)	-0.042**	(0.018)	0.003	(0.005)
Household size = 3	-0.022***	(0.007)	0.025**	(0.010)	-0.052***	(0.019)	-0.003	(0.008)
Household size = 4	-0.023***	(0.008)	0.016	(0.011)	-0.035	(0.024)	-0.001	(0.014)
Household size > 4	-0.021**	(0.009)	0.029*	(0.016)	-0.027	(0.031)	0.019	(0.038)
College degree	0.008**	(0.004)	-0.001	(0.006)	0.021	(0.019)	-0.038*	(0.022)
Homeowner	-0.006	(0.005)	0.033***	(0.005)	-0.034	(0.021)	0.000	(0.017)
Age	-0.001***	(0.000)	-0.000	(0.000)	0.001	(0.001)	0.000**	(0.000)
Female	-0.003	(0.004)	-0.013**	(0.006)	–	–	–	–
Constant	2.159***	(0.084)	0.111	(0.113)	2.179***	(0.212)	-0.165	(0.153)
Year Dummies	Yes		Yes		Yes		Yes	
Number of observations	12,524		12,524		12,524		12,524	
Kleibergen-Paap F statistic	16.81				6.12			

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table A5: Fixed-Effects Estimation Results for Static Specification (6) when Estimated with the Sub-Sample employed for Dynamic Specification (7) .

	Without Interaction Terms		With Interaction Terms	
	Fixed Effects		Fixed Effects	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln(p)	-0.027	(0.032)	-0.020	(0.034)
PV	-0.071	(0.045)	0.219	(0.248)
PV× ln(p)			-0.095	(0.086)
ln(Income)	0.067**	(0.030)	0.067**	(0.030)
Household size = 2	0.318***	(0.066)	0.318***	(0.065)
Household size = 3	0.508***	(0.074)	0.508***	(0.074)
Household size = 4	0.576***	(0.077)	0.576***	(0.077)
Household size > 4	0.654***	(0.088)	0.654***	(0.088)
College degree	0.065*	(0.035)	0.066*	(0.035)
Homeowner	0.078*	(0.047)	0.079*	(0.047)
Age	0.008*	(0.005)	0.008*	(0.005)
Constant	6.568***	(0.410)	6.548***	(0.411)
Year Dummies	Yes		Yes	
Number of observations	4,655		4,655	

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table A6: GMM System Estimation Results for Dynamic Specification (7) using the Subsample covering the years 2004-2011.

	Without Interaction Terms		With Interaction Terms	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln (eg_{t-1})	0.615***	(0.091)	0.640***	(0.092)
$\widehat{\ln(p)}$	-0.376**	(0.161)	-0.317*	(0.172)
$\widehat{PV}$	0.021	(0.054)	-0.463	(1.669)
$\widehat{PV} \times \widehat{\ln(p)}$	–	–	0.157	(0.559)
ln(Income)	0.024*	(0.014)	0.022	(0.014)
Household size = 2	0.188***	(0.045)	0.180***	(0.045)
Household size = 3	0.291***	(0.067)	0.277***	(0.068)
Household size = 4	0.318***	(0.077)	0.301***	(0.078)
Household size $>$ 4	0.388***	(0.088)	0.367***	(0.089)
College degree	-0.011	(0.010)	-0.010	(0.009)
Homeowner	0.048***	(0.017)	0.045***	(0.016)
Age	0.001	(0.001)	0.001	(0.001)
Female	-0.000	(0.009)	-0.000	(0.009)
Constant	3.796***	(0.816)	–	–
Year Dummies	Yes		Yes	
Number of observations	2,949		2,949	
Number of instruments	43		50	
Arellano-Bond test for AR(1)	p=0.000		p=0.000	
Arellano-Bond test for AR(2)	p=0.721		p=0.770	
Hansen test of overid. restrictions	p=0.731		p= 0.543	
Long-run price elasticity	-0.977**	(0.455)	–	–

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table A7: GMM System Estimation Results for Dynamic Specification (7) using Average Electricity Prices ap.

	Without Interaction Terms		With Interaction Terms	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln (eg_{t-1})	0.622***	(0.069)	0.613***	(0.066)
$\widehat{\ln(ap)}$	-0.433***	(0.163)	-0.332**	(0.161)
$\widehat{PV}$	-0.002	(0.042)	2.196	(2.375)
$\widehat{PV} \times \widehat{\ln(ap)}$	–	–	-0.688	(0.741)
ln(Income)	0.015	(0.009)	0.018*	(0.009)
Household size = 2	0.163***	(0.032)	0.172***	(0.031)
Household size = 3	0.247***	(0.048)	0.261***	(0.046)
Household size = 4	0.275***	(0.055)	0.289***	(0.052)
Household size $>$ 4	0.339***	(0.064)	0.356***	(0.061)
College degree	-0.012	(0.007)	-0.010	(0.007)
Homeowner	0.043***	(0.014)	0.045***	(0.013)
Age	0.001**	(0.001)	0.001**	(0.000)
Female	-0.000	(0.007)	0.001	(0.007)
Constant	4.081***	(0.807)	–	–
Year Dummies	Yes		Yes	
Number of observations	4,655		4,655	
Number of instruments	50		57	
Arellano-Bond test for AR(1)	p=0.000		p=0.000	
Arellano-Bond test for AR(2)	p=0.532		p=0.535	
Hansen test of overid. restrictions	p=0.566		p=0.419	
Long-run price elasticity	-1.146***	(0.434)	–	–

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table A8: Robustness Checks for Dynamic Model (7) based on the Blundell-Bond GMM System Estimator using Various Ways to Instrument the Lagged Consumption Variable.

Instruments	First-differences not collapsed		First-differences collapsed		Orthogonal-deviations not collapsed	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
$\ln(eg_{t-1})$	0.610***	(0.069)	0.603***	(0.082)	0.693***	(0.076)
$\widehat{\ln(p)}$	-0.168**	(0.081)	-0.202	(0.135)	-0.116	(0.107)
$\widehat{PV}$	0.037	(0.038)	0.000	(0.050)	0.012	(0.074)
ln(Income)	0.020*	(0.010)	0.023**	(0.011)	0.015	(0.011)
Household size = 2	0.188***	(0.033)	0.193***	(0.039)	0.159***	(0.035)
Household size = 3	0.282***	(0.049)	0.296***	(0.058)	0.234***	(0.054)
Household size = 4	0.321***	(0.055)	0.331***	(0.066)	0.260***	(0.060)
Household size > 4	0.387***	(0.066)	0.389***	(0.077)	0.314***	(0.074)
College degree	-0.018**	(0.008)	-0.015*	(0.008)	-0.013**	(0.006)
Homeowner	0.049***	(0.013)	0.050***	(0.015)	0.036***	(0.014)
Age	0.001**	(0.001)	0.001**	(0.001)	0.001*	(0.000)
Female	-0.008	(0.007)	-0.006	(0.007)	-0.004	(0.006)
Constant	3.221***	(0.561)	3.359***	(0.756)	2.487***	(0.719)
Year Dummies	Yes		Yes		Yes	
Number of observations	4,655		4,655		4,655	
Number of instruments	167		57		128	
Arellano-Bond test for AR(1)	p=0.000		p=0.000		p=0.000	
Arellano-Bond test for AR(2)	p=0.703		p=0.698		p=0.632	
Hansen test of overid. restrictions	p=0.209		p=0.044		p=0.211	
Long-run price elasticity	-0.432**	(0.211)	-0.509	(0.334)	-0.377	(0.318)

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Table A9: GMM System Estimation Results for Dynamic Specification (7) based on a Sample that is Matched by Propensity Score Matching.

	Propensity Score Matching			
	Without Interaction Terms		With Interaction Terms	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln (eg_{t-1})	0.614***	(0.084)	0.607***	(0.080)
$\widehat{\ln(p)}$	-0.315*	(0.185)	-0.251	(0.182)
$\widehat{PV}$	-0.088	(0.059)	-1.077	(1.768)
$\widehat{PV} \times \widehat{\ln(p)}$	–	–	0.343	(0.602)
ln(Income)	0.012	(0.013)	0.014	(0.012)
Household size = 2	0.196***	(0.042)	0.202***	(0.042)
Household size = 3	0.306***	(0.065)	0.315***	(0.064)
Household size = 4	0.335***	(0.071)	0.345***	(0.070)
Household size > 4	0.403***	(0.084)	0.409***	(0.080)
College degree	-0.018	(0.011)	-0.019	(0.012)
Homeowner	0.055***	(0.018)	0.055***	(0.017)
Age	0.001*	(0.001)	0.001*	(0.001)
Female	-0.010	(0.011)	-0.010	(0.011)
Constant	3.708***	(0.878)	–	–
Year Dummies	Yes		Yes	
Number of observations	4,488		4,488	
Number of instruments	50		55	
Arellano-Bond test for AR(1)	p=0.000		p=0.000	
Arellano-Bond test for AR(2)	p=0.575		p=0.549	
Hansen test of overid. restrictions	p=0.737		p= 0.730	
Long-run price elasticity	-0.815*	(0.487)	–	–

Note: Standard errors clustered at the household level are in parentheses. ***, ** and * denote statistical significance at the 1 %, 5 % and 10 % level, respectively.

Figure A2: Check for Common Support Assumption for Propensity Score Matching Results.

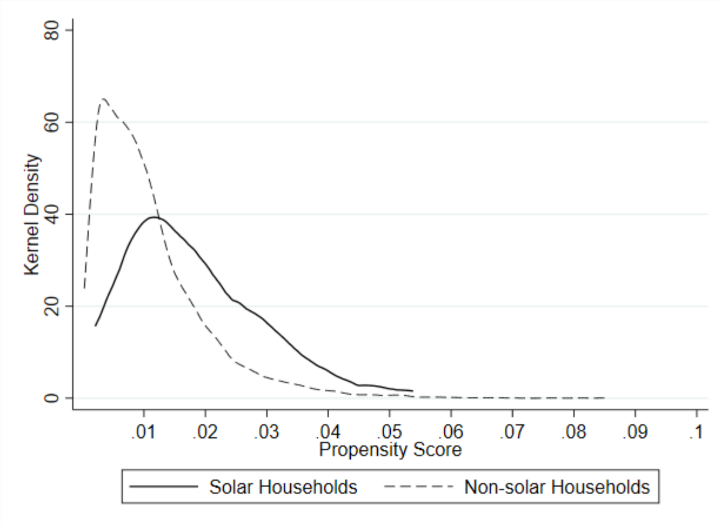


Table A10: Balancing Check for the Propensity Score Matching.

Variable		Means: Solar	Means: Non-solar	%reduct: %bias	%reduct: |bias|	t-test: t	t-test: p>|t|	Variance Ratio: V(T)/V(C)
$\overline{p}$	Unmatched	18.96	21.68	-66.1	–	-5.11	0.000	0.52*
	Matched	18.96	18.92	1.0	98.5	0.06	0.950	0.56*
$\overline{Income}$	Unmatched	3,209	2,797	37.0	–	3.10	0.002	0.79
	Matched	3,209	3,184	2.3	93.8	0.15	0.883	0.86
$\overline{Householdsize = 2}$	Unmatched	0.38	0.44	-13.0	–	-1.15	0.251	0.99
	Matched	0.38	0.39	-2.7	79.4	-0.17	0.865	1.01
$\overline{Householdsize = 3}$	Unmatched	0.20	0.16	9.1	–	0.84	0.399	1.22
	Matched	0.20	0.20	-0.9	90.4	-0.05	0.958	1.03
$\overline{Householdsize = 4}$	Unmatched	0.22	0.15	19.3	–	1.85	0.065	1.36
	Matched	0.22	0.21	1.0	94.6	0.06	0.951	0.99
$\overline{Householdsize > 4}$	Unmatched	0.12	0.05	26.2	–	2.89	0.004	2.17*
	Matched	0.12	0.11	4.6	82.5	0.25	0.804	1.05
$\overline{College}$	Unmatched	0.36	0.32	8.5	–	0.76	0.446	1.07
	Matched	0.36	0.35	0.6	92.9	0.04	0.970	1.00
$\overline{Homeowner}$	Unmatched	0.88	0.69	46.9	–	3.59	0.000	0.49*
	Matched	0.88	0.88	0.7	98.6	0.05	0.960	0.97
$\overline{Age}$	Unmatched	49.92	52.7	-21.9	–	-1.86	0.063	0.83
	Matched	49.92	50.1	-1.5	93.3	-0.09	0.925	0.88
$\overline{Female}$	Unmatched	0.23	0.33	-21.7	–	-1.83	0.068	–
	Matched	0.23	0.23	-0.7	96.6	-0.05	0.961	–

Note: %bias refers to the standardized percentage bias, which is the difference of the sample means of solar and non-solar households in percent for the matched and unmatched sub-samples as a percentage of the average standard deviation over both household groups (Rosenbaum and Rubin, 1985). The achieved percentage bias reduction in absolute values is denoted by |bias|. * indicates if variance ratio lies outside the interval [0.64; 1.56].

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