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On Home Energy Reports and Boomerangs: Evidence from Austria

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On Home Energy Reports and Boomerangs: Evidence from Austria

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Abstract

Home energy reports (HERs) have been shown to reduce electricity consumption via peer-comparisons, but evidence has also emerged that treatment heterogeneity may undermine their cost-effectiveness in some contexts. Using data elicited from a randomized control trial in Austria, we employ a model specification that captures an heretofore unexplored source of treatment heterogeneity, that emerging from the deviation between the household's pre-treatment electricity consumption and the mean electricity consumption of households in its zip code. We document a boomerang effect by which households below the mean electricity consumption increase consumption, while those above the mean decrease it. These offsetting effects yield a net effect close to zero. They moreover reveal only a narrow range of customers who reduce their electricity consumption, calling into question the cost-effectiveness of HERs in the absence of complementary measures like targeting.

JEL Codes: D12, D83, Q41.

Keywords: Social norms, Energy conservation, Randomized field experiments, Non-price interventions.

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1 Introduction

A large number of studies have shown that social norms affect people's choices and induce people to save energy (see e.g. Schultz et al., 2007; Nolan et al., 2008; Ferraro and Price, 2013; Brent et al., 2015). Home energy reports (HERs), which are either sent by post or electronically via e-mail, provide households with energy conservation tips and social norm information by comparing a household's energy use to that of neighbors. Through regular exposure to neighbor comparisons, HERs are intended to nudge reductions in household energy consumption. While evidence from the U.S. suggests that HERs reduce electricity consumption on the order of 2 to 5% (see e.g. Allcott, 2011; Allcott and Rogers, 2014; Henry et al., 2019), whether equally large effect sizes apply to other countries remains an open question. Andor et al. (2020), for example, argue that the U.S. may pose a special case owing to its high levels of average electricity consumption and of carbon intensity in electricity production. Based on a randomized control trial of HERs in Germany, they find considerably smaller effect sizes, and conclude that HERs would only be cost effective when targeted at highly-responsive subgroups.

The question of targeting has arisen in several other studies that probe heterogeneity in responses to norm-based interventions. It assumes particular relevance in the presence of what social psychologists call boomerang effects (Clee and Wicklund, 1980), when low-consumption users increase their consumption after receiving a HER. Social-norms theory has long recognized that such responses can arise from people's desire to avoid deviant behavior. This desire would explain why those whose energy consumption is below the social norm would increase consumption in response to a HER. Drawing on the focus theory of normative conduct (Cialdini et al., 1991), Schultz

et al.'s (2007) pioneering analysis of electricity consumption among a sample of 290 California households shows that the boomerang effect can be eliminated by including an injunctive message conveying that energy conservation is pro-social.

Injunctive messaging – usually represented with smiley and frowny emoticons – has since become a regular feature on HERs, and has generally been effective in eliminating boomerang effects. For example, Allcott (2011), Henry et al. (2019), and Andor et al. (2020) all find no evidence for a boomerang effect in households' electricity consumption. Ferraro and Price (2013) and Brent et al. (2015) likewise find no significant boomerang behavior in their studies of norm-based HERs on residential water consumption in the U.S. By contrast, Ayres et al. (2013) and Byrne et al. (2018) both uncover evidence for boomerang effects in electricity consumption from the U.S. and Australia, respectively, despite using injunctive messaging. Both studies conclude that conservation policy should target HERs to high-consuming households.

Building on this body of work, the present study assesses the effect of electronically transmitted HERs using data elicited from a randomized control trial of about 9,000 eco-electricity customers from Austria. A distinguishing feature of our analysis is in its specification of heterogeneity. The standard approach – used in all of the cited studies – captures heterogeneity by interacting indicators for different percentiles (e.g. deciles) of baseline consumption with the treatment. We instead employ a specification that allows for differential treatment effects according to deciles of the *deviation* between the household's pre-treatment electricity consumption and the average electricity consumption of households in its zip code. While our application of the standard specification reveals no significant treatment effect with no evidence for heterogeneity, this alternative specification indicates that households below the social norm respond by consuming more, by up to 4%, while those above the social norm respond by consuming less.

We consequently conclude that caution is warranted in reliance on HERs as a climate mitigation tool. We find only a narrow range of households for which targeting

would be cost effective. Moreover, the overall climate mitigation potential suggested by our results is negligible.

2 Data

We use electricity consumption data of 9,039 customers of an eco-electricity provider in Austria, spanning the years 2013 to 2016. These customer households were randomly assigned to the treatment and control group, with the former receiving up to four electronic HERs on a quarterly basis. Consumption data is available for two billing periods: A baseline period, in which no household received any treatment, and a treatment period in which treatment households received the HER by e-mail. Each HER provided the treatment households with energy savings tips and a social comparison component. The latter consisted of a comparison of a household’s consumption level with the mean consumption level of all households in the same zip code (see Figure A1 in the appendix).

Table 1: Descriptive Statistics for the Estimation Sample.

| | All | Control | Treatment | t-Statistic |
|------------------------------------|--------|---------|-----------|-------------|
| Daily baseline consumption, in kWh | 7.70 | 7.72 | 7.68 | -0.41 |
| Length of baseline period, in days | 309.72 | 309.98 | 309.46 | -0.24 |
| Number of households | 9,039 | 4,533 | 4,506 | |

In Austria, as in many European countries, households only receive a single electricity bill per billing cycle, with a billing cycle commonly lasting about one year. During the billing cycle, households’ electricity prices typically remain unchanged. In our sample, the number of days between the two metering points in the baseline period amounts to about 310 days for both the treatment and control groups (Table 1). To account for deviations in the lengths of billing periods and to make electricity consumption levels comparable between households and periods, we divide consumption data by the number of days of the respective billing period to arrive at a household’s average daily consumption data. The average baseline electricity consumption amounts to

7.70 kilowatt hours (kWh) per day and does not differ significantly between treatment and control group.

3 Methods

We employ a difference-in-differences (DiD) estimator to determine the average treatment effect (ATE) of HERs on electricity consumption. Our baseline model is specified as:

$$\Delta Y_i = \alpha + \beta * T_i + \tau_w + \epsilon_i, \quad (1)$$

where $\Delta Y_i = (Y_i^T - Y_i^B) / Y_{i,c}^T$ corresponds to the change in daily electricity consumption of household i before (Y_i^B) and after the HER treatment (Y_i^T), normalized by the average post-period control group consumption ($Y_{i,c}^T$) (see Allcott (2011)). T_i is the treatment dummy that equals unity for households that received the HER and ϵ_{it} denotes an idiosyncratic error term. β is the coefficient of interest capturing the ATE, expressed as average electricity savings as a percentage of the average consumption level. We include weekly dummies, τ_w , for both the baseline and treatment period to account for seasonality¹. Since the HERs were sent as e-mail to all treatment households on the same dates, but the final billing periods started and ended at differing dates for individual households, treated households received a varying number of mails in the treatment period. About 50% of treated households received between one to three mails, with the remaining 50% receiving all four mails (Figure A2). For our main model, we define the treatment dummy $T_{min.1}$ equal to unity as soon as a treated household received at least one mail within the treatment period. To test the robustness of simultaneously looking at households that differ with respect to the number of HERs received in the treatment period, the treatment dummy T_{all4} is used in another specification and

¹The weekly dummies for the baseline period equal 1 if a pre-treatment week falls into the billing period of a household, the weekly dummies for the treatment period accordingly equal 1 if a treatment week falls into the billing period of the household.

equals unity only if treated household received all four mails in the treatment period. Treated households that received less than four mails are dropped in this specification, such that the control group always consists of those households that received no HER.

To explore heterogeneous treatment effects with respect to the electricity consumption level, we hone in on the social comparison component of the HER. Other studies (e.g. Allcott, 2011; Byrne et al., 2018; Andor et al., 2020) have explored heterogeneity by interacting the treatment dummy with dummies indicating the household's decile of baseline electricity consumption. We take a slightly different tact by interacting the treatment dummy T_i with the deviation of the mean baseline consumption within a zip code from the household's baseline consumption, $(Y_i^B - \bar{Y}^B)$, with the model specified as:

$$\Delta Y_i = \alpha + \lambda_1 * T_i + \lambda_2 * (Y_i^B - \bar{Y}^B) T_i + \tau_w + \epsilon_i. \quad (2)$$

Equation (2) allows us to determine varying treatment effects depending on a household's consumption level in relation to other households in the zip code. Specifically, $\lambda_1 + \lambda_2 * (Y_i^B - \bar{Y}^B)$ captures the treatment intensity, defining how strongly the mean baseline consumption within a zip code deviates from a household's baseline consumption. This formulation has the advantage of distinguishing, for example, the effect of the treatment on a high consumption household surrounded by high consuming neighbors from the effect that would emerge were the same household surrounded by low consuming neighbors. Finally, we also estimate a variant of equation (2) to examine conditional average treatment effects for households in different deciles of the deviation of the mean baseline consumption in a zip code from their own baseline consumption. By interacting dummy variables for each decile of the deviation with the treatment effect, this specification allows for a more flexible and non-linear heterogeneity analysis.

4 Results

Table 2 presents the results from the models estimated on households that received at least one mail. The small and statistically insignificant coefficient of 0.079 from the baseline specification in the first column suggests that electronic HERs do not affect electricity consumption of our sample households. In a second step, we investigate whether treatment effects differ according to pre-treatment electricity consumption. As found by several studies, treatment effects vary with respect to pre-treatment consumption levels, showing larger effect sizes for high users that motivated researchers to recommend targeting according to baseline consumption levels to make HERs more cost-effective (see e.g. Allcott, 2011; Ayres et al., 2013; Ferraro and Price, 2013; Andor et al., 2020). Figure 1 illustrates the results of the treatment effects by decile of baseline consumption estimated by interacting the treatment dummy with the according decile dummy. In contrast to recent studies, we do not find any evidence for significant heterogeneity based on mere baseline consumption levels. A markedly different picture emerges from the model presented in the middle column of Table 2, showing that both the baseline model and the pre-treatment interaction model mask heterogeneous treatment responses as a function of the deviation between the household's baseline electricity consumption and that of its neighbors in the same zip code (equation (2)). This model indicates a boomerang effect, as evidence by the statistically significant interaction effect.

Table 2: Average treatment effect (ATE) on households' electricity consumption.

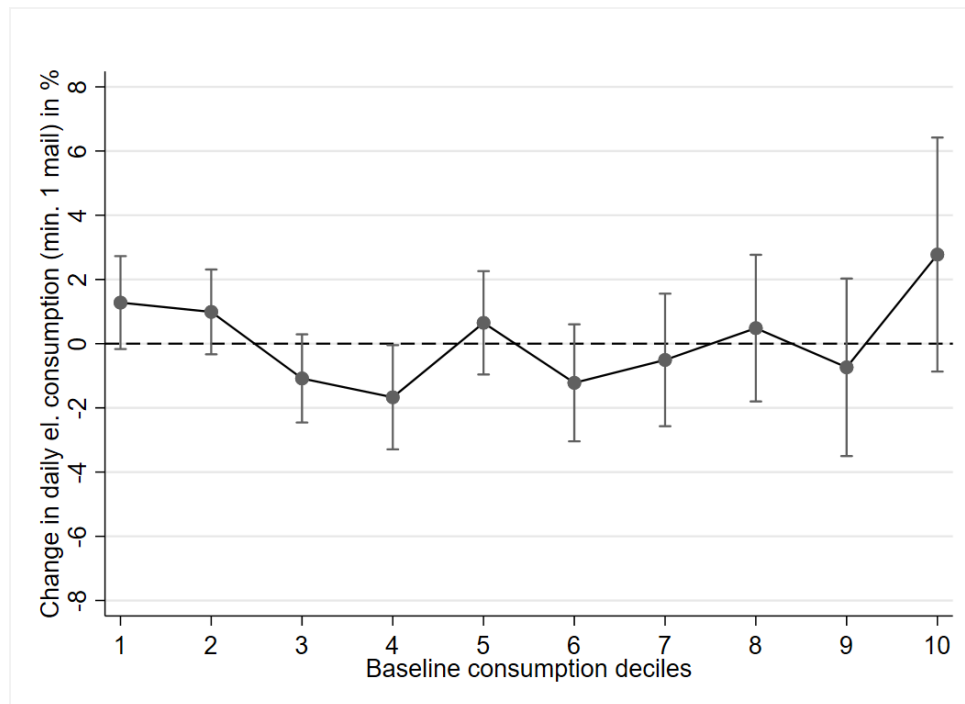
| | Main | | Linear deviation | |
|---------------------------------|--------|---------|------------------|---------|
| | Coeff. | s.e. | Coeff. | s.e. |
| $T_{min.1}$ | 0.079 | (0.335) | 0.024 | (0.338) |
| $T_{min.1} * \text{Difference}$ | – | – | -0.425*** | (0.084) |
| Constant | 1.871 | (8.867) | 5.454 | (8.841) |
| R^2 | 0.0880 | | 0.0933 | |
| Observations | 8,994 | | 8,994 | |

Notes: Robust standard errors are in parentheses. *** denotes significance at the 1 % level.

Further insight can be gleaned by presenting the marginal effects corresponding to

different levels of the deviation, presented in Figure 2 (a). For instance, if a household's daily consumption lies 4 kWh below the mean, the average HER treatment effect is a 1.72% increase that is statistically significant at the 1%-level. On the other hand, households whose baseline consumption figure lies above the average are found to decrease their daily consumption. The magnitude of the estimates falling on each side of zero in Figure 2 (a) is roughly symmetrical.

Figure 1: Effect of HER depending on pre-treatment consumption deciles.



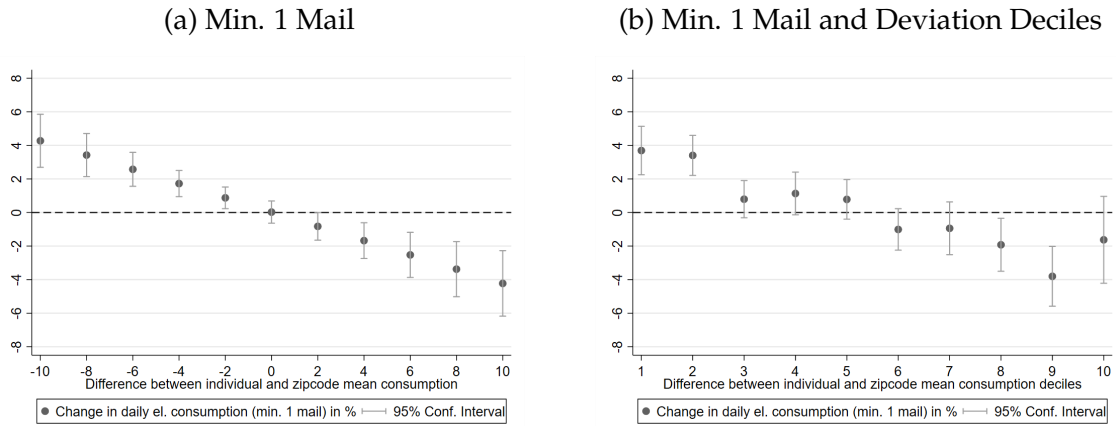
Rather strong positive and negative electricity changes can be seen at the lower and upper end of the difference between households' consumption and the zip code mean. However, 95% of the sample show deviations between -6.3 and $+5.3$ kWh per day, with only 5% depicting deviations below or above those levels.

An even more flexible heterogeneous pattern is seen when examining treatment effects according to deciles of the deviation of the mean zip code consumption from a household's baseline consumption. The results of this model specification using interactions between the treatment dummy and a dummy indicating into which decile of the deviation distribution a household falls are presented in Table A3 in the appendix.

To understand the pattern of heterogeneity with respect to deviation deciles, we again zoom in to the marginal effects corresponding to different deciles of the deviation. Overall, the distribution of the effect sizes shown in Figure 2 (b) shows a similar pattern as the linear form in Figure 2 (a), with boomerang effects for households whose baseline consumption lies below the zip code mean (deciles 1 to 5) and consumption reductions for those with baseline consumption levels above the zip code mean (decile 6 to 10). However, in contrast to the linear form, Figure 2 (b) shows that reductions in daily electricity consumption are only significant in the 8th and 9th decile of the deviation distribution and become insignificant again with very high positive deviations from the zip code mean as included in the 10th decile. The mean deviations in the 8th and 9th decile are at around 1.89 and 3.9 kWh and effect sizes are at -1.92 and -3.80% , respectively. Hence, for these households, effect sizes are of similar magnitude as consumption reductions found by Allcott (2011) and Henry et al. (2019) for the U.S., which lie between 1.4 to 3.3% of baseline consumption. On the other hand, boomerang behavior in daily consumption for households that have a consumption below the zip code mean is only significant in the first and second decile, where households' consumption levels lie on average 5.57 or 3.66 kWh below the zip code mean. The sizes of the boomerang effect, ranging from 3.69 to 3.40%, are non-negligible and are of similar magnitude as the consumption reduction in the 9th decile.

The heterogeneous effect of the social norm based HERs may be a result of moral licensing and moral cleansing behavior: Households that already perform better than the social norm compensate this moral behavior by consuming more electricity (moral licensing), whereas households that consume more than the perceived norm reported by the HER try to become more moral and consume less (moral cleansing) (see e.g. Dütchke et al. (2018)). At the same time, we do not observe any significant moral cleansing effect for households in the 10th decile of the zip code deviation whereas we observe a significant moral licensing effect in the first decile. In addition, 20% of our sample increase consumption on average by 3.69 and 3.40%, whereas only 10% of

Figure 2: Effect of HER depending on deviation of mean zip code consumption from individual baseline consumption for different specifications.



the sample decrease consumption with similar magnitude as the other 10% reveal an average reduction of only 1.92%. This asymmetry indicates that the moral licensing effect is stronger than the moral cleansing effect and points into the direction of the results from Ho et al. (2016), who study both in a lab and a contingent valuation framed field experiment the effect of induced culpability on individuals' behavior and find that the effect is larger when the information makes people feel good about themselves.

As a robustness test, we show that these results do not change significantly when restricting the sample to households that received all 4 mails. The overall effect on electricity consumption for this group is slightly smaller, but also insignificant, whereas significant heterogeneity with respect to the deviation from the mean zip code consumption can also be observed for this sub-sample (Table A2 and Figure A4). Hence, our results are robust to the number of mails that households receive.

Given the identified heterogeneous treatment effects, we test whether electronic HERs may be a cost-effective intervention in low-consumption countries like Austria and especially for low-consumption eco-electricity customers. Allcott (2011) and Andor et al. (2020) both show that the cost-effectiveness of the HER intervention depends on the treatment effect size, the electricity consumption level, the carbon intensity of electricity generation, as well as the cost of the intervention itself. Our results show that social comparison based HERs lead to adverse boomerang and overall null effects

when sent to our Austrian sample households. The heterogeneity analysis however reveals that certain households respond with significant consumption reductions as desired. If HERs are exclusively sent to those 20% of households whose consumption lies above the zip code mean and who were identified in our analysis to significantly reduce consumption, the HER intervention can successfully reach its electricity consumption reduction target. Assuming targeting based on households' deviation from the zip code mean, we test whether sending HERs to these specific customers with respective expected effect sizes results in a cost-effective intervention by determining the emission abatement costs of the HER intervention and comparing them with the social cost of carbon.

According to our decile analysis, significant electricity consumption reductions in the sample are achieved for households whose consumption levels lie on average about 1.89 to 3.90 kWh above the zip code mean. For these deviations, effect sizes are in the range of 1.92 to 3.80%. Taking the average consumption level of 7.70 kWh and the frequency of quarterly mails in the RCT, we can calculate the costs of the HER intervention per kWh of electricity saved according to equation (3)²:

$$\text{Cost} - \text{Effectiveness} = \frac{\text{Cost per HER} * \text{HER per Year}}{\widehat{\frac{ATE}{100}} * Y_0 * 365}, \quad (3)$$

Based on carbon intensity data from official data sets (IEA, 2021), we can then calculate the emission abatement costs of the HER intervention. For the sample, the costs lie between \$47 and \$92 per metric tonne CO₂ (Table 3). Using the comparatively higher average consumption level for the Austrian population leads per definition to lower abatement costs between \$33 to \$65 per metric tonne CO₂.

According to a first-best solution, carbon prices should equal the social cost of car-

²We assume that in contrast to letter-based HERs, sending out e-mails does not cost anything at all, but designing the HERs and withdrawing the social comparison information for every household leads to administrative cost of \$0.20 per HER. This figure may be conservative, as we expect the administrative cost to be one-time fixed costs for a computer scientist to prepare the programming that yields the social comparison for every household based on consumption data that usually is already available to every energy utility. As comparison, Allcott (2011) and Andor et al. (2020) assume cost of \$1 per HER for sending letter-based HERs and assume no administrative cost for simplicity.

Table 3: Cost-effectiveness of HER interventions.

| | (1) Average electricity consumption in kWh | (2) CO ₂ emissions in g/kWh | (3) Costs in Cents/kWh saved | (4) Abatement cost in \$/t CO ₂ |
|---------|--|--|------------------------------------|--|
| Austria | 4,002 | 161 | 0.52 – 1.04 | 33 – 65 |
| Sample | 2,809 | 161 | 0.75 – 1.48 | 47 – 92 |

Notes: Our calculations assume administrative cost of 0.20US\$ per HER, four HERs per year and average electricity reductions of 1.92 – 3.80%. Average electricity consumption data for 2015, the year which is mostly covered by our treatment period, is taken from Statistik Austria (2021b) and CO₂ intensities from electricity generation from 2015 as documented by IEA (2021).

bon. Comparing our calculated abatement cost to a proxy of the social cost of carbon, the most recent prices of the European Emission Trading System (EU-ETS), which have risen to \$67 per tonne of CO₂ (ECB, 2021)³, abatement cost of the HER intervention are in line with carbon pricing, both for overall consumption levels in Austria and our sample households. Hence, the identified effect sizes of our study imply that targeted and electronically-transmitted HERs may be a cost-effective measure to reduce household electricity consumption of Austrian households and even of eco-electricity customers. Yet, targeting needs to be based on the comparison of households' consumption levels with their peers, as we are otherwise unable to identify substantial and significant consumption reductions. Especially over time, with the administrative cost of a one-time preparation of the electronic HER approaching 0 at the margin, cost-effectiveness can be achieved in a country that has a rather renewable energy mix and hence low carbon intensity, with customers that have rather low consumption levels and treatment effect sizes that are moderate compared to what Andor et al. (2020) argue is necessary for letter-based HERs in Germany⁴. However, even with cheaper electronically-sent HERs, cost-effectiveness is highly unlikely without targeting as the pronounced boomerang effects of low consumers would offset the comparatively smaller reductions of high consumers.

³In the last IPCC Report, scholars suggested higher prices for 2030, ranging from \$135 to 5500 per tonne of CO₂ (IPCC, 2018).

⁴Based on their cost-effectiveness analysis, Andor et al. (2020) conclude that effect sizes of 6.6% would be necessary in Germany.

5 Conclusions

This study examines changes in household's electricity consumption following the receipt of electronic home energy reports (HERs). Based on an RCT in Austria, our results indicate that on average, electronic HERs do not lead to significant changes in electricity consumption of Austrian households. Given the recent findings by Andor et al. (2020), which point out that effect sizes are too small to make HERs a cost-effective instrument to reduce household consumption in Germany, our null results seem to support this finding despite looking at cheaper, electronic HERs. However, further analyses reveal a strong heterogeneity in the treatment effect: Households with high baseline consumption levels compared to their neighbors significantly decrease their consumption, and effect sizes are in line with findings from the U.S.. Yet, this positive effect comes at the cost of a significant increase in consumption of low-consumption households. In line with findings from electronic HERs in Australia (Byrne et al., 2018), we document a pronounced and significant boomerang effect for low consumers. In contrast to recent studies, we only find this heterogeneity with respect to the deviation from the social norm, whereas treatment effects according to baseline consumption deciles do not reveal any heterogeneity.

Hence, our results imply that giving social comparisons to households that already show energy saving behavior may backfire, as these households may be prone to moral licensing when seeing that they are performing better than their peers. Instead, we argue that HERs can only be a cost-effective intervention to combat climate change, if they are exclusively targeted to households whose consumption levels lie above those of their neighbors. Based on deciles of households' deviation, we find that only 20% of the whole sample fall within households that have consumption levels above their peers and react with significant consumption reductions.

Our cost-effectiveness calculation shows that effect sizes of households that reduce their consumption are large enough to ensure cost-effectiveness of the HER intervention in Austria as long as the reports are targeted only at these households. This result

holds up even though our sample households have already quite low consumption levels.

Looking into the future, rising carbon prices, which are a proxy for the real social cost of carbon, will make HER abatement cost relatively lower on the one hand, but reduce the carbon intensity of electricity generation on the other hand, in turn leading to increasing abatement cost of the HER intervention. Thus, effect sizes similar to those identified in the U.S. may in the long-term not be sufficient to ensure cost-effectiveness. Another point left open for discussion is the question of the effectiveness of the intervention in reducing emissions at a large scale. The need to target specific households points out that not all households can be addressed by the intervention, so that overall emission reductions remain quite small and despite cost-effectiveness, the impact may be rather low.

Appendix A

Figure A1: Social comparison element in HER (Translation of the original German Version).

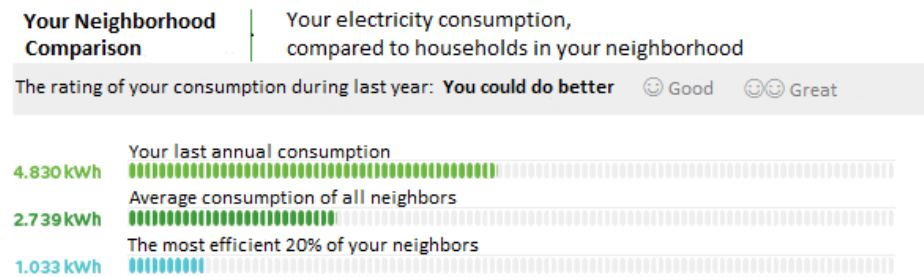


Figure A2: Number of mails received by treated households until end of study.

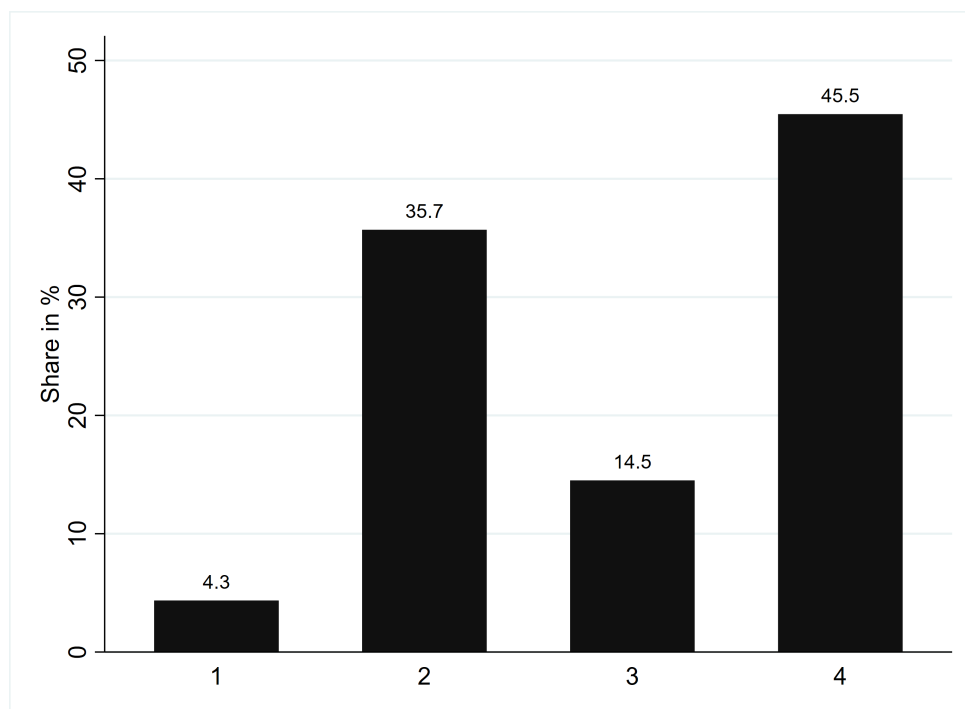


Table A1: Comparison of average consumption levels in sample with Austrian population, by county.

| | Estimation Sample | Austria | Sample Share (in %) |
|-------------------|-------------------|---------|---------------------|
| Wien | 2,290 | 3,261 | 50.22 |
| Niederoesterreich | 3,636 | 4,698 | 21.27 |
| Oberoesterreich | 2,942 | 4,555 | 10.34 |
| Salzburg | 2,836 | 5,262 | 0.59 |
| Tirol | 2,844 | 5,146 | 1.56 |
| Burgenland | 3,599 | 5,408 | 0.50 |
| Steiermark | 3,145 | 4,832 | 13.90 |
| Kaernten | 4,005 | 5,190 | 1.63 |
| Austria | 2,810 | 4,002 | |

Notes: Average electricity consumption data for Austria taken from Statistik Austria (2021b) for the most common treatment year of our RCT, 2015. Average electricity consumption data for 2015 for each county taken from Statistik Austria (2021a).

Table A2: Average treatment effect (ATE) on households' electricity consumption with sub-sample of households that received all 4 mails.

| | Main | | Linear deviation | |
|--------------------------------|--------|---------|------------------|---------|
| | Coeff. | s.e. | Coeff. | s.e. |
| T_{all4} | 0.036 | (0.528) | -0.081 | (0.538) |
| $T_{all4} * \text{Difference}$ | – | – | -0.451*** | (0.140) |
| Constant | 6.305 | (7.636) | 7.183 | (7.631) |
| R^2 | 0.0961 | | 0.0996 | |
| Observations | 6,561 | | 6,561 | |

Notes: Robust standard errors are in parentheses. *** denotes significance at the 1 %.

Table A3: Average treatment effect (ATE) on households' electricity consumption according to difference between household and zip code mean consumption deciles.

| | Min. 1 Mail | | All 4 Mails | |
|-----------------------------|-------------|---------|-------------|---------|
| | Coeff. | s.e. | Coeff. | s.e. |
| T | -0.059 | (2.492) | 7.963 | (4.978) |
| $T * \text{Deviation}_1$ | 3.751 | (2.578) | -4.342 | (5.084) |
| $T * \text{Deviation}_2$ | 3.462 | (2.555) | -4.854 | (5.057) |
| $T * \text{Deviation}_3$ | 0.852 | (2.542) | -7.342 | (5.035) |
| $T * \text{Deviation}_4$ | 1.193 | (2.556) | -7.149 | (5.067) |
| $T * \text{Deviation}_5$ | 0.841 | (2.544) | -7.440 | (5.030) |
| $T * \text{Deviation}_6$ | -0.949 | (2.547) | -9.712* | (5.030) |
| $T * \text{Deviation}_7$ | -0.883 | (2.591) | -9.742* | (5.131) |
| $T * \text{Deviation}_8$ | -1.864 | (2.612) | -9.734* | (5.102) |
| $T * \text{Deviation}_9$ | -3.743 | (2.626) | -10.878** | (5.150) |
| $T * \text{Deviation}_{10}$ | -1.568 | (2.807) | -10.210* | (5.426) |
| Constant | 2.971 | (8.230) | 4.220 | (7.353) |
| R^2 | 0.0971 | | 0.1021 | |
| Observations | 8,994 | | 6,561 | |

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 1 % and 5 % level, respectively.

Figure A3: Effect of HER depending on pre-treatment consumption deciles.

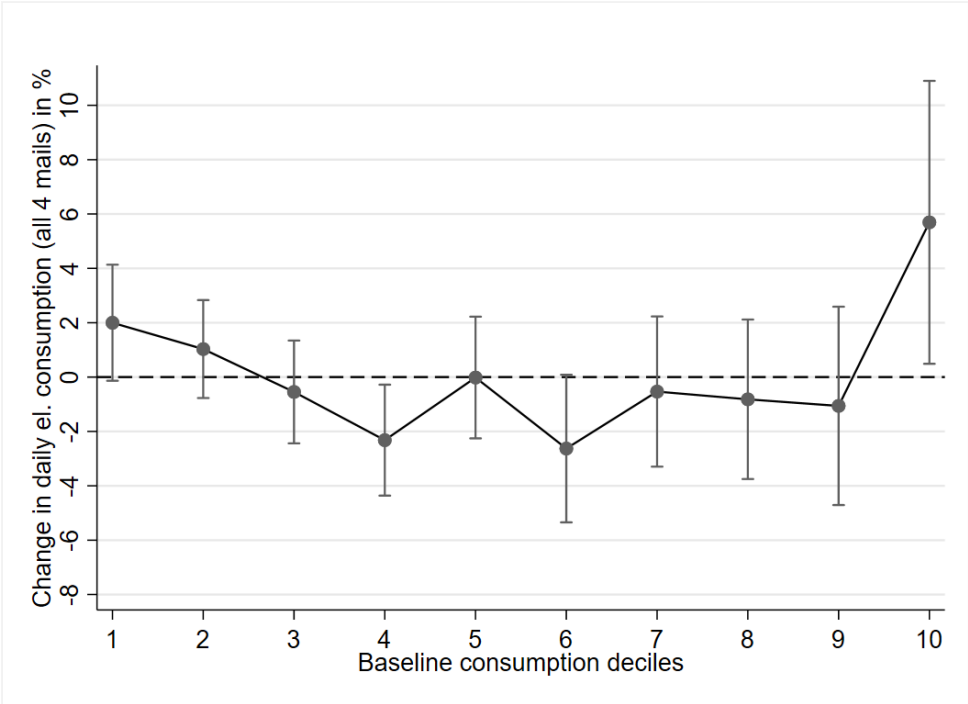
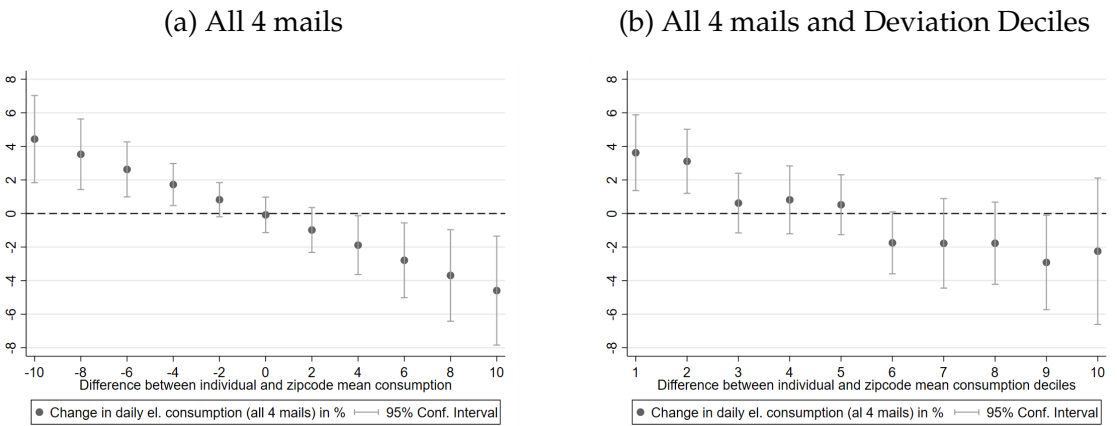


Figure A4: Effect of HER depending on deviation of mean zip code consumption from individual baseline consumption for different specifications and sub-sample of households that received all 4 mails.



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