Peak demand and time-of-use pricing in a field study of residential electricity demand in Germany

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Abstract

In this paper we evaluate the effects of time of use (TOU) pricing in a field experiment in Germany on the ratio of residential peak to off-peak demand, which involves more than 1500 households in the TOU treatment and the control group. The TOU experiment lasted for six months and the ratio of peak-to off peak prices was 177%. Results from econometric difference-in-difference analyses suggest that

TOU pricing corresponds to average percentage reductions in peak-demand of 6% to 7%, for a household in the TOU treatment group. In comparison, the TOU tariff was not found to affect off-peak demand. Households mainly respond to TOU tariffs by shaving peak demand, but not by shifting demand from peak periods to off-peak periods. Thus, TOU pricing also lowers total electricity use. Our findings further suggest that there is no difference in the effects of TOU pricing between workdays and weekends. Finally, we find no differences in the effectiveness of TOU pricing over time.

1. Introduction

Setting electricity prices at levels reflecting the marginal costs of production has long been advocated as a means to improve efficiency (Boiteux 1949, Houthakker 1951, Hirshleifer 1958, or Kahn 1970), to trim down price volatility at wholesale markets, to lower peak load or to reduce the need for reserve ca-pacity or for additional investments in the transmission infrastructure (e.g. Borenstein 2005, Faruqui et al. 2010, Faruqui and Palmer 2011, Joskow 2012). Ideally, such dynamic prices reflect the fluctuating real-time scarcity in the system's capacity over time. Also, as pointed out by Borenstein and Holland (2005), dynamic pricing increases the elasticity of (residual) demand, and may hence limit utilities' ability to exert market power in unregulated wholesale markets. Finally, dynamic pricing also helps to integrate fluctuating renewables (notably wind and solar) and plug-in electric vehicles into the electric grid and is thus conducive to meeting energy and climate policy targets. Dynamic pricing for residential customers typically include time-of-use (TOU) pricing, real-time-pricing (RTP) and critical-peak pricing (CPP) schemes. While under TOU pricing the tariff rates differ by a limited number of time blocks (usually peak and off-peak periods), under RTP electricity prices may vary hour-by-hour, typically based on the day-ahead wholesale price. Under CPP, the tariff rate is fixed for most of the day, but may be extremely high during a few pre-specified hours. Implementation of these dynamic tariff schemes requires so called smart meters / Advanced Metering Infrastructure (AMI) enabling two-way communication between the meter and the utility. For the European Union, the EU Energy Services Directive 2006/32/EC, requires smart meters to be installed in EU Member States when an existing meter is replaced, when a new building is connected to the grid, or when an existing building undergoes major renovations as far as this is technically feasible and economically reasonable. Directive 2006/32/EC also requires that since the end of 2010 utilities offer final customers of electricity a tariff which varies by load or by time of use. The EU Electricity Directive 2009/72/EC foresees the roll-out of smart meters to 80 % of consumers in EU Member States by 2020, and full deployment by 2022, but the roll out of smart meters in the Member States may be subject to a cost-benefit analysis (CBAs). Among others, consumption reduction and the transfer of load from peak to off-peak periods are considered relevant quantifiable indicators in these CBAs (European Commission 2012a, b). In accordance with the principle of subsidiarity in the EU, Member States decide on their own implementation strategies.

Currently, around 10% of all households in the EU are equipped with some kind of smart meters (European Commission 2011a), but the shares differ substantially across Member States. While in Italy, France or Sweden smart meters are installed in most residential households, the penetration of smart meters in Germany, Austria or the Czech Republic is rather low. In the majority of EU countries, smart meters and dynamic pricing schemes are just starting to diffuse in response to the EU regulation, primarily via pilot projects (see Torriti et al. 2010, European Commission 2011b). ´

Since the 1970ies more than hundred (quasi)experiments involving different types of feedback on electricity use and dynamic pricing schemes in the residential sector have been carried out, mostly in North America. The majority of dynamic pricing experiments involve TOU pricing. For example, around 70% of the dynamic pricing pilots included in VaasaEET (2011) employed TOU pricing and 5% included RTP, but technological progress is expected to further advance the use of RTP schemes. Other reviews of dynamic pricing projects in the residential sector include Faruqui and Malko (1983), Faruqui and Sergici (2010), Newsham and Bowker (2010), Ehrhardt-Martinez et al. (2010), Faruqui and Sergici (2011) and Faruqui and Palmer (2012). The survey results suggest that residential consumers respond to financial incentives provided by dynamic pricing in the desired way, i.e. they shave peak loads and they reduce the ratio of peak to off-peak demand. However, whether this also entails a shift from peak-load to off-peak load is often not explored, since the impact of dynamic pricing on off-peak load it is not the primary purpose of such programs. Studies analysing the effects of TOU pricing on off-peak demand find mixed effects, i.e. the level of off-peak demand was found to increases, to decrease or to be stay the same upon the introduction of TOU tariffs. In a recent study, Allcott (2011) finds that RTP leads to a mere conservation of energy electricity in peak hours but not to a shift of energy electricity from peak to off-peak hours. Also, the empirical evidence is mixed, whether the effects of TOU pricing differ between workdays and weekend days, and whether observed effects are persistent or transitory. In general, TOU pricing may be expected to lower peak demand by around 5%, but the range of findings is much wider.

The response in the peak to off peak demand is typically estimated via the cross price elasticity of the elasticity of substitution. In the studies surveyed by Faruqui and Malko (1983) the cross-price elasticity of peak demand ranges from 0 to 0.28 and is smaller than the own price elasticity. Drawing on the same pool of experiments as Faruqi and Malko (1983) Caves et al. (1984) estimate the elasticity of substitution (for the summer season) for the typical consumer at -0.14, but -0.07 for a household with no major appliances and -0.21 for a household with all major appliances (including air conditioners). In a more recent survey, Faruqui and Sergici (2010) report substitution elasticities between -0.07 and -0.40.

Substantially higher peak shaving and shifting rates can be achieved if enabling technologies are employed. For example, smart appliances (e.g. smart air conditioners or smart washing machines) are “set-it-and-forget-it” type technologies, which respond to information from the grid or the smart meter and allow consumers to easily adjust their own energy use. In general, larger price differentials between peak and off-peak periods are associated with larger load shifts, but at a decreasing rate (e.g. Faruqui and Palmer 2012). It should be kept in mind though, that comparing studies and drawing consistent conclusions is difficult since the projects differ in terms of design, methodology, and scope.

In this paper, we econometrically estimate the effects of TOU pricing on the ratio of peak to off-peak demand of household electricity consumption. Our data stems from a field trial carried out in eight German municipalities and one Austrian utility in 2010 involving more than 1500 households, of which more than 100 faced TOU pricing. The (quasi) experimental design allowed for comparisons of these demand variables over time (before the TOU tariff was implemented and afterwards) and across the treatment group (TOU group) and a control group. We also explore whether the effects of TOU pricing differ between workdays and weekends, and whether they are persistent or fade over the time the TOU field study was conducted. Econometric difference-in-difference estimations are carried out to estimate the effects.

The remainder of our paper is organised as follows. Section 3 describes the design of the field trial in detail. The statistical framework is developed in section 4. Data and variables are described in section 5. Section 6 presents and discusses the results of the econometric analysis. Section 7 concludes.

2. Design of field trial

Eight municipalities located in five federal German states participated in the demand response field trial: Celle, Hassfurt, Kaiserslautern, Krefeld, Münster, Oelde, Schwerte and Ulm. In addition one municipality from Austria, Linz, also joined the field trial. Around 2000 participating households were randomly assigned to a pilot group and a control group of about equal sizes (see also Schleich et al. 2013).

The demand response field trial included two types of “treatments”. First, pilot group households received feedback on their electricity use and information on energy saving measures (either once a month by post or via access to an internet portal with a one day delay). For technical reasons, the starting dates of this “feedback pilot” ranged from May to November of 2009 for the different municipalities. All feed-back pilots ended in November of 2010.[1] Second, a subset of 100 pilot group households in the German municipalities

[1] Schleich et al. (2013) analyze the „feedback pilot“ for the largest participating municipality, i.e. Linz, and find that on average households saved around 4.5% of total electricity consumption. Since data on electricity consumption prior to the start of the „feedback pilot“ was not sufficiently available, a difference-in-difference approach to assessing the effects of feedback on electricity consumption was not feasible. Instead, the analysis by Schleich et al. (2013) is based on cross-sectional data

Kaiserslautern, Ulm and Schwerte also participated in a "TOU pilot", which lasted for six months, from May to October 2010 (TOU period). Participation in the TOU-group was voluntary, and may thus not have been be totally random.

For households in the "treatment" group (TOU group) in the TOU pilot the tariff rate of 27.4 € ct/kWh during peak times (10 am to 6 pm) was almost twice as high as during off-peak times (15.5 € ct/kWh) (see Table 1). Note that the same TOU rates were applied to workdays and weekend days. All other households, i.e. the original control group households and the pilot group households without TOU tariff, continued to face the standard (time-constant) rate (20.65 € ct/kWh for Kaiserslautern, 23.07 € ct/kWh for Ulm and 25.14 € ct/kWh for Schwerte). The TOU tariff corresponds to an increase in the price level during the peak period by about 20.9%, and to a decrease in the price level during the off-peak period by about 31.6% for the average TOU group household.

Table 1 Tariff rates and timing in the field experiment

	Before May 2010		May to October 2010	
	Peak	Off peak	Peak	Off peak
TOU group	standard	standard	27.4 € ct/kWh	15.5 € ct/kWh
Control group	standard	standard	standard	Standard

Thus, the TOU pilot did not encompass enabling technologies allowing for direct load control. Instead observed changes in load patterns are attributed to indirect factors mainly a changed behaviour of household members, induced by the change in the tariff structure. Also note that the lack of variability in peak/off-peak tariffs in the field experiment does not allow to econometrically estimate the own price or cross-price elasticites, or the elasticity of substitution. Last but not least, the timing and the duration of the field trial and of the TOU experiment did not lead to sufficient data to allow comparisons of observations for the same months across different years.

3. Statistical model

We analyse the effects of TOU pricing on the ratio of peak to off-peak demand, which may be described as[2]

$$Y_{it}^{P/O} = \delta_0 + \beta_0 TP_t + \beta_1 TARIFF_{it} + \mu_i + \varepsilon_{it} \qquad (1)$$

where $Y_{it}^{P/O}$ reflects the share of peak electricity demand to off-peak demand of household i during period t. TP is a dummy variable which takes on the value of one, if the observation relates to the period, where the time-varying tariff is in place (TOU period), and zero otherwise. Hence TP captures effects on demand which are the same across the TOU group and the control group, but which vary over time. TARIFF is a dummy variable, which takes on the value of one if household i belongs to the tariff-pilot group in period t, and zero otherwise. The variable μ_i stands for an unobserved effect which varies across households, but is constant over

[2] See for example, Gleerup et al. (2010) for a similar approach to analyze the effects of providing feedback about household electricity consumptions. See also Moffit (1991), Meyer (1995) Heckman et al. (1998) or Blundell and Costa Dias (2000). Gleerup et al. (2010) refer to Duflo et al. (2008).

time. For example, μ_i could reflect a household's unobserved attitude towards electricity savings, which may differ between the TOU group and the control group. In panel data analysis, μ_i is also referred to as a "fixed effect". In particular, μ_i may be correlated with TARIFF, and hence a household's decision to participate in the tariff-group, e.g. because it has a higher potential to shift loads.[3] The idiosyncratic error term ε_{it} varies over individuals and time. The parameter β_0 reflects the difference in peak demand between periods for the control group. Most notably, β_1 captures the effect of introducing the TOU tariff on peak electricity demand.

Differencing equation (1) by one period yields

$$\Delta Y_{iTP}^{P} = \beta_0 + \beta_1 TARIFF_{iTP} + \Delta\varepsilon_{iTP} \tag{2}$$

Note that $TP_t = 1$ for all households. Also, the individual „fixed effect" μ_i drops out when taking the first difference. Hence, any unobserved household-specific factor which affects selection into the tariff-group does not lead to a biased parameter estimate of β_1. With only one observation for each household, time subscripts may be dropped, and equation (2) yields the so called "difference-in-difference" (DiD) estimator. The DiD approach implies that the effects of "background" variables which are common for the tariff group and the control group (for instance, a change in daylight savings time cancel out because one looks at differences between the TOU and the control groups. Likewise, differencing between periods before and after the TOU tariff was introduced implies that permanent differences between households such as different weather conditions or starting positions (including also participation in the pilot or control group) are removed. The same reasoning also holds for unobserved latent household characteristics of the subjects as long as these characteristics remain constant over time, i.e. continue to have the same influence on peak demand before and after the new tariff system was introduced. Identification then makes use of the so called common trend assumption, i.e. the expected change in peak demand under the old tariff scheme would be the same for the TOU group and the control group in the absence of the TOU pricing.

Including a set of other "explanatory" variables Z_i may control for other factors (besides participation in the TOU group) which affect the change in peak demand between periods (e.g. Angrist and Pischke 2009, p. 23). Z_i may differ systematically between the TOU group and the control group, and may also be correlated with $TARIFF_i$ or with μ_i, and hence with participation in the TOU group. The regression equation may then be written as

$$\Delta Y_i^{P/O} = \beta_0 + \beta_1 TARIFF_i + \beta_2 Z_i + \Delta\varepsilon_i \tag{3}$$

Note that adding Z_i as additional regressors on the right-hand-side of equation (3) reduces the standard errors and hence renders the estimates more efficient (precise) even if the participation in the TOU group is independent of Z_i.

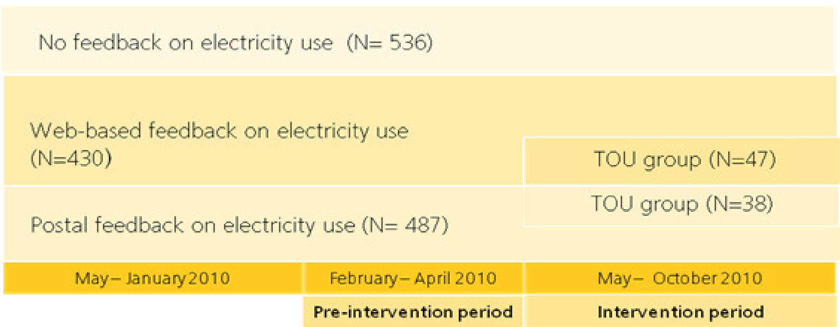
[3] In this case, estimating (1) via simple OLS would result in biased parameter estimate of β_1.

3. Data, variables and summary statistics

The smart metering systems provided hourly consumption data, which could be read at the end of each day by a remote system. Since the meters were usually installed in a cellar room, the display was not visible to the consumer without additional effort. Data on electricity consumption was stored in the meter and transferred once a day to a data concentrator via a narrow band power line communication. The data concentrator collected the data from several meters and transferred them twice a day to the data server of the utility. These data were then transported via automated data export to the project server platform.

During the field trial computer-assisted telephone interviews were carried out with all households employing standardized questionnaires about household socio-demographic characteristics and appliance stock. Eventually, after correcting for households which relocated during the time of the field phase or which encountered insurmountable technical problems, data for all relevant variables was available for 1538 households, of which 85 are TOU group households (47 from “web feedback group” plus 38 from “postal mail feedback group”) and 1453 are control group households (536 from “no feedback group” plus 430 from “web feedback group” plus 487 from “postal mail feedback group”). By construction, 100% of the TOU households had also received feedback on electricity use prior to the start of the TOU experiment. For the control group, this share is 63.1%. See also Figure 1.

Figure 1. Design of field trial on TOU pricing



Our dependent variable (diff_peak_offpeak_ratiol) measures the difference in average daily peak demand in Wh in the TOU period compared to the pre-intervention period, i.e. the period before the TOU tariff was introduced. The pre-intervention period is February to April 2010. Average daily peak demand per household was constructed by adding up demand per hour during peak hours (10 am to 6 pm) for the TOU period for each household and dividing this sum by the number of days in the TOU period. Similarly, the second type of dependent variable (diff_offpeak_level) corresponds to the difference in average daily demand during off peak hours.

To explore whether the effects differ between workdays and weekends, we also conduct the econometric analyses for workdays in addition to all days during the week. Hence, four different dependent variables are considered in total. Likewise, to analyse whether the effects are persistent over the TOU period, we consider the first three months of the TOU period (May to July 2010) in addition to the full TOU period (May to October 2010).

The additional variables included on the right-hand-side of equations (3), and (4) may also proxy for factors affecting differences in the “dependent” variables over time, which are not related to the TOU pricing. For example, composition of households (number of members, age) may reflect presence in the apartment during peak and/or off-peak hours and hence affect electricity demand patterns over time (e.g. seasonal fluctuations).

Three variables reflect age composition and are calculated as the number of household members in the following age groups: 0-17 (ageto17), 18-60 (ageto60), >60 (age60plus). The remaining explanatory variables reflect the average monthly electricity consumption in kWh during the pre-intervention period (electricity), the size of the apartment (floorsize) in m^2 and the number of electric appliances (appliances). Hence, the additional explanatory variables are quite similar to those employed by Gleerup et al. (2010).

Table 1 also provides descriptive statistics of the explanatory variables used in our econometric analyses for the TOU group and for the control group. For example, a mean of 0.44 for age60plus means that on average there were 0.44 people aged 60 or older in a sample household. The figures in Table 2 generally indicate that households in the control group and in the TOU group are quite similar, but small differences exist. T-tests for means indicate that statistically significant differences exist for electricity only ($t = 3.13$, $p<0.01$). This difference may be explained by the fact that households lower electricity use in response to feedback. While all TOU households had received feedback on electricity consumption prior to the start of the TOU experiment, more than 1/3 of the control group did not receive such feedback. [4]

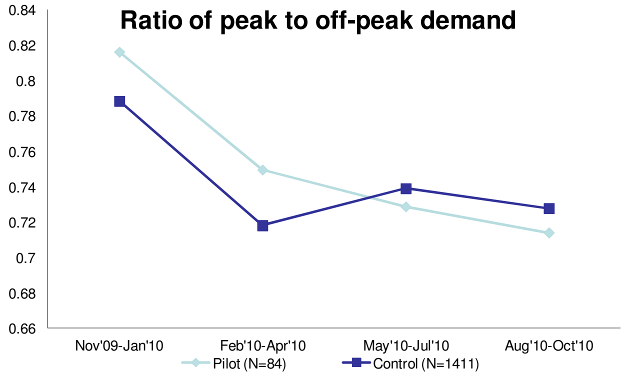
Table 2 **Descriptive statistics of the dependent and explanatory variables**

Variable	Unit	TOU group mean	Control group mean
peak_off_peak ratio (pre intervention)		0.75	0.72
ageto17	number	0.60	0.57
ageto60	number	1.41	1.49
age60plus	number	0.44	0.44
Electricity	kWh/month	243	293
Floorsize	m^2	104	110
Appliances	number	12	12

Our estimation (and identification) procedure hinges on the common trend assumption. While one cannot test this assumption, we follow Hastings (2004) and visually inspect whether it appears plausible using observations prior to the reference period (here for November 2009 until January.2010). According to Figure 2 this seems to be the case.

[4] We also estimated a discrete choice Probit model of participation in the TOU program, similar to Gleerup et al. (2010). In addition to the variables described in Table 2 municipality dummies were included as covariates to capture the fact that TOU tariffs were only available in some municipalities (because of collinearity *peaklevel* but not *electricity* was included). Except for the parameters associated with the municipality dummies for Kaiserslautern, Schwerte and Ulm, no other parameter turned out to be statistically significant (at $p<0.1$). That is, relying on information about observable household characteristics we have no indication that participation in the TOU group is systematically biased.

Figure 2 **Ratio of peak to off-peak demand before and after the intervention**



4 *Results*

Equation (3) is estimated separately via OLS regression. Table 3 presents the estimates together with heteroskedasticity-robust standard errors in parentheses. The first and second results columns give the results for all days and for workdays for the entire TOU period (May to October). Results for the first three months of the TOU period are displayed in columns three and four.[5]

[5] Tests for collinearity based on variance-inflation factors (VIFs) suggest that the covarates are not highly inter-correlated. All VIFs are below 2.5 and the mean VIF is 1.57.

Table 3: **Difference-in-difference regression estimates of the average effect of TOU pricing on the peak ratio**

	diff_peak_offpeak_ratio			
	May to October		May to July	
	all days	workdays	all days	workdays
tariff	-0.0362 ***	-0.0306 **	-0.0372 ***	-0.0328 *
	(0.0122)	(0.0149)	(0.0143)	(0.0182)
ageto17	-0.0141 ***	-0.0136 ***	-0.0116 ***	-0.0099 **
	(0.0039)	(0.0040)	(0.0044)	(0.0046)
ageto60	-0.0046	-0.0032	-0.0080	-0.0070
	(0.0055)	(0.0056)	(0.0058)	(0.0060)
age60plus	-0.0055	-0.0042	-0.0059	-0.0050
	(0.0079)	(0.0083)	(0.0084)	(0.0085)
electricity	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
floorsize	0.0002 **	0.0002 **	0.0003 ***	0.0003 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
appliances	0.0015	0.0016 *	0.0011	0.0012
	(0.0009)	(0.0010)	(0.0010)	(0.0011)
constant	-0.0325 ***	-0.0300 ***	-0.0352 ***	-0.0283 **
	(0.0110)	(0.0112)	(0.0119)	(0.0127)
F	7.43	7.73	10.25	10.13
Prob>F	0.00	0.00	0.00	0.00
R^2	0.035	0.033	0.038	0.036
Sample size	1538	1538	1538	1538

Note: *** indicates significance at p<0.01, ** indicates significance at p<0.05 and * indicates significance at p<0.1 in an individual two-tailed t-test

For regression equations in Table 3, the parameter estimate associated with tariff is statistically significant (at p<0.01). Hence, the findings suggest that households respond to TOU pricing by lowering the peak share. Further, the parameter estimates of tariff hardly differ across columns in Table 3 and Table 4. From a statistical point of view, they are indistinguishable. [6]

The point estimates for the effectiveness of TOU pricing in Table 3 correspond to a reduction of the ratio of peak demand to off-peak demand by 3 to 4 percentage points. For and average day, these figures correspond to a reduction in the peak ratio of around 4.5% to 5.5%. Since the peak ratio is higher on a weekend than on a workday, the percentage change for weekends is at the lower end of this range.

Significant values for the covariates suggest that differences in the ratio of peak to off-peak demand between the pre-intervention period and the tariff period tend to vary with age composition, with the size of the

[6] We ran additional sets of regressions relying (i) on households from German municipalities only, and (ii) including only households which received feedback on electricity consumption prior to the start of the TOU experiment. Results of these additional regressions are generally quite similar to those presented, but standard errors are somewhat higher (note that the sample size is reduced to 465 for (i) and to 1002 for (2)). For example, the point estimate for the parameter associated with tariff is -0.047 for (i) and -0.048 for (ii) compared to -0.037 in the first results column in Table 4. The p-values are higher, but remain well below 0.01 in (i) and (ii). Hence, our results appear robust to alternative choices for the control group.

apartment (potentially reflecting lighting needs), with electricity use in the pre-intervention period and with the number of appliances.

The lack of variation in the tariff structure does not allow us to econometrically estimate price elasticities. Instead we manually calculate these elasticities using the regression results for the impact of TOU pricing on demand, and the changes in the tariff structure compared to the average electricity price for the TOU group households in the pre-intervention period. The calculated value for the elasticity of substitution is -0.07.

5 Conclusions

In this paper we evaluated the effects of TOU pricing in a field experiment in Germany on the ration of residential peak to off-peak demand. The (quasi) experimental design allowed for comparisons of these demand variables over time (before the TOU tariff was implemented and afterwards) and across a treatment group (TOU group) and a control group. The peak price was employed daily between 10 am and 6 pm between May and October in 2010 (TOU period). It was almost twice as high as the off-peak price during the remaining hours of a day. The peak price is about 21% higher and the off-peak price is almost 32% lower than the standard electricity price TOU group households had faced prior to the introduction of the TOU tariff. Unlike the TOU group households, the control group households continued to face the same standard electricity price as before. Econometric difference-in-difference estimations are carried out to assess the development of the electricity demand variables in the TOU period relative to a pre-intervention period (February to March) between the TOU group and the control group. The common trend assumption to identify the TOU effect appears to hold.

The point estimates correspond to average percentage reductions in the peak to off-peak ratio of 4.5% to 5.5%. Hence, our findings are well in line with the results from most TOU pricing experiments in other regions, even though in our study the ratio of peak to off-peak prices is “only” 177%, and hence lower than in most other TOU pricing studies. On the other hand, since residential electricity prices in Germany are much higher than for example in the US, the economic incentives to clip (and possibly shift) demand are also higher in Germany for a given peak to off-peak price ratio.

Further, our findings for the point estimates do not suggest difference in the effects of TOU pricing between workdays and weekends. Of course, from the perspective of the energy system, peak reductions are likely to create larger economic benefits on a weekday than on a weekend, since the load profile of the entire system is less pronounced on weekends, primarily because large parts of electricity demand from industry is missing. Likewise, our findings do not show differences in the effectiveness of TOU pricing over time. Since the experiment lasted for six months only, the change in demand patterns is likely to be the results of behavioural change, rather than investments in energy-saving (and possibly also smart) appliances. This, somewhat speculative conclusion is consistent with results from an ex-post survey – although the response rate was not high enough to allow for a statistical analysis. From this perspective, longer TOU periods would be expected to lead to stronger effects in the long run. On the other hand, the TOU effects may not sustain if households return to long-term habits after a certain time. Hence, future research could further explore the persistence of TOU effects. Future studies may also analyse whether TOU effects interact with socio-economic variables, attitudes, or individual and social norms.

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