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The hidden cost of real time electricity pricing *

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Abstract

In theory real time pricing ensures more efficient electricity markets than time of use pricing. However, people are prone to habits and regularity, so real time pricing may impose a greater cost of reacting on consumers. In a randomized field experiment we compared the cost of reacting to incentives under these two pricing regimes. We utilized smart-metered hourly power consumption to unobtrusively measure treatment effects. We found that real time pricing reduces consumer surplus from reacting to incentives by half, compared to reacting under a corresponding time of use pricing regime. This suggests a substantial economic value to households of the regularity and predictability provided by time of use pricing.

JEL Classifications: L51, L94, C93, Q41,

Keywords: real time electricity pricing, time of use electricity pricing, field experiment, household cost of reacting.

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I. Introduction

Imperfections of the regulated electricity markets have been studied by many economists beginning in the early 1950's (e.g. Houthakker 1951, Boiteux 1960) theoretically and later empirically. Allcott (2013) points out that distortions in the electricity markets are often caused by the way in which regulated utilities price their services. In the long run, traditional flat rate pricing leads to overinvestment in capacity if high peak supply is to be ensured (Borenstein 2005). Economic theory (e.g. Borenstein, Jaske, and Rosenfeld 2002) suggests that this excess in investment of capacity could be avoided if utilities used real time pricing (RTP) in retail markets. High peak prices would create an incentive for consumers to shift usage to lower price periods. Real time pricing would also help to accommodate variable supply sources such as wind and solar power generation, benefitting the environment and human health (De Jonghe, Hobbs, and Belmans 2011). In addition, a price responsive demand would drive overall costs down and discourage generators from exercising market power during high demand periods, as these instances would be reduced (Borenstein, Jaske, and Rosenfeld 2002).

The underlying assumption on which RTP theory is based is that the consumer costs of reacting to dynamic price variation is low, implying that consumers react to varying prices and that it is efficient to expose them fully to the power systems real time price variation. The theoretical and simulation work of Borenstein and Holland (2005) found that under this assumption, pricing schemes that are not allowed to vary over time for all consumers according to wholesale market cost fail to achieve first-best, even second-best price and investment level optimality. Allowing all consumers to see real time prices leads to a Pareto efficient allocation in the short-run and to long-run efficiency of capacity markets.

However, if consumers incur transaction costs in connection with observing prices, planning and implementing their reactions to price changes, then fully dynamic pricing may not be efficient. In fact, there is substantial evidence that we are prone to regularity, routine habits in our daily lives[1] and e.g. Macey and Brown 1983, Ehrhardt-Martinez 2011, Allcott and Rogers, 2014, Ito et al., 2018, suggest that this is also the case for activities that use power. If this is so, it may be costlier for consumers to react to power price changes that occur irregularly and that cannot be predicted compared to changes that occur regularly and can be predicted. It is the size of these transaction costs from reacting to RTP compared to time of use (ToU) pricing that we investigated[2]. In this

[1] This literature includes transportation choice (e.g. Aarts, Verplanken and Knippenberg 1998, Thogersen 2006, Gardner 2009), shopping behavior (Sheth and Venkatesan 1968, Chiu et al. 2012), recycling (e.g. Tonglet et al., 2004), exercise (Charness and Gneezy, 2009) water conservation (Ferraro et al., 2011).

[2] In addition, RTP exposes consumers to risk which implies a welfare cost if consumers are risk averse. There are also concerns about the wealth redistribution that RTP may cause (Borenstein, Jaske, and Rosenfeld 2002). We leave these concerns aside.

paper we quantify consumers' reaction to ToU compared to RTP tariffs and from this we derive the resulting relative consumer utility loss.

We designed a field experiment that allows us to compare reactions to ToU and RTP tariffs. All participating households were given incentives in the form of rebates, either to increase or decrease electricity consumption during the same specific 3-hour time slot each day. The only difference between the two treatments was how the direction of the incentivized consumption change was allocated. In the first treatment, hereafter called the ToU treatment, half of the households got the rebate to increase consumption; while the other half of the households got the same rebate to decrease consumption during the same time slot. In the second treatment, hereafter named the RTP treatment, the same rebate was applied during the same time slot, but the instruction to increase or decrease consumption changed randomly from one day to another.

As a result of the randomized allocation, households in either treatment had the same range of possibilities of response to incentives (e.g. by changing the timing or scale activities that use power, such as doing the laundry, dish washing, cooking, watching TV, etc.). Intuitively, the key difference between the two treatments was that households in the first treatment could plan ahead, adjust their habits and possibly their appliances because they knew that they would get the same incentive every day for the whole duration of the program. For households in the second treatment this was more difficult because incentives arrived in an unpredictable, randomized way as is the case with RTP incentives. Keeping in mind that the time of treatment for all the households was the same, the experiment design hence enabled us to investigate whether the households in the two groups had the same transaction costs for the reaction to the treatment.

By utilizing smart meters, we unobtrusively measured power consumption in our treatments. This allowed us to estimate the effect of the the two tariff structures. During the first two months of the experiment, we found that the RTP treatment induced half of the response compared to that of the ToU treatment. Assuming standard functional forms, this translates into a 50% reduction in consumer surplus under ToU tariffs when consumers instead are subject to RTP tariffs where habit adjustment and predictability is impeded. The advantage of RTP tariffs is that marginal costs of electricity production are precisely signaled to consumers. In theory RTP tariffs make it possible to generate a welfare gain from reallocating power production and consumption that can be shared between electricity consumers and utility owners. The hypothesis tested is that there may be important downside in the form of greater consumer transaction costs from reacting RTP tariffs that should be taken into account. Our result suggests that the optimal tariff structure is likely a combination of ToU and RTP tariffs, with ToU pricing possibly being the cornerstone of such a tariff system. Our results are, of course, particular for the electricity supply area and field setting we investigated. Nevertheless, the incentives in our experiment potentially affected the broad set of repeated household activities that use power such as cooking, doing the dishes, laundry, watching TV, etc. Thus, if seen in the broader context of inducing changes in household behavior, what we found for southern Denmark suggests that electricity consumers generally could have substantial added transaction costs from reacting to RTP tariffs.

Compared to the substantial body of literature on the impact of electricity pricing experiments[3], the innovation in our design is that we combine fixed and dynamic tariffs in a randomized trial so as to be able to control for confounders, making it possible to identify the cost to households for reacting to RTP vis-à-vis ToU tariffs. To our knowledge, this has not been attempted before.

In the following section we discuss the reasons for expecting increased transaction costs of reacting to RTP, compared to ToU pricing and how we will estimate the effects on consumers' utility to switching tariff systems. The third section provides a description of the field experiment. The fourth section presents and discusses our results and the fifth section draws the conclusions of the paper.

II. The cost of reacting to RTP tariffs

Habits allow us to expend less cognitive effort on life's smaller decisions, thereby reducing the conscious decision-making costs associated with that behavior. We often do the same things in the same way without thinking much about it. It may, for example, be efficient to start the washing machine in the morning before going to work and then loading the dryer first thing when returning from work. If this way of doing the laundry becomes a habitual part of the day's activities, it's done without much planning or deliberation and with a small risk of forgetting. Thus, habits imply lower cognitive costs of repeated behavior in connection with household production; but probably also imply reduced day-to-day responsiveness to changing conditions around the activity governed by a habit. However, when permanent changes in the conditions are perceived (e.g. a higher price of electricity in the peak load period), habits can presumably be re-optimized to take them into account. Verplanken et al., (2008) argues that new habits are formed after a disruptive change in the context in which the habits used to be activated (e.g. the birth of a child in the household, moving home). Allcott and Rodgers (2014) study suggests that such disruptive context changes needn't be dramatic. They find that introducing a nudge in the forms of the O-power energy report feedback to home owners, affects behavior through a combination of changes in energy utilization habits and changes to physical capital stock. Ito et al., 2018, who finds that changes in electricity rates can induce changes in habits associated with electricity consumption.

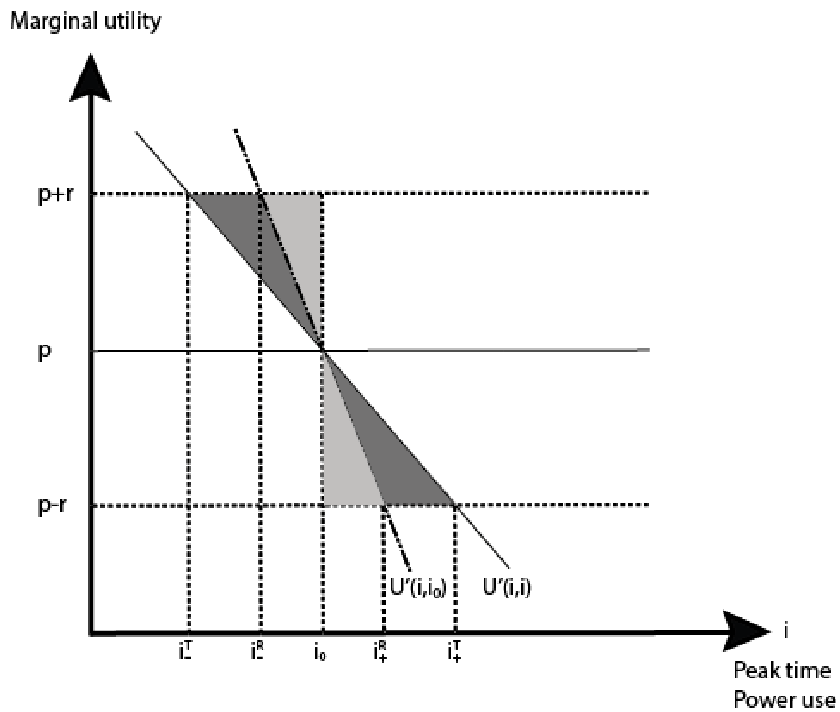
[3] Studies investigating reaction to time of use pricing are numerous (see, e.g. Faruqui and Sergici, 2010 for a comprehensive review of electricity pricing experiments) and more recently, a number of experimental investigations using real time pricing have been published (see e.g. Wolak, 2011, Kessels et al., 2016).

In terms of the habit model of Becker and Murphy (1988), it may be possible for a household to invest in a re-optimization of its stock of habits when electricity prices change. However, such a re-optimization is costly (in terms of effort) and so it is more likely to be worthwhile if the change in conditions is long lasting, than if the change is temporary. This implies that the marginal cost of reacting to a change in the conditions relevant for a repeated power using activity, likely depends on whether the change is anticipated to be temporary or permanent. When reacting to a temporary change in the electricity price under a RTP- tariff system, habits may not be re-optimized. If the household is to react to the price change, it must deviate from the consumption pattern for which habits are optimized. This entails the use of cognitive resources to evaluate, plan and execute the deviation each time a price change is announced, which may result in a smaller reaction to the price change. When reacting to a price change resulting from introducing ToU tariffs, the change in price is permanent (or at least long term). Re-optimizing habits to take the changed conditions into account may be worthwhile. If habits are re-optimized, this reduces the marginal cognitive cost and therefore increases the net benefits of reacting to the price change. This implies a stronger reaction to a given change in price, if it is implemented under a ToU tariff system compared to the same price change under a RTP tariff system.

We illustrate this in

Figure **1**, where electricity demand (i) during a given peak period of the day is depicted along the x-axis and marginal utility in monetary units along the y-axis. The current flat rate price of electricity which also applies during peak time is *p* and i_0^P indicates the scale of peak time power use at this price, for which we assume the household's habits are also optimized. Let *U'(i,h)* be the marginal utility from power consumption when habits are optimized for consuming *h* kWh of electricity during the peak. The broken curve $U'(i,i_0^P)$ in Figure 1 is the falling marginal utility of power consumption as peak consumption increases when habits are optimized for consuming i_0^P. The solid line curve *U'(i,i)* in Figure 1 is the marginal utility curve that applies when habits are adjusted to the current scale of peak time consumption. By definition, the curves cross at i and intuitively since adjusting consumption up or down from i is easier when habits are also adjusted the *U'(i,i)* curve is flatter.

Figure 1: Reactions and utility gain under ToU and RTP pricing.



Consider electricity consumption on a day after the introduction of a simple ToU tariff that lowers the peak time price to *p-r* (while the keeping the off-peak electricity price unchanged at *p*). Because ToU tariffs allow planning and habits to adjust, consumer reactions follow the flatter *U'(i,i)*-curve and electricity consumption increases to i_+^T . Now consider electricity consumption on a day after the introduction of a simple RTP tariff that sometimes lowers the peak time price to *p-r* (while the keeping the off-peak electricity price unchanged at *p*). Because RTP tariffs do not allow planning and habits to adjust, consumer reactions follow the steeper $U'(i,i_0^P)$-curve and so only increase consumption to i_+^R. Thus, the consumer surplus derived from implementing correct peak electricity prices using ToU tariffs is the sum of the light grey and dark grey areas (denoted $U^T(r)$), while the consumer surplus derived from using RTP tariffs is only the light grey area (denoted $U^R(r)$). Thus, the utility value of being allowed to adjust habits to the new benefit curve is the dark gray area (that is $U^T(r)$-$U^R(r)$). The corresponding symmetric social welfare value for implementing correct *high peak* prices is also illustrated. A useful measure is the proportion of the welfare gain of using RTP tariffs (the light grey area), to welfare gain from ToU tariffs (the light and the dark grey area) when the same incentives are implemented:

$$\alpha = U^R(r) / U^T(r) \tag{1}$$

We call this the *relative consumer value of RTP* because it indicates the proportion of consumer surplus welfare lost when implanting incentives using RTP instead of ToU. In order to identify relative consumer value of RTP, we undertook a field experiment where we induced an increase/decrease in the price of electricity of r per kWh electricity consumption. As an approximation we measured:

$$\alpha \approx \frac{\boldsymbol{i}_{+}^{R} - \boldsymbol{i}_{-}^{R}}{\boldsymbol{i}_{+}^{T} - \boldsymbol{i}_{-}^{T}} \tag{2}$$

This approximation holds exactly if we assume that habit adjustment implies a proportional increase in the scale of reaction to any given price incentive (see Appendix 1). Given that we don't know the underlying functional forms this seems a reasonable approximation. In our experiment, $\boldsymbol{i}_{+}^{R} - \boldsymbol{i}_{-}^{R}$ is the treatment effect estimated in the RTP treatment and $\boldsymbol{i}_{+}^{T} - \boldsymbol{i}_{-}^{T}$ is the treatment effect estimated in the ToU treatment.

III. Description of the experiment

The field experiment was conducted in Denmark by the electricity utility company SE[4]. A sample of 2,625 households was randomly selected[5] from SE's customer database and invited to join the MovePower program[6]. All customers received an invitation E-mail (see Appendix 2) during April 2014 asking whether they would be willing to participate in the program. In this E-mail, all households received the same general information about MovePower (that they would receive suggested time slots for moving their power use through text messages (SMSs)). After receiving their formal consent to participate, the households were randomly allocated into treatments and only then given more specifically detailed information about each treatment (see Appendix 3 and Appendix 4).

In total, 93 customers agreed to participate in the MovePower program[7]. Two households were removed from the analyzed sample *ex post* due to faulty remote measurement meters[8]. Both treatment groups were sent SMSs requesting them to increase or decreases some of their daily power consumption in the same 3-hour time slot (between 20:00 and 23:00). The first text messages were sent on the 27th of May 2014. We analyzed the households' reaction to the experiment up until the 31st July 2014. Both treatment groups were given the same types of incentives in the form of rebates. The proportion of text messages with rebates for increasing consumption during the 3-hour time slot and for decreasing consumption was the same in ToU

[4] More information about the utility company SE can be found on their website: https://www.se.dk/.
[5] Prior to randomization, businesses and seasonal dwellings were excluded.
[6] SE's database of customers who give SE permission to contact them contains 40,490 of SE's more than 247,010 customers in Southern Denmark. Of the 2,625 invited households, 1,175 received the invitation by e-mail, while 1,345 received the invitation by letter.
[7] In total, 131 households signed up, but of these, 38 were allocated to treatments not reported in this paper.
[8] Including them in the analysis with the 18 days and 20 days out of 92 days observation periods where remote measurements reported power consumption has a negligible effect on the results. We chose to remove from the analysis because meter errors that result in report fallout of this magnitude might also corrupt data when meters are reporting. We have no reason to believe that metering errors are affected by treatment allocation.

and RTP treatments (50% in each direction). Treatment groups differed, however, in the proportion of increase/decrease instructions given to the *individual* household and in the frequency with which the instructions were given. In the ToU treatment group, every household received instructions to shift power use in the *same direction on all days.* Households in this treatment were randomly allocated to one of two sub-groups (50% of households in each): one sub-group would always receive a rebate for decreasing power usage in the time slot (ToU1 sub-group), while the other group would always receive the rebate to increase power usage in the time slot (ToU2 sub-group). Households in the ToU treatment received one SMS per week reminding them of their incentive. In the RTP treatment, each household also received a rebate each day if they shifted power use during this time slot, but we *randomly varied* whether they should increase or decrease consumption in order to receive the rebate. All households in this treatment received one SMS daily.

The exact pricing incentives were varied across households, but we ensured in our randomization equal allocation of incentives in all treatments[9]. Finally, an equal proportion of households in each treatment were also notified that SE would increase sustainable electricity production in proportion to the amount of electricity they moved within the treatment period (Table 1).

Table 1: Summary statistics on monetary and environmental incentives

Treatment	No. of house-holds	Average rebate awarded on treatment days (DKK per kWh moved)	Proportion of households also told that moving power would increase sustainable electricity production
ToU	47	1.02	38%
RTP	44	1.07	75%

To check the randomization,

[9] Some households received a rebate (0.50 DKK, 1.00 DKK or 1.50 DKK) per kWh power moved in accordance with the text messages. 1 DKK is approximately equivalent to 0.15 USD (average exchange rate during April 2019)

Table 2 presents various summary statistics on power consumption before the treatment and the dwelling type for the two treatment groups.

Table 2: Summary statistics on demographics and power consumption for treatment groups.

Treatment group no. & type	No. of house-holds	Average daily power consumption* (in kWh)	Average power consumption: hours 20:00 – 23:00* (in kWh)	Average birth year**	Type of dwelling Share of house
ToU	47	4.386	1.551	1959	96%
RTP	44	4.491	1.587	1957	94%

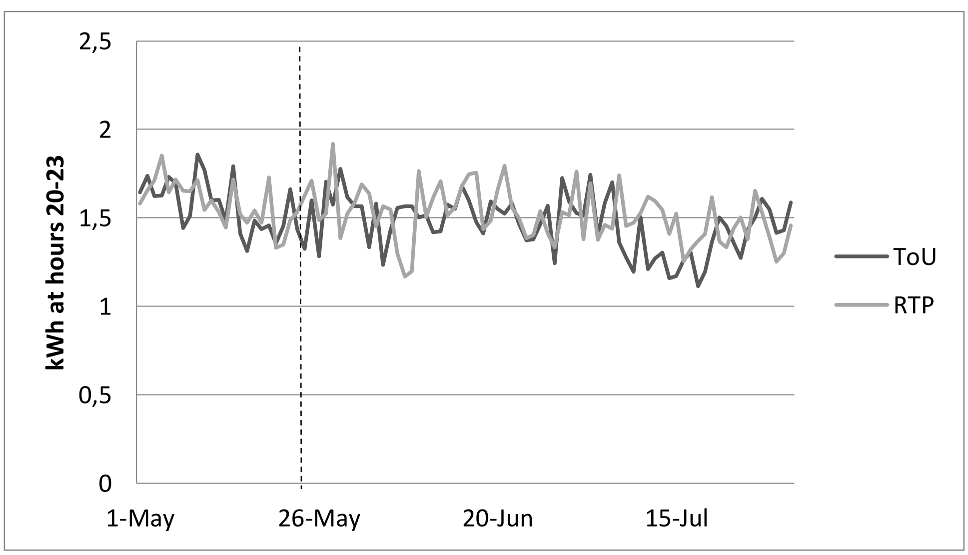
* Before treatment, during the period of the 1st May 2014 to the 26th May 2014.

** Birth year of the person in the household who signed the household up to the MovePower program.

The resulting differences after randomization are small (and statistically insignificant), which suggests that the randomization had been successful. When estimating the treatment effects below, we control for remaining differences before treatment power consumption and variation in power use over time by including household and time-specific fixed effects.

Figure 2 presents daily observations of mean consumption for each of the two treatments during the relevant time slot before and during the experiment. If randomization has been successful, we would like these to follow each other closely both before the experiment, which we see is the case. If the effect of incentives given to decrease and to increase power consumption within each treatment net out, the plotted *mean* power demand for each treatment group should also follow each other during the experiment, which we see is also the case.

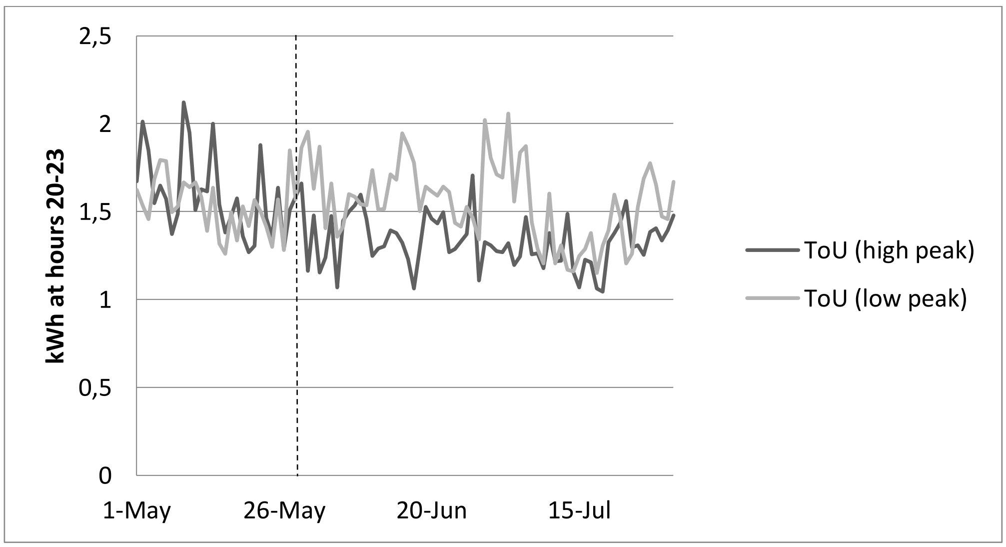
Figure 2: Daily mean power consumption (during the hours 20:00 – 23:00) ToU and RTP treatments



IV. Estimation and results

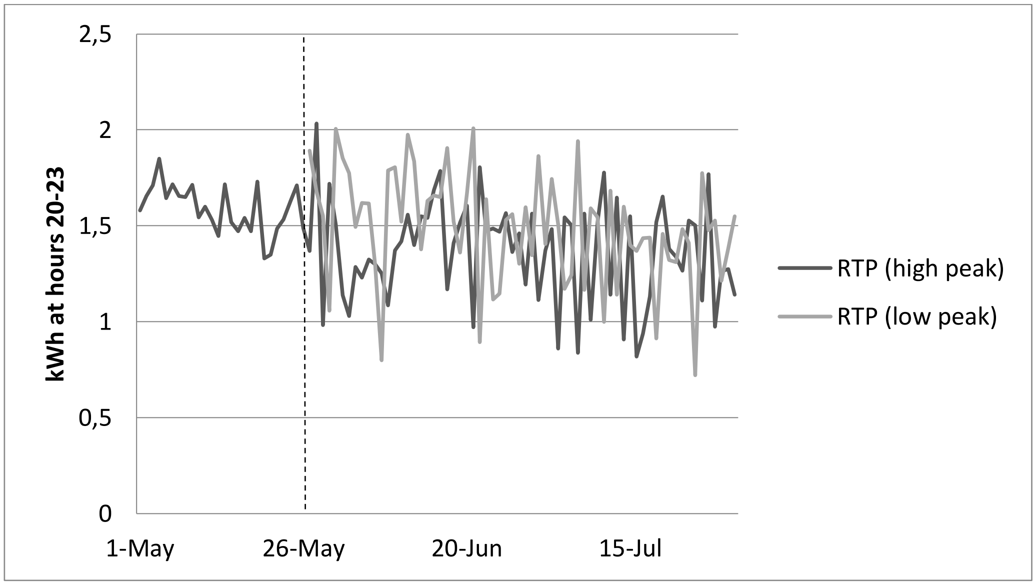
Before the estimation results, we present graphs depicting the performance of our treatment groups before and after the start of the experiment. In Figure 3, we present the daily mean consumption during the peak for each of the two sub-treatments in the ToU treatment. We see that mean consumptions in the two ToU sub-groups follow each other reasonably well during the pre-experiment period, indicating that randomization of households into ToU1 and ToU2 sub-groups was successful. Further, mean consumption then deviates in the expected direction after the start of the experiment with households in ToU1 increasing consumption and the households in ToU2 treatment decreasing consumption, in accordance with the incentives they got during the experiment.

Figure 3: Daily mean power consumption (during the hours 20:00 – 23:00) of the two ToU treatments



In Figure 4, we present the daily mean of peak time consumption for the RTP treatment households. Before the experiment, the mean is taken across all households. During the experiment, each days observations are divided into two: those for households that on that day received an incentive to increase consumption (*low peak*), and those for households that on that day received an incentive to decrease consumption (*high peak*). We see some indication that consumption deviates in the expected direction, though much less so than for the ToU treatment[10].

Figure 4: Daily mean power consumption (during the hours 20:00 – 23:00) of the RTP treatments



[10] We also see a substantial increase in consumption variance at the start of the experiment. This is because the pre-experiment sample is twice as large as the two sub-treatments, post-experiment which increases variance of the mean.

Table **3** presents the average power consumption in the time slot of treatment for the 2-months treatment period, and for the 1-month just prior to households receiving the invitation to join the Movepower program[11]. For the RTP treatment group and the two ToU treatment sub-groups, the average power consumption during the treatment time slot is calculated for the pre-treatment period (third column). For the treatment period, the average consumption during the treatment time slot is calculated for days and households receiving incentives to increase/decrease power usage separately (the fifth column). Finally, in the last column, we present a raw calculation of the diff-in-diff treatment effect (the difference between the two incentives directions are calculated as the difference between pre and during treatment power consumption).

[11] The period before treatment runs from 1st May 2014 to 26th May 2014. The treatment period is from 27th May 2014 to 31st July 2014.

Table 3: Raw treatment effect result

Treatment	Before treatment Daily average power consumption during 20:00 – 23:00 (in kWh)	During treatment Daily average power consumption during 20:00 – 23:00 (in kWh)		Raw Difference in Difference*
ToU2 (27 households)	1.517	*low peak*	1.557	0.302
		high peak	No obs.	
ToU1 (20 households)	1.596	*low peak*	No obs.	
		high peak	1.334	
RTP (44 households)	1.500	*low peak*	1.595	0.115
		high peak	1.480	

*The difference in difference figure is given by: (mean $kWh_{\textit{low peak},\text{during treatment}}$ – mean $kWh_{\text{before treatment}}$) - (mean $kWh_{\textit{low peak},\text{during treatment}}$ – mean $kWh_{\text{before treatment}}$).

Table **3**, we see that power consumption before and during the treatment is similar, indicating that seasonal variation has little influence. For each treatment group, the average consumption during *low peak* treatment is higher than for that during the *high peak* treatment, which was expected. Finally, the row presenting the difference in difference treatment effect for the ToU treatment is 0.302 kWh, while the corresponding treatment effect for the RTP group is 0.115 kWh, indicating a substantially larger treatment effect for the ToU group. These treatment effects are, however, not corrected for household-specific effects or seasonal variation. This limitation is addressed in the following.

To estimate the treatment effects, the data is organized into a panel of 91 households with daily observations of power use before and during the treatment period. The dependent variable in each observation is the household's power consumption in kWh during the 20:00 – 23:00 timeslot normalized by the household's sample mean consumption one month before the intervention, during the same timeslot. The explanatory variables are fixed effects for each household and for each day, a dummy indicating whether there was any treatment (*high peak* or *low peak*) on that day and a dummy indicating whether the treatment on that day was *low peak*. The normalization implies that daily fixed effects, and stochastic variations as well as the treatment effects are assumed to be proportional to mean household consumption. The following specification was estimated for each of the treatment groups in order to identify the treatment effect:

$$y_{id} = \delta_i + \lambda_d + \beta^0 * TREAT_{id} + \beta^1 * LOW_{id} + \varepsilon_{id} \qquad (3)$$

Where

y_{id} is normalized power consumption during the hours 20:00 – 23:00 of i*th* household on day d,

δ_i is a fixed effect for each household,

λ_d is a fixed effect for each day,

$TREAT_{id}$ is a dummy for days the i*th* household is given either *low peak* or *high peak* treatment,

LOW_{id} is a dummy for days the i*th* household is given *low peak* treatment (the treatment effect),

β^0 is the estimated parameter to *TREAT* for each treatment,

β^1 is the estimated parameter to *LOW* for each treatment,

ε_{id} is a stochastic error term.

We include household-specific fixed effects in our estimation to control for sampling variation across treatments, and date-specific fixed effects to control for weekly and seasonal variation. The parameter β^1 indicates the difference in power use on days with *low peak* and *high peak* notifications - this is the treatment effect we want to estimate. The size of this treatment effect for the ToU and RTP treatments corresponds to $\boldsymbol{i}_1^T - \boldsymbol{i}_0^T$ and $\boldsymbol{i}_1^R - \boldsymbol{i}_0^R$ respectively in equation (2).

The estimation is conducted using the OLS procedure in STATA, using cluster-robust standard errors. It is likely that the error terms are correlated across time for the same household, which the cluster-robust standard errors correct for when we cluster on individual households (Cameron and Trivedi 2010).

Table 4: Estimation results

	Treatments	
	ToU	RTP
LOW treatment days, β^1	0.351***	0.182***
	(0.086)	(0.051)
ALL treatment days, β^0	-0.304	-0.157
	(0.210)	(0.150)
Fixed effect day, λ_d	Yes	Yes
Fixed effect household, δ_i	Yes	Yes
Observations	4321	4045
No. of households	47	44
R-squared	0.110	0.105
H: $\beta^1_{ToU} = \beta^1_{RTP}$ (Two tailed t-test)	p= 0.088 *)	
H: $\beta^1_{ToU} \geq \beta^1_{RTP}$ (One tailed t- test)	P= 0.044 **)	

Standard errors are reported in parentheses.

*** indicates that the parameter is significant at 1% level.

**) t-test on hypothesis cannot be rejected at a 5% level.

*) t-test on hypothesis cannot be rejected at a 10% level.

As presented in

Table **4**, both estimated treatment effects (β^1) are significant at the 1% level. In addition, the ToU treatment effect is significantly greater than the RTP treatment effect at the 5% level (one sided test). We may use (2) to calculate:

$$\text{Relative consumer value of RTP} = \frac{U^R}{U^T} \approx \frac{\boldsymbol{i}_+^{\boldsymbol{R}} - \boldsymbol{i}_-^{\boldsymbol{R}}}{\boldsymbol{i}_+^{\boldsymbol{T}} - \boldsymbol{i}_-^{\boldsymbol{T}}} = \frac{0.182}{0.351} = 0.52$$

This implies that impeding planning and adjustment of habits are relevant for the power using activities when using RTP tariffs instead of ToU tariffs, all other things being equal, reduces the consumer surplus of implementing correct prices by half. This is a substantial reduction. This reduction may be an underestimate because of the slightly greater incentives (see Table 1) and reminder frequency in the RTP treatment. On the other hand, the estimate excludes the one-time investment costs that households in the ToU treatment incurred when they adjusted their habits to the new tariff structure at the start of the experiment. However, if changes in the utility pricing system are rare then these costs are negligible.

V. Conclusion

In this paper, we used a randomized field experiment to quantify cost of reacting to a RTP tariff structure compared to ToU pricing. We found that implementing more transparent incentives through RTP instead of ToU tariffs reduces the estimated consumer surplus by half - when the investment cost of adjusting habits at the beginning of the experiment for the ToU group is disregarded. The implication is that stability and predictability of the environments in which power consuming activities are undertaken is important for consumer surplus and welfare. This is an important drawback of RTP tariffs which must be weighed against the advantage of RTP tariffs in allowing utilities to more precisely signaling the marginal cost of electricity production to consumers. Our result suggests that the optimal tariff structure likely is a combination of ToU and RTP tariffs and that ToU-tarrifs may be the cornerstone in the optimally combined system. Looking forward, the need to integrate higher shares of renewable energy sources, especially wind power in the Danish market and broader intermittent renewable sources in other energy markets will require greater flexibility of consumers. A wide adoption of smart metering, in-house automation and enabling technologies that can reduce transaction costs, seem relevant avenues of future research.

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Appendix 1: Proportionality

In this appendix we show that assuming proportionality of demand reactions to a given price change, under RTP and ToU tariffs, implies the same proportionality of the two consumer surpluses generated from these reactions.

Consider a *low peak* initially subject to a uniform electricity price *p*, where a price reduction *r*, is implemented through RTP tariffs. The first order condition for optimal household electricity demand becomes:

$$p\text{-}r = U'(i,i) = \boldsymbol{U}'(i) \tag{A.1}$$

This implicitly defines optimal power use as a function of the price reduction, i.e.:

$$i = f(r) = \boldsymbol{U}'^{-1}(p\text{-}r) \tag{A.2}$$

Thus, the increase in utility that results from a price decrease of *r* under a ToU tariff is:

$$U^T(r) = \int_{q=0}^{r} (f(q) - i_0)dq \tag{A.3}$$

In the same way, we define $g(r) = U'\text{-}^{1}(p+r, i_0^P)$, whereby the increase in utility that results from RTP implementation of a price reduction of *r* is:

$$U^R(r) = \int_{q=0}^{r} (g(q, i_0) - i_0)dq \tag{A.4}$$

Now assume that habit adjustment implies a proportional increase in the scale of reaction to any given price incentive *r* so that:

$$g(r) - i_0 = \alpha(f(r) - i_0) \tag{A.5}$$

Inserting (A.5) in (A4) and then (A.4) and (A.3) we have that:

$$U^R(r) = \alpha U^T(r) \tag{A.6}$$

implying that generated consumer surplus from reacting increases with the same proportion. Since we measure $\boldsymbol{i}_R^- = g(r)$ and $\boldsymbol{i}_T^- = f(r)$ in our experiment we can identify:

$$\alpha = \frac{\boldsymbol{i}_R^- - \boldsymbol{i}_0}{\boldsymbol{i}_T^- - \boldsymbol{i}_0} \tag{A.7}$$

In the same way we can identify α from a corresponding price increase as:

$$\alpha = \frac{\boldsymbol{i}_0 - \boldsymbol{i}_R^+}{\boldsymbol{i}_0 - \boldsymbol{i}_T^+} \tag{A.8}$$

Adding (A.7) and (A.8) and rearranging we get.

$$\alpha = \frac{\boldsymbol{i}_R^- - \boldsymbol{i}_R^+}{\boldsymbol{i}_T^- - \boldsymbol{i}_T^+} \tag{A.9}$$

Thus, assuming proportionality of price effects implies the same proportionality of the resulting consumer surpluses.

Appendix 2: Invitation letter

Three versions of the invitation were used. One promised participation in a lottery for an iPad, the second asked for help with the transmission to green energy in Denmark, while the third did both. Invitations were randomized across invited customers and the customers who were invited by each invitation were randomized over treatments after recruitment. The invitation letter (combined version) is presented below.

Win an
iPad

Read the newsletter online

Become a test pilot - win an iPad* and help us with a transition to more green energy in Denmark

Dear Customer

We need your help. Become a test pilot and help us find new ways to accelerate the transition to green energy and at the same time take part in a draw to win an iPad to the value of 3,699 DKK*. As a test pilot, during the test period, you will receive text messages that tell you when it is best to use power and what it will mean if you choose to move your consumption. For example, you can change the time for when you wash clothes / turn on the dishwasher, etc. Of course, it doesn't mean that you have to cook roast pork at 3am. But moving the timing of your power consumption just a little has many advantages. We call the trial MovePower.

Among SE's customers, there is widespread desire to promote green energy, which is something we would like to satisfy. In Denmark, promoting a green transition through wind energy seems the obvious thing to do, but wind power is difficult to use because there are large fluctuations in production during the day. Therefore, it is important to get private households to play a role so we can exploit wind energy better. Initially, only a limited number of customers will be asked to take part in the pilot test. You have been selected as representative of a number of our customers. It is important for us to gather as many different customers' experiences as possible. Therefore, your participation means a lot to us.

What is MovePower?

- During the test period, you will receive text messages that tell you at what time of day it is best to use power.
- It is completely up to you whether you decide to change the timing of your electricity consumption based on the information you receive or not.
- MovePower will not affect your current electricity contract.
- The extra service in MovePower is free.
- MovePower also includes an additional offer of remote control. This is free, and you can decide for yourself whether it's something for you.
- Initially, it will be in the form of a pilot test, which last 1 year and only involves selected Se customers.

If you would like to participate in MovePower, you can sign up on the following website: www.se.dk/testpilot

Use Code: TWELVE DIGIT CODE1

If you don't want to participate, let us know by sending a message on the following homepage: www.se.dk/besked

Use code: TWELVE DIGIT CODE2

Kind regards
SE

P.S. If you have any questions about MovePower, you are welcome to contact us on the following number: 7011 5095

*The winner will be drawn at the start of May 2014 and will be contacted directly. The prize consists of an iPad Air 16GB and WiFi to the value of 3,699 DKK, which can be exchanged for cash. Employees of SE are not allowed to participate-

SE | E-mail: se@se.dk | Edison Park 1 | DK-6715 Esbjerg N | Telefon +45 7011 5000 | Fax 7011 5001

Appendix 3: Terms of MovePower

Incentives were varied across households, but are randomized across treatments to ensure equal incentives in all treatments. Some households (Group 1) received a rebate (0.50 DKK, 1.00 DKK or 1.50 DKK[12]) per kWh power moved in accordance with the text messages. Other households (Group 2) in addition to the monetary incentive received an environmental incentive where SE promised to increase wind power generation by 0.50 kWh, 1.00 kWh or 1.50 kWh per kWh power moved in accordance with the text messages. Below are the terms of MovePower for the 0.50 DKK and 0.50 kWh incentives.

Here are the terms of MovePower:

- As a pilot test, during the test period, you will receive text messages that tell you at what time of day it is best to use power.
- (Group 1) If you choose to follow the recommendations you receive in the text messages and move the timing of your electricity consumption, you will earn 0.50 DKK in discount for each kWh you move. In this way, you will save money.
- (Group 2) If you choose to follow the recommendations you receive in the text messages and move the timing of some of your electricity consumption, you will earn 0.50 DKK in discount for each kWh you move, SE will move 0.5 kWh of conventional electricity production to wind-based electricity production for each kWh you move. At the same time, SE will move 0.5 kWh of conventional electricity production to wind-based electricity production for each kWh you move. In this way, you will save money and help to reduce the environmental impact.
- If you choose not to react to the information you receive, nothing will happen. Whether you decide to make use of the information and move the timing of your consumption is entirely up to you.
- To give you an overview, once a month you will receive a text message telling you how many kWh of your electricity consumption you have moved - as suggested in the text messages.
- We calculate how many kWh you have moved through a comparison with your average power consumption from the previous year.
- (Group 1) If you earn a discount, you will receive the money when MovePower ends in one year.
- (Group 2) If you earn a discount and a reduction in environmental impact, you will receive the money and SE will increase the wind turbine capacity when MovePower ends in one year.

[12] 1 DKK is approximately equivalent to 0.15 USD.

- MovePower is a limited pilot project and you will receive notification when the project starts and ends.

If you would like to know more about how you can move the timing of your energy consumption, go to: www.se.dk/FlytStroem

Appendix 4: Information given to subjects about how to move power

MovePower

In Denmark, promoting a green transition through wind energy seems the obvious thing to do, but wind power is difficult to use because there are large fluctuations in production during the day. Therefore, it is important to get private households to play a role, so we can exploit wind energy better. This is what we are testing with MovePower, which encourages you to move the timing of your consumption to when wind energy is available.

When should I move the timing of electricity consumption?

As part of MovePower, during the test period, you will receive text messages that tell you at what time of day it is best to use power and what it will mean if you choose to move the timing of your consumption.

The information in the text messages will sometimes be sent at short notice, but at other times it will be sent several hours in advance, so how much time you have before you need to move the timing of your electricity consumption will vary.

How to move the timing of your electricity consumption

To determine how to move the timing of your electricity consumption, it's a good idea to think about what would be easiest for you. For example, moving the start time of the:

- dishwasher,
- washing machine,
- tumble dryer,

or you could use the automatic timing for, e.g. the dishwasher. You can also postpone or speed up the charging of electronic appliances, e.g. PC/iPads/mobile phones, etc. We hope this has inspired you to move the timing of your electricity consumption.