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Renewable rebound: Empirical evidence from household electricity tariff switching

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Abstract

Potential environmental benefits of green tariffs may be mitigated if households increase electricity consumption after they subscribe to green tariffs. Using metered data of household electricity consumption from a large provider of green electricity in Germany, our quasi-experimental analysis finds that household switching to a green tariff leads to a non-monetary renewable rebound effect of around 8.5 %. Further, our findings imply that this renewable rebound effect is persistent over at least four years. These findings may be explained by moral licensing effects which induce households to permanently change their habitual behaviours and/or to acquire additional electricity-consuming technologies. Thus, failure to account for a renewable rebound in policy evaluation may lead to systematically underestimate the costs of achieving energy and climate targets.

Key words: rebound; renewable rebound; green tariffs; moral licensing.

Highlights:

- Analysis of household electricity use before and after switch to green tariff.
- Difference-in-difference estimation suggests a renewable rebound of about 8.5 %.
- Renewable rebound is persistent over at least four years.

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1 Introduction

Starting with the liberalization of the electricity market in 1998, an increasing number of households in Germany has switched to green tariffs (green electricity products), i.e. electricity backed by Guarantees of Origin (GoA). The number of green tariffs offered in Germany has risen from 810 products in 2013 to 1157 products in 2017 (Umweltbundesamt 2019). Currently, around 80 % of electricity suppliers offer at least one green electricity tariff. During this period, the demand for green electricity has increased by 22 %, and amounted to 95.6 TWh in 2017 (Umweltbundesamt 2019). Likewise, the share of electricity sold through green tariffs has increased steadily from around 5 % in 2008 to 28 % in 2019 (BNA 2020).

The effectiveness of green tariffs in reducing CO_2-emissions, however, has been questioned. First, due to the setup of the electricity system, increased demand for green tariffs does not automatically lead to a decrease in emissions. In terms of physical flows, the electricity of green tariff customers is determined by the power plants that are producing electricity on the grid at the time the electricity is used. Unless this happens to be a renewable electricity plant, electricity use of a green tariff customer therefore typically causes emissions.[1] Tariffs and providers may be certified via green electricity labels such as 'Grüner Strom Label', ok-power, and 'TÜV-Süd' in Germany, which are supposed to signal that the green electricity products have real environmental benefits. For example, for a tariff to be certified via green electricity labels, (parts of) the electricity sold must be generated by new renewable energy sources (RES-E). In addition, green tariffs (or installing PV systems) will not lower CO_2-emissions in the European Union (EU), at least in the medium term. Because total emissions of installations covered by the EU Emissions Trading System (EU ETS) are fixed via an emissions cap, any emission reductions by a fossil-fuelled power plant covered by the EU ETS will be exactly matched by an increase in emissions of other installations in the ET ETS (so-called waterbed effect, e.g. Perino et al. 2019).[2] Therefore, at least in the short to medium term, it is doubtful whether green tariffs directly entail environmental benefits. In the longer term, however, an increase in subscriptions to green tariffs (or in installations of PV systems)

1 In 2017, more than half the providers in Germany offered at least one green electricity product with such a label (Umweltbundesamt 2019).

2 In the longer term, however, such measures may lead to adjustments in the emissions cap and hence lower total emissions in the future.

may lead to a tighter emissions cap, ceteris paribus, and hence lower total emissions in the future. More generally though, as pointed out by Markard and Truffer (2006), green tariffs may spur social acceptability of the energy transition and induce utilities to offer additional eco-oriented services and products. Similarly, they may promote innovation in complementary technologies such as battery storage (Sinsel et al. 2020).

Second, and similar to the findings presented hereinafter, recent empirical studies provide evidence for a 'renewable rebound' in the residential sector: electricity use may increase after households subscribe to green tariffs (net of potential price effects), thus mitigating any potential environmental benefits. In particular, analysing data from a field experiment in Memphis, Tennessee (USA), where participants could choose to purchase one or more blocks of green electricity in a voluntary utility-sponsored green-electricity program, Jacobsen et al. (2012) find a measurable increase in electricity consumption of 2.5 % for households participating at the minimum level of one block, but no change for households purchasing more blocks of green electricity. According to Jacobsen et al. (2012), individuals may thus exhibit a 'buy-in' mentality because only those households engaging at a minimum level show a behavioural response whereby households who purchased more blocks do not alter their behaviour. Similarly, for conservationist households, who may have restrained their electricity consumption because of concerns for the environment and who participate in a green tariff program in Michigan (USA), Kotchen and Moore (2008) do not observe a change in electricity consumption compared to a control group despite a price premium for the green tariff. In comparison, non-conservationists are found to reduce their electricity consumption by an amount which can be explained by the green tariff premium. In contrast, for a large data set of households in Germany, Sommer (2018) finds that conservationist households in particular lower their electricity consumption by more than what could be explained by a premium on green tariffs. In a related effort, Harding and Rapson (2019) employ about two years of billing data (2008–2010) from a field experiment in California (USA), where a utility offered to offset its customers' electricity-related CO2 emissions at an additional cost. Customers who enrolled in the program were estimated to have increased electricity consumption by 1 to 3 % compared to control group households. For low income groups, the rebound is estimated at 11 %. These findings are similar to the 'solar rebound' found in empirical studies analysing the adoption of PV systems in private households (e.g. Spiller et al. 2017; La Nauze 2019; Oliver et al. 2019; Qiu et al. 2019; Frondel et al. 2020). In these studies, total electricity consumption of prosumer households was found to increase in response to the adoption of a PV system. For example, for households in the USA, Spiller et al. (2017) estimate a solar rebound of approximately 9 %. That is, an increase in household solar electricity generation by 1 kWh results in an increase in household total electricity consumption by 0.09 kWh. Similarly, also for households in the USA, Qiu et al. (2019) estimate the solar rebound at 18 %. Relying on a demographically representative household panel for Germany, Frondel et al. (2020) estimate the 'solar rebound' to range between 3 % and 10 %. They further argue, however, that at least in the past, the solar rebound in Germany is likely to have been small. Rather than self-consuming the electricity generated by their rooftop PV systems, households in Germany probably sold the electricity generated by their PV systems into the grid at the rate of the existing feed-in tariff (FiT). In other words, because the FiTs were high, the opportunity costs of self-consumption in terms of foregone remunerations for each kWh were too high to render self-consumption profitable. For Australia, Deng and Newton (2017) and Tanaka et al. (2021) find that household electricity consumption increases if FiTs increase, thus providing indirect empirical evidence for a rebound via an increase in the share of renewables in the national electricity mix.

In addition to these quantitative studies, several qualitative analyses have employed interviews with prosumer households to explore the solar rebound. According to a recent review of this emerging literature, most (but not all) qualitative studies find a positive solar rebound (Dütschke et al. 2021). In sum, most studies suggest that households change behaviour in response to using (or producing) more renewable electricity.

Following Dütschke et al. (2018), the reasons underlying the observed renewable rebound include monetary (i.e. economic) and non-monetary (i.e. psychological) factors. For example, if switching to green tariffs or installing a PV system lowers the costs of electricity per kWh, households may respond to the lower per-unit costs of energy services by increasing their electricity consumption. This monetary effect is similar to the direct rebound effect the literature has found in the context of energy and fuel efficiency improvements in heating, transportation or lighting (e.g. Sorrell et al. 2009; Madlener and Alcott 2009; Schleich et al. 2014; Frondel et al. 2017). Psychological rebound effects include, in particular, moral licensing (e.g. Blanken et al. 2015). Accordingly, perceived moral behaviour such as switching to a green electricity tariff or installing a rooftop PV system may ‘liberate’ individuals to be less moral in other domains, such as the level of electricity demand (e.g. Effron and Conway 2015; Tiefenbeck et al. 2013). Alternatively, because individuals may strive to behave consistently (Thøgersen and Crompton 2009), installing a solar PV system or switching to a green tariff might lead to lower electricity consumption, as shown in Sommer (2018).

In this paper, we empirically analyse the renewable rebound in household electricity consumption in Germany. To this end, we employ quasi-experimental difference-in-difference (DID) and before-after analyses using metered electricity consumption data obtained from a large green electricity supplier (LGES) on household switching from grey to green electricity tariffs.[3] Thus, our study adds to the emerging empirical literature on renewable rebound in general, and to the scant literature on renewable rebound pertaining to green tariffs in particular. In addition, unlike previous literature, we explore whether rebound-effects are transitory or persistent. Households may change their electricity consumption via two channels: by changing habitual behaviours such as turning off lights and using devices less, or by changing their purchasing behaviour pertaining to, for example, quantity, type and energy-class of new appliances and electronic devices. Behavioural changes may only have a transitory effect on electricity use if households return to their long-practiced habits after a certain time. For example, for households in the USA, Houde et al. (2013) conclude that feedback on electricity consumption mainly leads to transitory changes in household habitual behaviours. In contrast, for households in Austria, Schleich et al. (2017) find that such feedback leads to electricity consumption reduction that is persistent over time periods suggesting permanent changes in habitual behaviour and/or investments in energy-efficient technologies.

We organize the remainder of our paper as follows: section 2 describes the methodology, including the data set, the variables and the econometric models. Section 3 presents and discusses the results. The final section 4 summarizes the main findings and offers implications for policy-makers and utilities.

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3 We use the acronym LGES to guarantee the anonymity of this large green electricity provider.

2 Methodology

2.1 Data

Data was made available by a large green electricity provider in Germany which was founded in the wake of the liberalization of the electricity market. We received metered data on customer electricity consumption between 2003 and 2019 for three switching periods 2004/2005, 2010/2011 and 2015/2016. For households switching to LGES in year *t*, data on electricity consumption is available for *t-1* from the previous provider, and from t to t+3 on electricity consumption and tariff from LGES. For example, for a household that switched to LGES in 2004, we know electricity consumption between 2003 and 2007. Because we have data for one pre-intervention year only, we cannot assess whether the so-called parallel trend assumption holds (Angrist and Pischke 2008). We also know the name of the previous providers, but not the tariff households faced in year t-1 when they were with their previous providers. Therefore, we contacted all previous suppliers and two large online portals (Verivox and check24) to collect data on the types of tariffs the previous suppliers offered in year t-1. In total, our data based includes 518 previous suppliers for the first switching period, 269 for the second switching period, and 254 for the third switching period. Based on this information, we classified previous suppliers as green suppliers if in the year t-1 they only had tariffs on offer that were based on 100 % renewable energy sources. Similarly, we classified previous suppliers as grey-suppliers if in the year t-1 they only had tariffs on offer that were based on conventional sources. Hence, a given supplier may be classified as ‘grey’ in one year and as ‘green’ in another year. In our database, the share of green previous suppliers increased from about 3 % for the first switching period to about 7 % for the second switching period and about 17 % in the third switching period. At the same time, the share of grey previous suppliers was about 12 % for the first switching period, about 9 % for the second switching period, and about 11 % for the third switching period. For the first switching period, for example, our list of green suppliers included providers such as Greenpeace Energy eG, NaturStromHandel GmbH, BayWa Ökoenergie GmbH and NaturEnergie AG. Likewise, our list of grey suppliers included Bonus Strom GmbH, 365 AG and many small and large municipal utilities ("Stadtwerke") such as Stadtwerke Barth GmbH or Stadtwerke Bielefeld GmbH.

Our original data set comprised of 291538 observations for 58368 customers. About 83 % of those observations pertained to the first switching period, about

12 % to the second switching period, and about 5 % to the third switching period. Unfortunately, we were not able to retrieve the historic tariff portfolios of a large share of previous providers, particularly for the first and the second switching period. For the second and the third switching period, in particular, many providers simultaneously offered both grey and green tariffs, and thus for many previous providers, it was not possible to unambiguously classify them as 'green' or as 'grey'. Customers for whom we could not retrieve the historic portfolio or for whom the previous provider could not be clearly classified as green or grey had to be dropped from our data set. Our empirical analyses therefore pertain to 1934 customers, about 47 % of which belonged to the first switching period, 27 % to the second switching period, and 26 % to the third switching period.

2.2 Econometric model

Our quasi-experimental approach involves econometric difference-in-difference (DID) analysis and compares electricity consumption across households and over time, distinguishing when households subscribed to a green tariff rather than a grey tariff. We estimate the following model:

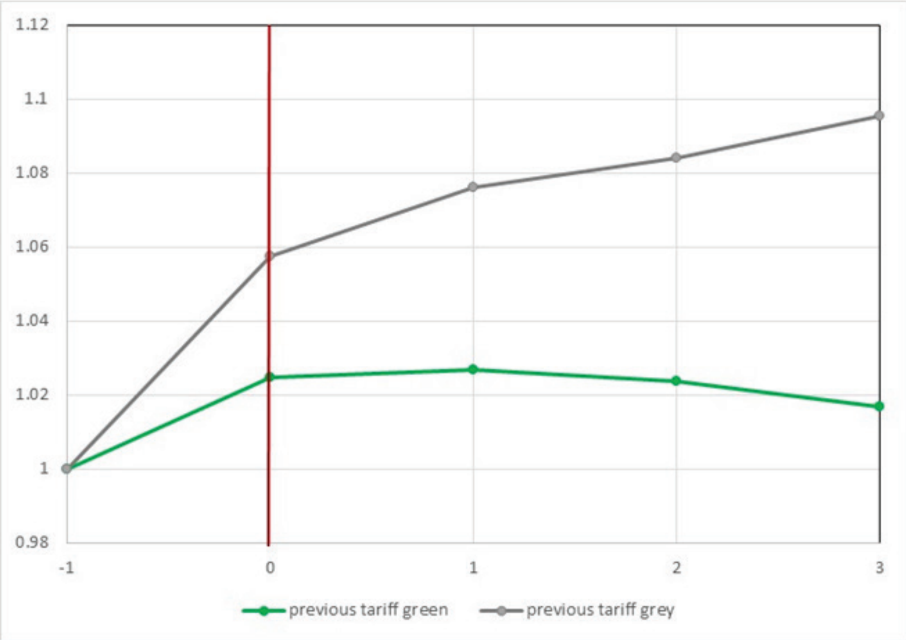
$$\mathrm{electricity}_{it} = \mathrm{constant} + \sum_t \beta_t \mathrm{treat}_{it}^{gt} + \gamma \mathrm{price}_{it} + \tau_{t'} + \alpha_i + \varepsilon_{it} \quad (1)$$

i indexes the household and *t* indexes the year. The variable $electricity_{it}$ stands for metered annual average daily electricity consumption of household *i* in year *t*. The data on electricity consumption per household were provided by LGES. Daily average electricity consumption per household was calculated by dividing total household electricity consumption by the number of days in year t. To eliminate data from dwellings which are barely used (e.g. vacation homes) and data that are deemed unreasonable, we only used observations where average household electricity consumption per day ranges between 55 and 200 kWh. Similarly, to further mitigate data reporting errors, we eliminated observations where the change in electricity use after switching suppliers ranges between 0.5 and 2.5 (i.e. between a decrease of 50 % and an increase of 250 %). This leads to a loss of about 3 % of observations. Further, we normalize consumption data by setting the year in which each household became an LGES customer to t = 0 and by setting electricity consumption to 100 for t = -1. These normalizations allows us to interpret parameter estimates as percentage deviations from the pre-switching period and to pool observations from the three switching periods, thereby increasing degrees of freedom in our econometric analysis. Figure 1 displays normalized electricity consumption distinguishing between those households who subscribed to a green and those who subscribed to a grey electricity tariff prior to becoming a customer of LGES. We are particularly interested in $treat_{it}^{gt}$ which is an indicator variable equal to one if household *i* subscribed to a green tariff in year *t*, and zero otherwise. Households are considered to be 'treated' once they subscribed to a green tariff, i.e. when they are potentially subject to a renewable rebound effect. In our notation, households who switched from a grey electricity supplier to LGES belong to the treatment group (see Figure 1). Likewise, households who switched from a green electricity supplier to LGES belong to the control group. Employing a control group allows us to account for effects on household electricity consumption which are common for both groups during the period of analysis. In particular, because households often switch suppliers (and hence tariffs) when they move (e.g. Schleich et al. 2019) we control for changes in electricity use pertaining to a change in household size or dwelling size. Indeed, according to Figure 1, electricity use increased for both the control and the treatment group in the years after they had switched electricity tariffs, i.e. after t = 0. The coefficient β captures potential (non-monetary) renewable rebound effects such as moral licensing (e.g. Blanken et al. 2015). In addition, our specification allows potential renewable rebound effects to vary between year 0 (i.e. the year of tariff switching) up to year 3 (i.e. three years after the tariff switch). The variable $price_{it}$ reflects the electricity price and thus controls for a potential monetary rebound effect. Our estimate of the coefficient γ quantifies this effect. More specifically, $price_{it}$ stands for the energy component (i.e. the variable part) of the electricity price that household i faced in year *t*. The literature seems ambiguous about whether households respond to marginal (i.e. variable) or to average prices (e.g. Ito 2014). From an economic perspective, however, households should respond to marginal prices. Further, individuals are more likely to be aware of the marginal price rather than the average price because for the latter they would need to divide their total electricity expenditure (i.e. the variable and fixed price components) by their total electricity consumption. In addition, estimates of the price elasticity are biased towards unity when the tariffs include a fixed fee and average prices are used to estimate the elasticity (e.g. Frondel and Kussel 2019). Data on $price_{it}$ was available for all LGES customers and often also for the previous providers (see section 2.1). Still, for about 80 % of the customers in our final data set, we could not recover information on the electricity price of the previous suppliers. For previous grey electricity suppliers where price information was missing, we use instead the average electricity tariff for a household in Germany that uses 3500 kWh/year (BDEW 2019). For green suppliers where data was missing, we use the price charged by LGES. In an alternative specification, we replace missing price data by the average of the tariffs for those green and grey suppliers where this information could be retrieved. This alternative specification leads to qualitatively and quantitatively very similar findings as those presented in section 3. Further, we deflate all electricity prices using the consumer price index for electricity, natural gas and other fuels available from the German Federal Statistical Office (series CC13-04). To do so, we use the year 2015 as the base year. Finally, $\tau_{t'}$ are fixed effects in year t' (t' runs from 2004 to 2019), α_i reflects household-specific unobservable effects which are constant over time, and ε_{it} is the idiosyncratic error term.

Employing a control group allows us to account for effects on electricity consumption which are common for both groups during the period of analysis, e.g. technological developments such as changes in the stock of appliances and electronic devices or changes in usage behavior (e.g. because the household had moved to another dwelling). In our set-up, however, treatment is not random because households voluntarily select a green tariff. If it were possible to randomly assign households into treatment and control group, we could estimate the population average treatment effect (PATE) on electricity consumption under standard identifying assumptions. However, in this study and similar to Harding and Rapson (2019), we are interested in estimating a behavioral renewable rebound effect on green tariff customers. We therefore seek to estimate the population average treatment effect on treated households (PATT). Thus, the self-selecting nature of choosing a green tariff is the very treatment that we expect to cause the behavioral rebound (see Harding and Rapson 2019, pp. 935). In this case, identification requires that stochastic shocks which may lead households to choose a green tariff (e.g. reports in the media about global warming or extreme weather events) do not directly affect electricity consumption. In our context, this assumption seems reasonable. Identification is further based on the standard yet untestable parallel lines assumption. Our set-up, however, does not capture if households feel guilty about an anticipated increase in electricity consumption and therefore switch from a grey to a green tariff, thus leading to a potential endogeneity problem.

For comparison, we also conduct a simple before-after-analysis. This means that we only use observations of the treatment group, i.e. households who switched from a grey electricity supplier to LGES. In this case, identification of the treatment effect is based on variation in the timing of households subscribing to a green tariff only. That is, any difference in observed household electricity consumption between the pre-treatment and post-treatment periods is ascribed to the switch from a grey to a green tariff.

Figure 1: Normalized electricity consumption (2003–2019)



3 Results

We present results from estimating the tariff switching model as specified in equation (1) via a fixed-effects panel estimator in Table 1. Standard errors are clustered at the household level to make statistical inference robust to potential serial correlation of household electricity consumption. We document descriptive statistics of the dependent variable in Appendix Table A1. Turning first to the findings for the DID model for our main specification, we notice that the coefficients associated with our treatment indicators *treat_0* to *treat_3* are positive and statistically significant. Thus, households switching from a grey to a green tariff are found to increase electricity consumption post switching compared to households switching from a green previous supplier to LGES. Using the point estimates, this renewable rebound is estimated to range between 5.4 % for the switching year and 9.2 % for the third year after (t = 3) the switching year (t = 0) compared to the year prior to the switching year (t = -1). Thus, in terms of size, the renewable rebound is substantial and somewhat larger than the rebound effect found by in Jacobsen (2012) and Harding and Rapson (2019) in slightly different contexts. Our findings are also line with the empirical literature pointing to the role of psychological factors such as moral licensing which previous literature have found to help explain rebound effects in climate-related behaviour in general (e.g. Tiefenbeck et al. 2013; Meijers et al. 2015; Nash et al. 2017; Maki et al. 2019; Burger et al. 2021). Further, our findings offer no indication that the renewable rebound is transitory, i.e. that the β-coefficients decline over time. In fact, the β-coefficients appear to increase somewhat over time, but the differences in the β-coefficients are not statistically different. For example a two-sided F-test of $H_0: \beta_0 = \beta_3$ yields a test statistic F(1, 1840) = 1.18 which corresponds to a p-value of 0.278. Thus, according to our findings the renewable rebound appears to be persistent and of similar magnitude over the three years following the switch from a grey to a green electricity provider. Households appear to have permanently changed their habitual behaviours, used electricity-consuming technologies more intensively, and/or invested in additional electricity-consuming technologies after they had subscribed to a green electricity tariff. Thus, psychological factors such as moral licensing appear to have non-transitory effects on household electricity consumption.

Lastly, the coefficient associated with *price* is statistically significant and, as expected, negative (-0.26). Its magnitude is consistent with the thrust of the empirical literature which finds household electricity demand to be inelastic and rather small in size. For example, the recent meta-analysis by Labandeira et al. (2017)

estimates the mean short-run price elasticity of electricity demand at –0.1 and the mean long-run price elasticity at –0.4. Our finding for the *price* coefficient implies that if the marginal price was higher for a green tariff than for a grey tariff, switching from a grey tariff to a green tariff would lower electricity consumption, thus counterbalancing a non-monetary rebound effect. Because of missing data on electricity tariffs of the previous provider for a substantial part of our sample, however we cannot robustly infer this for our sample.

To examine the robustness of our findings when information on the electricity price is not included – e.g. because for many observations price data was not available and had to be estimated – we estimate a model where we drop *price* from the set of explanatory variables. The results for this model also appear in Table 1. Accordingly, the findings of this model are very similar to the findings of our main specification – the coefficient associated with *treat_3*, however, is just shy of being statistically significant at conventional levels of significance. Overall though, our findings appear very robust to excluding *price* from the model.

We further tested whether our results are robust to an in-time type placebo test. To this end, we included an additional pre-treatment dummy (*treat_-1*) in our DID model which captures differences in electricity consumption between the treatment and the control group in the year before the tariff switch. We document the results of this model in Appendix Table A2. Accordingly, the coefficient associated with *treat_-1* is not statistically significant. Thus, our findings provide no indication that pre-existing differences between the control and the treatment groups cause our results.

Table 1: Results for tariff switching model (fixed-effects panel regression) (2003–2019)†

	difference-in-difference		before-after	
treat_0	0.054*** (0.002)	0.056*** (0.002)	0.093*** (0.000)	0.095*** (0.000)
treat_1	0.077** (0.010)	0.071** (0.016)	0.119*** (0.001)	0.115*** (0.001)
treat_2	0.088** (0.033)	0.074* (0.067)	0.132*** (0.003)	0.121*** (0.006)
treat_3	0.092* (0.059)	0.070 (0.138)	0.140*** (0.008)	0.121** (0.017)
price	-0.259*** (0.009)		-0.259* (0.052)	
constant	1.199*** (0.000)	0.934*** (0.000)	1.173*** (0.000)	0.912*** (0.000)
year fixed effects	YES	YES	YES	YES
F-Statistic (p-value)	4.85 (0.000)	4.91 (0.000)	2.80 (0.000)	2.94 (0.000)
Observations	8,271	8,273	7,245	7,247
Number of households	1,841	1,842	1,772	1,773

† Robust p-values in parentheses; ***p<0.01, **p<0.05, *p<0.1

We now turn briefly to the findings for the before-after-analysis. As shown in Table 1, the findings for the before-after-analysis are qualitatively similar to those obtained via the DID analysis. The renewable rebound effect, however, is estimated to be higher for the before-after-analysis than for the DID analysis. This finding implies that a before-after analysis may lead to overestimating the renewable rebound by failing to account for factors which increase electricity consumption in both the control and the treatment group. For example, households may switch tariffs when they move to a larger dwelling because the family has grown. In a simple before-after-analysis the increase in electricity consumption due to the increase in family size would be erroneously ascribed to the renewable rebound effect.

4 Conclusion and Policy Implications

The findings from our quasi-experimental econometric analysis of household electricity consumption based on metered data from a large provider of green electricity in Germany suggest that switching to a green tariff leads to a non-monetary renewable rebound effect of around 8.5 % (averaged over the years after the switch). Further, our results imply that this renewable rebound effect is persistent over at least four years, possibly reflecting moral licensing effects that induce households to permanently change their habitual behaviours and/or to acquire additional electricity-consuming technologies. Because we have no information on household characteristics or individual attitudes, our data unfortunately did not allow us to account for potential heterogeneity in findings by socio-economic groups. Such analyses must be left for future research. Further, because of missing data on electricity tariffs of the previous provider, we had to use proxies for a large share of customers in our data set. Thus, we cannot robustly estimate the potential (negative) monetary rebound for switching from a grey tariff to a possibly more costly green tariff.

Yet, our findings have several implications for policymakers and electricity providers. In particular, to limit potential negative effects of the non-monetary renewable rebound, policy makers could provide additional information. More specifically, such information may vividly describe the mechanisms which have been found to result in non-monetary renewable rebound effects in response to tariff switching. In addition, such information could explain the negative environmental effects such as higher greenhouse gas emissions pertaining to the renewable rebound effect. Such information could be targeted at individuals likely to subscribe to green tariffs, i.e. females, households/individuals with large incomes, high education levels, low electricity consumption, and ecological orientation (e.g. Sommer 2018; Ziegler 2020).

Regarding policy analysis and design, ex-ante policy assessments carried out to define energy and climate policy targets should take renewable rebound effects into account. Failure to do so may lead policy makers to systematically underestimate the costs of achieving these targets. Our findings further suggest that these assessments should be based on difference-in-difference estimations rather than before-after analyses. Because the latter do not take into account developments which would have happened without the treatment – in our case moving into a larger dwelling, for example – they may lead to an overestimation of renewable rebound effects. Last but not least, utilities' procurement of green electricity needs to account for a non-transitory increase in electricity consumption for new and old customers switching to a green tariff.

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Appendix

Table A1: Descriptive statistics

	Mean	Min	Max	Std. Dev.		
				overall	between	within
Electricity consumption per day [in kWh]	8.30	1.51	53.22	6.02	5.93	1.37
Number of households	1842					
Number of observations	8273					

Table A2: Results for tariff switching model - placebo test (fixed-effects panel regression) (2003–2019)†

	difference-in-difference	
treat_0	0.066*** (0.002)	0.067*** (0.002)
treat_1	0.088*** (0.007)	0.082** (0.011)
treat_2	0.099** (0.022)	0.085** (0.046)
treat_3	0.103** (0.042)	0.081 (0.101)
treat_-1	0.020 (0.249)	0.019 (0.271)
price	-0.262*** (0.008)	
constant	1.194*** (0.000)	0.926*** (0.000)
year fixed effects	YES	YES
F-Statistic (p-value)	4.61 (0.000)	4.65 (0.000)
Observations	8,271	8,273
Number of households	1,841	1,842

† Robust p-values in parentheses; ***p<0.01, **p<0.05, *p<0.1

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