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Photovoltaics and the Solar Rebound: Evidence for Germany

Abstract

Recent research suggests that households increase their electricity consumption in the aftermath of installing photovoltaic (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 existence of a 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 does not change the amount of electricity taken from the grid. As we derive theoretically, this outcome implies a solar rebound that is bounded from above by about 50%, while back-of-the-envelope calculations provide us with a lower bound of 12% and an average solar rebound of 35%.

JEL-Codes: C23, H10, Q41

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

January 2023

1 Manuel Frondel, RWI and RUB; Kathrin Kaestner, RWI; Stephan Sommer, Bochum University of Applied Sciences and RWI; Colin Vance, RWI and Jacobs University Bremen. *– We are highly grateful for valuable comments and suggestions by two anonymous reviewers, participants of the VfS 2021 annual conference of the Verein für Socialpolitik and the Mannheim Conference on Energy and the Environment 2021, Mannheim, the RWI brown-bag seminar, Gunther Bensch, Marco Horvath, Gerhard Kussel, Jörg Peters, and Joachim Schleich. We gratefully acknowledge financial support by the Collaborative Research Center "Statistical Modeling of Nonlinear Dynamic Processes" (SFB 823) of the German Research Foundation (DFG), within Project A3, "Dynamic Technology Modeling" and by the Federal Ministry of Education and Research (BMBF) under grant 03SFK5C0 (Kopernikus Project Ariadne) and grant 01UT1701A (Project License).* *- All correspondence to: Manuel Frondel, RWI, Hohenzollernstraße 1-3, 45128 Essen, Germany, e-mail: manuel.frondel@rwi-essen.de*

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 rate tariffs, commonly for 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 12.0 Gigawatt (GW) in 2000 to 132.1 GW in 2020 (BMWi, 2021). Photovoltaics (PV) and onshore windmills experienced the largest increase, with PV capacities sky-rocketing from about 1 GW in 2004 to nearly 54 GW in 2020 (BMWi, 2021). Today, PV represents almost a quarter of total electricity production capacities in Germany (Frondel et al., 2020). More than 1 million rooftop solar installations of private households contributed to this capacity increase (ISE, 2021).

Recent research indicates that such "solar" households 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; Caird et al., 2008; Keirstead, 2007; Motlagh et al., 2015), 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 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), but in practice the effect on household consumption differs with the PV promotion scheme: For households that are net-metered, solar electricity is evaluated at the retail price and the energy bill is determined by the difference between total household consumption and solar generation, hence triggering a rebound effect by a decreased energy bill and a perceived reduction in the average price. Net-metering is a widespread mechanism in the United States and also in some European countries, for instance in Belgium (Boccard and Gautier, 2021; Dusonchet and Telaretti, 2015). At the other extreme are countries where all solar electricity is exported to the grid and remunerated with a feed-in tariff, like in France, where the solar rebound effect may arise as a pure income effect (Dusonchet and Telaretti, 2015; Qiu et al., 2019). Germany's system of *net feed-in* represents a hybrid case, combining self-consumption of solar electricity with opportunity costs given by the feed-in tariffs (see e.g. La Nauze, 2019).

Drawing on household data originating from the German Residential Energy Consumption Survey (GRECS), this paper contributes to the scant body of evidence on the solar rebound by investigating whether households under Germany's net feed-in system change the amount of electricity taken from the public grid in the aftermath of installing a PV panel. Several features make Germany a particularly interesting case to consider the solar rebound: First, with about 17% of the global total, Germany has a massive stock of PV capacity, the result of more than a decade of generous subsidies. Second, contrasting with the focus on self-consumption in the U.S., households in Germany have strong incentives to maximize the feed-in of solar electricity owing to exceptionally high feed-in tariffs, which in former years were as high as four times the electricity price. Third, as solar households in Germany first self-consume and then sell the excess solar electricity at a fixed feed-in tariff, a solar rebound may be driven both by a price and income effect, the latter being due to revenues from feeding solar electricity into the grid. Fourth, as the German feed-in tariff system is a global role model that is applied in many other countries to support renewable energy technologies, in particular in Southern European countries, we believe that our empirical results are transferable to many other countries with feed-in tariffs in place.

Exploiting longitudinal data 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 changes in the grid consumption of solar households, 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 tackle these endogeneity problems. First, following Frondel et al. (2019), we employ the sum of regulated electricity price components as an instrumental variable for the potentially endogenous price. Second, on the basis of the theory of *peer effects*, which are a type of social spillover based on the assumption that consumers' actions indirectly influence other consumers, we employ the number of installed PV systems per zip code as an instrument for the likely endogenous variable indicating PV ownership (see e.g. Bollinger and Gillingham, 2012.

Based on our preferred econometric model, which controls for dynamic effects and endogeneity, our empirical results indicate that PV panel adoption of households does not change the amount of electricity that they take from the public grid in a statistically significant way. As theoretically derived below, this outcome implies a solar rebound that is bounded from above by about 50%, but a back-of-the-envelope calculation using the econometric estimate yields a solar rebound that is rather on the order of 35%. That this estimate falls well below the theoretical upper bound likely owes to the high opportunity cost of self-consumption in terms of foregone remunerations for each kWh solar electricity fed into the grid. Nevertheless, as it is technically infeasible for German solar households to feed 100% of solar electricity into the grid (Ruf, 2018), and as regulation in Germany has partly prohibited the feed-in of more than 90% of solar electricity (Masson et al., 2016), this minimum required share of self-consumption implies a lower bound of the solar rebound of 12%.

Our study adds to other empirical research on the recently emerging topic of the 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 an increase in household electricity consumption by 0.18 kWh. In other words, the solar rebound amounts to 18%.

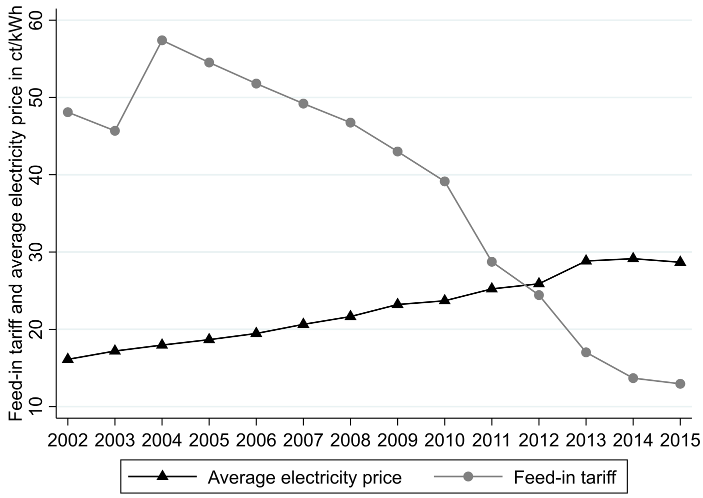
In the subsequent section, we provide a theoretical derivation of the solar rebound effect and discuss the economic incentives for households to produce solar electricity. Section 3 describes the data set used for the estimations, while Section 4 presents our methodological approach. The empirical results are discussed in Section 5. The last section summarizes and concludes.

2 Economic Incentives and Theoretical Background

Germany experienced a PV boom around 2010 that 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 (see Figure 1). Between 2000 and 2012, feed-in tariffs were substantially higher than the average electricity price for households with an annual electricity consumption of 3,500 kWh. Decreasing module prices, together with state and municipal funding to support PV installation, as well as generous feed-in tariffs above electricity prices, made the installation of PV panels and the maximization of feeding-in solar electricity particularly attractive for households that installed PV panels before 2012 (see e.g. Andor et al. (2015)).

With a net feed-in system in place, solar households do not export their entire solar electricity production to the public grid, as for example French households. Rather, in Germany, solar households self-consume a fraction of their solar electricity and only

Figure 1: Feed-in tariffs for solar households with a PV capacity below 10 kW (BNetzA, 2020), which is mostly installed by solar households (ISE, 2021), and Average electricity prices for households with an annual electricity consumption of 3,500 kWh (BDEW, 2016).



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sell the excess solar electricity at FiT rates to the grid, as it is technically infeasible for German solar households to feed 100% of the solar electricity into the grid.[1]

In fact, due to high costs of battery storage units and households' supply and demand profiles, the share of self-consumption among solar households in Germany has been rather uniform at about θ =25% (ZSW, Bosch & Partner, 2019). Yet, generous feed-in tariffs imply high opportunity cost of self-consuming and, hence, provide strong disincentives for solar households to increase their electricity consumption by overly consuming self-produced solar electricity, rather than feeding it into the grid. This disincentive renders the prevalence of a strong solar rebound unlikely, at least for owners of PV panels that were installed in the years before 2012, when feed-in tariffs were relatively high (see Figure 1).

Inspired by the theoretical discussion by Oliver et al. (2019) on the solar rebound, we now derive the null hypothesis underlying our empirical research, thereby taking account of the fact that solar households buy electricity from the public grid to cover their demand at times of no or insufficient solar production. Given that only this grid

[1] To facilitate a reliable grid management of the distribution system operators (DSOs), for PV systems with a maximum power of up to 30 kilowatt, which is the case that holds true for solar households, DSOs are allowed to limit the feed-in power of each installation to 70% of the maximum power (Ruf, 2018).

electricity consumption eg, but not the amount of solar electricity epv produced by a household, is metered in Germany, the total electricity consumption e of a solar household, equaling the self-consumption of solar electricity plus the electricity eg taken from the grid, is unknown:

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

where the amount of electricity eg that a solar household gets from the public grid depends on the solar electricity production epv 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 while the rate of self-consumption θ generally varies to some extent, the degree of variation should be moderate for two reasons: First, this rate is primarily determined by technical issues, rather than the behavior of solar households. Second, the PV capacities installed on rooftops are typically below 10 kilowatts in German solar households (BMWi, 2014), with only a moderate variation around the average installed capacity of 6.12 kW as reported by the German transmission system operators (TSO, 2017). Therefore, assuming a constant self-consumption rate θ seems to be a warranted first approximation to the households' actual consumption behavior. We subsequently test the sensitivity of our conclusions to this assumption.

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:

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

We now demonstrate that the solar rebound is limited by 2θ as an upper bound, as can be derived by taking the derivative of equation (1) for electricity consumption e with respect to epv:

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

This expression indicates that $\partial e / \partial epv = \theta$ when $\partial eg / \partial epv = 0$, that is, when there is no change in electricity taken from the grid due to the emergence of a solar rebound effect. From this follows

$$SR = \frac{\partial \ln e}{\partial \ln epv} = \frac{epv}{e} \frac{\partial e}{\partial epv} = \frac{epv}{e} \theta < 2\theta, \tag{4}$$

as in practice epv can safely be assumed to be lower than double the electricity consumption e of a household and, hence, the solar rebound SR is bounded from above by 2θ. This reasoning stems from the fact that the typical solar production of households amounts to about 5,500 kWh, which is far less than double the mean annual electricity consumption of 3,650 kWh of our solar households (Table 1), so that $epv/e < 2$.[2]

Condition $\frac{\partial eg}{\partial epv} = 0$ means that the amount of electricity taken from the grid remains unchanged upon PV adoption, because there is a solar rebound and the produced solar electricity epv serves to increase electricity consumption e, rather than reducing the amount of electricity eg taken from the grid. In practice, though, while the produced solar electricity is largely fed into the grid, it is partially self-consumed by the solar household, where self-consumption reduces the amount of electricity taken from the grid to at least some degree, so that, generally, $\frac{\partial eg}{\partial epv} < 0$.

In the absence of data on the solar electricity production epv of individual households, as well as their total 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 null hypothesis H_0 against the alternative hypothesis H_1:

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

[2]According to installation data provided by the German transmission system operators (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 full-load hours for rooftop PV panels (TSO, 2019), the average annual solar production thus amounts to $5,459$ kWh.

where PV is an indicator of a household's PV panel ownership and H_0 is the discrete counterpart of condition $\frac{\partial eg}{\partial epv} = 0$.

A necessary 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 condition, 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 may be partly used to meet the household's own demand, rather than fed entirely into the grid, 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.

3 Data

The data used for this research 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). *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 (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 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).

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. Likewise, all other information is self-reported using a state-of-the art survey tool that provides visual assistance to the respondents, particularly with respect to electricity bills.

The billing information includes the amount of electricity drawn from the grid, marginal prices, monthly fixed fees and total electricity expenditures, and is taken from the households' bills that cover the years prior to each survey year.[3] Unlike in the U. S. and some European countries, in Germany households only receive a single electricity bill per billing cycle, with a billing cycle commonly lasting about one year.[4] Taken together with the fact that households' electricity prices typically remain unchanged during a billing cycle, annual data is the appropriate frequency to test for behavioral changes due to price increases and PV installations in Germany.

With respect to the socio-economic characteristics, it bears noting that 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 in some respects our sample is

[3]For the 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.

[4]Numerous other European countries such as Austria, Italy, the Netherlands, Switzerland, etc. also follow the German model of billing frequency.

not representative for the German population (see Table A2 in the appendix). For instance, the share of single-person households is significantly lower in our sample than in the German population, whereas the share of high-income households tends to be higher. This feature should be borne in mind when interpreting our results. To the extent that the solar rebound is inversely related to household income, as demonstrated by Toroghi and Oliver (2019), our estimate may be subject to downward bias.

Table 1: Descriptive Statistics for the Estimation Sample.

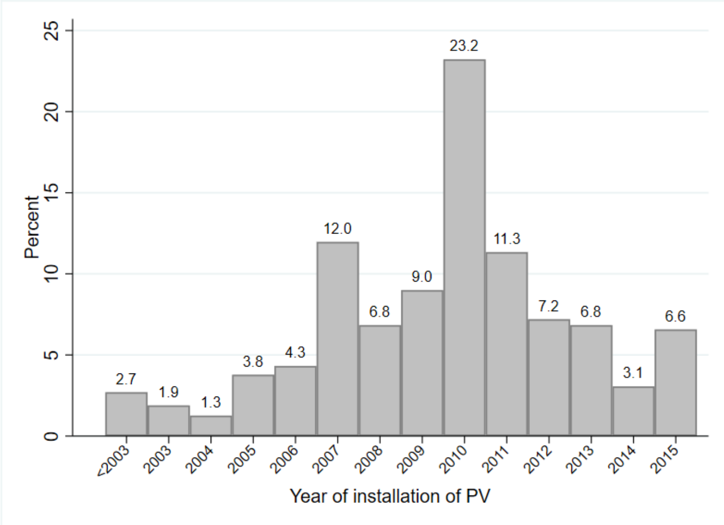
Variable	Explanation	Mean	Std. dev.
Age	Age of household head	52.63	12.97
Female	Dummy: 1 if household head is female	0.305	–
College	Dummy: 1 if household head has a college degree	0.317	–
Household size=1	Dummy: 1 if household comprises one member	0.186	–
Household size=2	Dummy: 1 if household comprises 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 installed PV panels	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: 15,873 and 7,948, 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.

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 the solar households of our sample installed a PV panel before 2012, with almost a quarter of all installations emerging from the single year 2010 (Figure 2). This mimics the small-scale PV installations in Germany, where

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



the annual number of new installations peaked in 2010 and 2011 (see Figure A1 in the appendix).[5] The large share of PV installations in 2010 and 2011 can be explained by module prices that drastically plummeted as of 2009 and coincided with high feed-in tariffs. The tariffs were only gradually reduced afterwards, thereby reducing the incentive to install a PV system (see Andor et al. (2015) for a more detailed discussion). Given that the majority of sample households installed their PV panels before 2012, these households receive feed-in tariffs that are substantially higher than average electricity prices (Figure 1).

The PV indicator, capturing whether a household owns a PV system, is likely to be an endogenous measure, as the decision to install a PV panel may be influenced by unobservable characteristics that both affect the likelihood to install a PV panel, as well as electricity consumption. For instance, a change in the salience of climate change, e.g. through extreme weather phenomena, may increase the likelihood to install a PV panel and simultaneously affect electricity consumption. As an instrumental variable (IV) for the likely endogenous PV variable, we use the number of PV systems within a zip-code area as of the previous year, denoted by z_{PV} and provided by the four Ger-

[5] Although we have no capacity information, 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 maximum size for residential PV systems in Germany (BMWi, 2014).

man Transmission System Operators (TSO, 2017). Peer effect studies for the U.S. and Germany indicate that households are more likely to install a PV panel the higher the number of installed PV panels in the neighborhood (Bollinger and Gillingham, 2012; Barton-Henry et al., 2021).

At time t, the instrument is equal to the cumulative number of completed installations in a certain zip code, with the PV panel of the household for which the instrument is used being excluded. Averaged over all 12 years, z_{PV} amounts to about 131 PV panels per zip-code area (Table 1). We explored the validity of the instrument by employing a placebo test suggested by Bound and Jaeger (2000) and popularized by Altonji et al. (2005) and Angrist et al. (2010) – see also van Kippersluis and Rietveld (2018). The test involves regressing the outcome variable on the instrument using a subsample of households without PV panels. A statistically insignificant coefficient would lend support to the exclusion restriction, i.e., that the instrument does not directly affect the outcome. As presented in Table A5 of the appendix, this is found to hold true.

As the electricity price measure, we use the marginal, rather than the average electricity price, given that the dominating pricing model in Germany includes a constant marginal price mp per kWh, as well as a monthly fixed fee f, which both remain unchanged over the billing cycle. If households do not know the marginal price, they can quickly retrieve it from their bill. If at all, households are thus rather aware of the marginal than of the average price, which they would have to calculate themselves by dividing total expenditures by the electricity eg taken from grid: $ap := \frac{eg \times mp + f}{eg}$. Hence, the information cost of understanding the marginal price is clearly lower than for the average price – see Frondel and Kussel (2019) for a more detailed discussion of the appropriateness of using the marginal price to estimate the price elasticity of electricity demand of households in Germany. Note that a robustness check using the average electricity price indicates that this has no bearing on our key results – see Section 5.

It also bears noting that prices are also likely to be endogenous given that households in Germany – as elsewhere in Europe – have the possibility to freely choose both suppliers and tariffs. To deal with this issue, we use the sum of regulated price components of the electricity price as an instrumental variable, denoted by z_p. These regulated components include, for instance, local grid and concession fees, levies and taxes, such as the German eco-tax, and account for more than 50% of the average electricity price for households (BNetzA and Bundeskartellamt, 2020). The use of this instrumental variable follows Frondel et al. (2019) and Frondel and Kussel (2019), who provide evidence for its validity and relevance. While grid fees are regional-specific and taxes and levies are uniform for all households, the sum of these price components is the same for all households of a certain region and is thus exogenous to households. The sum of the regulated price components 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, equaling 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 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.

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. This is a strong assumption, particularly given that electric appliances have long life cycles and households often have to incur substantial costs to adapt their appliance stock. 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:

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

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:

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

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, ... 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 other words, applying the GMM system estimator to a dynamic setting as specified in equation (7) always requires estimating both equation (7) and equation (8).

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. This method also allows the inclusion of external instruments, given here by the sum of regulated price components as the instrumental variable z_p for prices (Frondel et al., 2019), as well as the number of installed PV systems per zip code as the 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 our 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, but not statistically significant. 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: $t = |-3.\bar{5}| > t_{1-0.001} = 3.09$.

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 $\times \ln(p)$. Being the product of two endogenous

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.

variables, this interaction is also endogenous. We therefore instrument it using the interaction of the instruments for PV and the electricity price, $z_{PV} \times z_p$. The results, reported in the right panel of Table 2, provide no indication of a distinct price responsiveness of solar households.

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 (8), 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 the 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 of the appendix.

Addressing 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 prevents us from ruling out a solar rebound, which is derived in Section 2 to be bounded by 2θ (see equation (4)) and may be on the order of 50% for solar households in Germany.

Yet, even if some solar rebound is present, we are skeptical that its magnitude reaches 50%, as the overwhelming majority of our sample households were guaranteed feed-in tariffs that were much higher than their electricity prices (Figure 1) and, hence, households faced a strong economic incentive to limit the self-consumption of solar electricity. We illustrate our argument of the high opportunity cost of self-consuming solar electricity by a back-of-the-envelope calculation: Assuming 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 $\theta = 25\%$ of the produced solar electricity into the grid may be as high as about €570 per year.

For households that enjoy 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 €$1,000$ per year. Therefore, foregone remunerations due to self-consumption 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 mean electricity price of 24.4 ct/kWh (see Table 1).

Taking the mean annual household electricity consumption of $3,651$ kWh as the benchmark before installing a PV system and presuming that $\theta = 25\%$ of the average annual solar production of about $5,500$ kWh is self-consumed by a solar household, another back-of-the-envelope calculation provides us with a crude estimate for the solar rebound if we assume that upon the adoption of a PV system, a solar household reduces the amount of electricity taken from the grid by 2.9%, as suggested by the coefficient estimate of -0.029 on the PV indicator resulting from dynamic model (7). Under these assumptions, the solar rebound can be gauged at $[0.25 \times 5,500 + (1 - 0.029)3,650]/3,650 - 1$ = 35%, given that $0.25 \times 5,500 + (1 - 0.029)3,650$ reflects the total electricity consumption in the aftermath of PV adoption. Recognizing the statistical insignificance of the PV indicator, if we instead insert 0 for the coefficient estimate, rather than -0.029, we obtain a slightly higher solar rebound of 38%.

Moreover, noting that the solar rebound is often measured empirically as a percentage of the electricity produced by the PV system – see, for example, Qiu et al. (2019) –, calculating the solar rebound in this way would yield an effect size of about 23%, rather than of the order of 35%, as calculated above.[6] The difference in the effect sizes stems from the fact that Qiu et al. (2019) estimate the rebound at the margin. That is, conditional on having installed a PV system, they estimate the electricity consumption change in response to a marginal change in PV output, whereas our analysis, as well as the study by Beppler et al. (2021), measures the discrete rebound effect resulting from PV adoption.

To further classify the solar rebound effect, we identify a lower bound by assuming again that households reduce the amount of electricity taken from the grid by 2.9%, as indicated by the dynamic model estimate, and by considering the lowest share of self-consumption possible for German households. For our back-of-the-envelope calculation, we set the minimum share of self-consumption to 10%, which yields a minimum solar rebound of $[0.1 \times 5,500 + (1 - 0.029)3,650]/3,650 - 1$ = 12%.[7]

Lastly, only when assuming a self-consumption rate of 35%, rather than 25%, would the rebound effect be as high as $[0.35 \times 5,500 + (1 - 0.029)3,650]/3,650 - 1$ = 50%. Such a high rebound effect, which is the result of a high self-consumption rate of 35%, is rather unlikely, though, as economically viable battery technologies that help to store solar electricity and increase the self-consumption rate of solar households were virtually unavailable prior to 2016, the period in which the observations from our sample households fall.

[6]The effect size of about 23% results from relating the increase in total electricity consumption of $[0.25 \times 5,500 + (1 - 0.029)3,650] - 3,650 = 1,269$ kWh upon PV adoption to the amount of 5,500 kWh of solar electricity that is generated annually by an average German solar household: 1,269/5,500 $\approx$ 23%.

[7]The minimum share of 10% is given for two reasons: First, due to technical restrictions, German solar households are unable to feed 100% of solar electricity into the grid (Ruf, 2018). Second, the so-called "market integration model", which was introduced in Germany towards the end of our study period, only allowed 90% of the annually generated electricity to be remunerated with the FiT, setting the incentive for solar households to self-consume a minimum share of 10% (Masson et al., 2016). This share constitutes the minimum feasible share of self-consumption. It is noted that this rule only applied to PV installations above 10 kW, whereas solar households typically have PV installations below 10 kW. Nevertheless, we set the minimum to 10% to define the lowest bound possible for these households.

Our skepticism that the solar rebound effect is as high as 50% is further 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.

Table 3: GMM Estimation Results for Dynamic Model (7) based on the Blundell-Bond GMM System Estimator, which also requires Estimating Equation 8.

	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 are also more aware of electricity prices.

This mechanism is clearly not at work in our empirical example: By exploiting information on households' knowledge about electricity prices, as well as information about whether a household changed its electricity provider, which is available for a subset of our sample, the regression results presented in Table A6 of the appendix suggest that solar households are equally aware of electricity prices as non-solar households and equally likely to switch their electricity provider.[8] Moreover, 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 presented. First, employing the sub-sample with which we have estimated dynamic specification (7), we re-estimate 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 A7 of the appendix is statistically significant at the 10% level and quite close to the estimate of -0.096 originating from of static specification (6) when it

[8]Price knowledge is defined as a household's estimate of the marginal price, which deviates less than $\pm$ 20% from the actual marginal price paid. The binary variable supplier change captures whether households changed their electricity supplier during the three years prior to the survey. Data for both variables is only available after 2010.

is estimated on the basis of the full sample.

Second, we investigate the robustness of our results for dynamic specification (8) 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 A8), 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, to further explore differential effects over time, we employ a modification of equation (7) akin to Clark et al. (2008) that allows the effect of PV ownership to vary according to the years since PV installation. Specifically, the PV dummy in equation (7) is replaced with a series of dummy variables indicating those who have had a PV panel for 0-1 years, 1-2 years, 2-3 years, and so on, up to the last group who have had a panel for 10 years or more. Similar to the results reported in Table 3, these dummy variables are found to be statistically insignificant throughout (see Table A9).

Fourth, 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 A10).

Fifth, 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.[9] The results of this exercise, for which we vary the way in which the endogenous lagged variable is instrumented, are presented in Table A11 of the appendix. While the number of instruments varies, in statistical terms, the estimates on the PV variable do not differ across the variants.

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

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.[10] 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 the dynamic model (7) based on the matched sample (see Table A12 of the appendix) are quite similar to the unmatched results.[11] Most notably, the estimate of -0.088 for the coefficient on PV reported in Table A12 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 adequately, 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 PV panels 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

[10] 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.

[11] 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 A13). The variance ratio for the marginal price falls outside the allowed interval [0.64; 1.56], but is very close to 0.5, which is the lower bound for reasonable balancing according to Rubin (2001).

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 50% for German households. Yet, we are skeptical that there is such a large rebound effect, given the strong economic incentives to feed solar electricity into the public grid, particularly in the years 2000 to 2012. In fact, as our back-of-the-envelope calculations presented in the previous section have demonstrated, foregone remunerations due to a solar rebound may be easily in the range of average residential electricity costs per annum and the solar rebound should thus be much lower than 50%. Our skepticism about a substantial rebound is further corroborated by empirical studies for Australia and the United States, which find solar rebound effects on the order of about 20% (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.

Nonetheless, understanding behavioral responses due to solar PV adoption, such as the solar rebound, is highly important for policymakers because a significant rebound effect tied to rooftop solar would affect overall power demand and result in complications for power generation planning, as well as grid management and reliability. Such issues are highly important given that Germany's new government strives to almost quadruple PV capacities to 200 GW in 2030 (SPD, Bündnis 90 /Die Grünen and FDP, 2021), an objective that may assume increased urgency in light of the conflict in Ukraine.

Another key question is whether the reduction in electricity demand from conventional generation sources resulting from the incentivized adoption of residential PV systems justifies the cost of providing economic support for this technology (Beppler et al., 2021). Supporting PV adoption through feed-in tariffs has changed the traditional utility-customer relationship and has invigorated policy discussion about how to efficiently and equitably encourage continued growth of solar while maintaining cost-reflective electricity prices and grid reliability. The behavioral response of household electricity consumption, not least the solar rebound effect, must be better understood to evaluate whether distributed solar is contributing as expected to the displacement of conventional electricity generation and the reduction of carbon emissions (Beppler et al., 2021). In the end, ignoring solar rebound effects may imply the overestimation of environmental benefits, such as the reduction of both greenhouse gases and local environmental pollutants.

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).

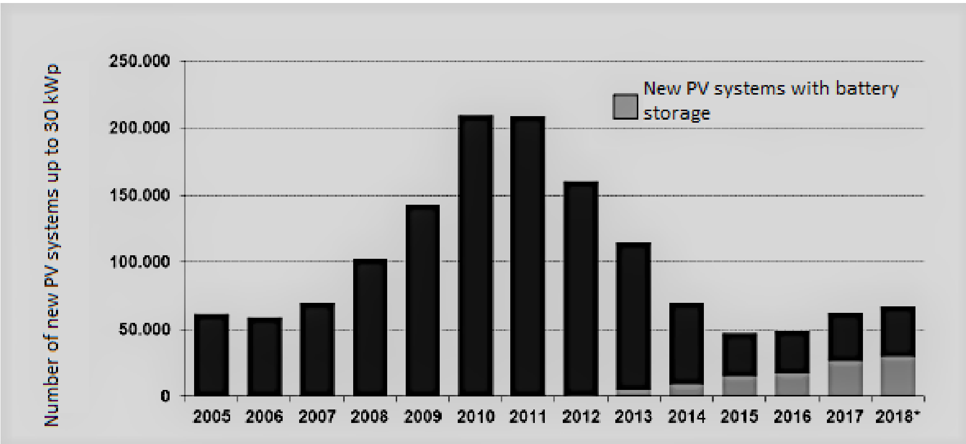


Table A2: Comparison of the Estimation Sample with the Population of German households

	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: Placebo Test of the Amount of Electricity taken from the Public Grid on z_{PV} for Sub-Sample without Solar Households.

	Fixed Effects	
	Coeff.	Std. Err.
ln(p)	-0.035**	(0.017)
z_{PV}	-0.000	(0.000)
ln(Income)	0.018	(0.018)
Household size = 2	0.282***	(0.032)
Household size = 3	0.441***	(0.036)
Household size = 4	0.517***	(0.036)
Household size > 4	0.595***	(0.044)
College degree	0.021	(0.023)
Homeowner	0.173***	(0.043)
Age	0.004	(0.003)
Constant	7.477***	(0.218)
Year Dummies	Yes	
Number of observations	13,855	

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

Table A6: Fixed-Effects Estimation Results for the Determinants of Price Knowledge and Supplier Change

	Price Knowledge		Supplier Change	
	Coeff.	Std. Err.	Coeff.	Std. Err.
ln(p)	0.906***	(0.061)	0.068	(0.042)
PV	0.053	(0.082)	0.023	(0.017)
ln(Income)	-0.019	(0.078)	-0.070	(0.183)
Household size = 2	-0.133	(0.082)	-0.109	(0.067)
Household size = 3	-0.148	(0.091)	-0.128*	(0.078)
Household size = 4	-0.215**	(0.099)	-0.138	(0.084)
Household size > 4	-0.382***	(0.123)	-0.134*	(0.078)
College degree	0.069	(0.117)	0.195	(0.224)
Homeowner	0.148	(0.124)	0.103	(0.282)
Age	0.002	(0.011)	0.089	(0.139)
Constant	-2.171**	(0.954)	-4.679	(8.189)
Year Dummies	Yes		Yes	
Number of observations	6,945		5,358	

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: 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 A8: 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 A9: GMM System Estimation Results for Dynamic Specification (7) With Varying Effects for Years since Panel Adoption.

	Varying PV Effect	
	Coeff.	Std. Err.
ln (eg_{t-1})	0.620***	(0.076)
$\widehat{\ln(p)}$	-0.282**	(0.123)
PV panel 0 – 1 years	0.002	(0.022)
PV panel 2 – 3 years	0.026	(0.020)
PV panel 4 – 5 years	0.004	(0.032)
PV panel 6 – 7 years	-0.029	(0.048)
PV panel 8 – 9 years	-0.029	(0.071)
PV panel 10 – 11 years	-0.011	(0.123)
ln(Income)	0.024**	(0.010)
Household size = 2	0.181***	(0.035)
Household size = 3	0.280***	(0.054)
Household size = 4	0.309***	(0.060)
Household size > 4	0.379***	(0.072)
College degree	-0.013*	(0.007)
Homeowner	0.048***	(0.015)
Age	0.001**	(0.001)
Female	0.000	(0.007)
Year Dummies	Yes	
Number of observations	4,655	
Number of instruments	71	
Arellano-Bond test for AR(1)	p=0.000	
Arellano-Bond test for AR(2)	p=0.916	
Hansen test of overid. restrictions	p=0.605	
Long-run price elasticity	-0.742**	(0.307)

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

Table A10: 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 A11: 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 A12: 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.

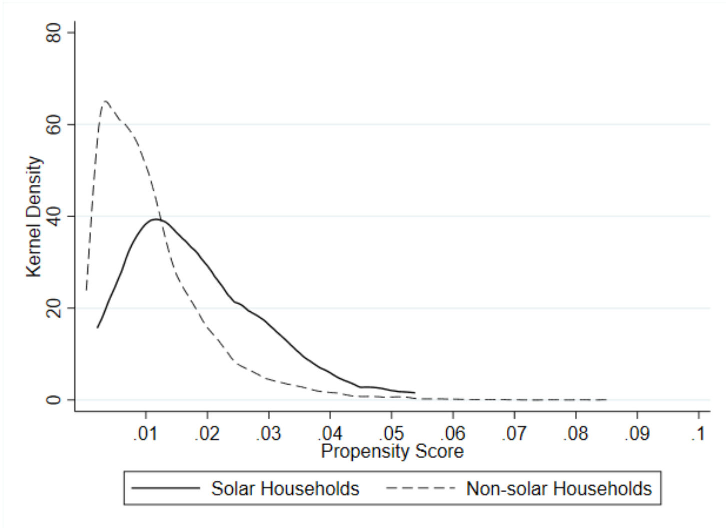


Table A13: Balancing Check for the Propensity Score Matching.

		Means		%reduct		t-test		Variance Ratio
Variable		Solar	Non-solar	%bias	|bias|	t	p>|t|	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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