Using Real-Time Pricing and Information Provision to Shift Intra-Day Electricity Consumption: Evidence from Denmark*

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Abstract

Wind and solar energy are supplying an increasing share of electricity in many jurisdictions, but the availability of these resources can change dramatically across hours of the day. This potential for significant unpredictable positive and negative supply and demand imbalances substantially changes the role of active demand-side participation. We report results from a large field experiment that with a few hours prior notice provided Danish residential consumers with dynamic price and information signals aimed at causing them to shift their consumption either into certain hours of the day or away from other hours of the day. The experiment yields the surprising result that the same price signal produces substantially larger in absolute value consumption shifts into target hours relative consumption shifts away from target hours. The experiment also finds that these incentives to shift consumption into a set of target hours yields reduced consumption in the hours of the day that surround these target hours. The same qualitative results hold for purely informational signals: (1) the shift-into results are significantly larger in absolute value than the shift-away results and (2) there is stronger evidence that shifting consumption into a time period reduces consumption in the surrounding periods than there is that shifting consumption out of a time period increases consumption in the surrounding time periods. The paper closes with simple theoretical model of household demand uncertainty that rationalizes both the dynamic pricing and information provision results.

JEL Classifications: C93, L51, L94, Q41
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1. Introduction

An increasing number of jurisdictions have implemented policies to increase significantly the contribution of renewable energy to meeting their electricity needs. These goals are being met primarily with wind and solar energy. A major reliability challenge associated with this approach is the uncertain amount of the energy these resources produce each hour. Depending on availability of the underlying wind or solar resource, the amount of electricity produced each hour can change dramatically across hours of the day. In contrast, the hourly aggregate demand for electricity follows a smooth pattern throughout the day, starting at its lowest point in the early morning and steadily increasing during the daylight hours and eventually peaking during the late afternoon or early evening, depending on the season the year. This difference between the pattern of aggregate demand and the pattern of renewable energy production throughout the day can create a substantial imbalance between the hourly supply and demand of electricity, particularly as the share of intermittent renewable generation capacity in the jurisdiction increases.

This potential for significant unpredictable positive and negative supply and demand imbalances substantially changes the role of active demand-side participation. Historically, managing the system balance in power systems dominated by dispatchable thermal generation units focused on reducing peak demand below the available hourly supply of electricity. In systems with significant intermittent generation there can be hours when the amount of energy produced from these resources can exceed system demand. For example, if there is enough wind capacity that produces primarily during hours of the day when demand is low, some of the energy that can be produced from this wind capacity may need to be curtailed in order to maintain system balance. Even a region that primarily relies on solar energy that produces during the high demand hours of the day could face the same challenge if there is enough installed solar generation capacity. These reliability challenges imply a new and equally important role for active demand-side participation in shifting demand from hours with less renewable energy production to hours with more renewable energy production.

This paper presents the results of a field experiment that provided Danish residential consumers with dynamic price and information signals aimed at causing them to shift their consumption into certain hours of the day or away from certain hours of the day. Consumers are notified of these price and information signals through text messages to their cell phones with between 2 to 12 hours prior warning. For price signals, customers were offered rebates on their electricity bill that depended on the total amount of electricity they moved either into or away from the targeted hours. Specifically, customers could receive a 5 percent, 20 percent, or 50 percent rebate off of the price they paid for electricity for each KWh of energy they managed to either shift away from the target hour or shift into the target hour. For the purely informational signals, customers were told how much greenhouse gas (GHG) emissions would be reduced as result of their load-shifting activities, but where not offered any financial compensation.

The experiment yields the surprising result that the same marginal price signal produces a two to three times larger in absolute value estimated load shift into target hours relative to the absolute value of the estimated load shift away from target hours. The experiment also finds that the incentives to shift load into a set of target hours yields reduced consumption in the hours of the day that surround these target hours. For the away-from target hours, the experiment finds slightly increased the consumption in hours of the day that surround the target hours. The purely informational signals produced qualitatively similar results. The absolute value of the shift-into effect is significantly larger in absolute value than the shift-away effect and there is stronger evidence that shifting consumption into a time interval reduces consumption in surrounding time periods than is the evidence that shifting consumption away from a time-interval increases consumption in the surrounding time periods.

We then present a simple model of household electricity demand under uncertainty that rationalizes these results. This model exploits the "option to quit" identified in Wolak (2010) associated with rebate-based dynamic pricing plans relative to pure dynamic pricing plans. Specifically, under a rebate-based dynamic pricing plan if the customer is unable to reduce her consumption below the level necessary to receive a rebate during a shift-away period then she can pay for all of the electricity she consumes at the standard retail fixed price. In contrast, a customer on a traditional dynamic pricing plane pays the higher dynamic price for all consumption during a shift-away period and does not have the option to avoid paying this higher marginal price. This "option to quit" is far less relevant for into events, because customers are more likely to be able to exceed the level of consumption necessary to receive a rebate with some advance notice than they are to be able reduce their consumption below the level necessary to receive a rebate during away events, which explains the larger in absolute value treatment effect for into events versus away events for both the price and information treatments.

Our results support the argument that regions with a significant intermittent renewable capacity should focus on using price signals and information to encourage consumption during periods when the renewable capacity produces the most energy. Based on the results of this experiment, using price and informational signals to shift consumption into hours of the day with the excess renewable energy production is a more cost-effective approach to managing the supply and demand balance in regions with significant amounts of renewable generation capacity using rebate-based mechanism for dynamic pricing because into events are less to prone to the "option to quick" problem with reduces the average treatment effect of an intervention.

The remainder of the paper proceeds as follows. The next section presents two examples of the economic benefits of both into and away load-shifting in regions with significant renewable energy goals met with intermittent generation resources. Section 3 describes the experimental design and the data collection process for the experiment. Section 4 presents the empirical results. Section 5 presents our model of customer demand uncertainty that rationalizes these empirical results. Section 6 discusses possible extensions and implications of these results for the active involvement of final demand in regions with significant intermittent renewable generation capacity.

2. The Economics of Load-Shifting with Significant Renewable Generation Capacity

This section discusses two examples of how significant amounts of renewable generation capacity in a region increases the need for the load-shifting actions of electricity consumers both into and away from certain hours of the day. Different from the case of regions with only dispatchable thermal generation, increasing electricity consumption during certain hours of the day can reduce the cost of meeting a given renewable energy goal, particularly if this increase in consumption reduces consumption during other hours of the day.

Figures 1(a) and 1(b) illustrate the challenges facing Denmark with managing a grid with more than 30 percent of the electricity coming from intermittent wind generation units. Figure 1(a) displays the pattern of wind generation and aggregate electricity consumption and Figure 1(b) the Danish wholesale price for the period January 13 to 19, 2014. Figure 1(a) shows the smooth pattern of aggregate consumption throughout the day and across days of the week. In contrast, the total output of wind generation units is extremely irregular both within the day and across days of the week. There are hours when almost no wind energy is produced and hours when wind energy production exceeds Denmark's electricity consumption.

Wholesale prices in Denmark vary inversely with the amount of wind energy produced. Hours with the least wind energy production have the highest prices and hours with the most wind energy production have the lowest prices. This inverse relationship occurs because the difference between total consumption and renewable energy production must be met with dispatchable generation that is costly operate, typically because it requires burning an input fossil fuel to produce electricity.

Figure 1 demonstrates that by shifting consumption into the hours with high wind energy production or shifting consumption away from the hours with low wind energy production, consumers could save on their wholesale energy purchase costs. They would be buying more energy in low-priced hours and less energy in high-priced hours.

This volatility in the difference between total electricity consumption and total renewable energy production is not unique to Denmark. California has extremely ambitious renewable energy goals. It renewables portfolio standard (RPS) requires 33 percent of the state's electricity consumption to come from qualified renewable sources—primarily solar, wind, biomass, geothermal, and small hydro—by 2020. This share increases to 50% by 2030. Solar generation capacity is currently thought to be the major technology that will be used to meet these renewable energy goals. This has given rise to the so-called "Duck Curve" shown in Figure 2. This figure shows the expected residual demand—total system consumption for the California Independent System Operator (ISO) control area less total renewable energy output in the California ISO control area—for different amounts of solar generation capacity in California. This net load curve is called the "Duck Curve" because of its shape within the day.

Figure 2 demonstrates that shifting consumption into the daylight hours and away from the evening and early nighttime hours can save consumers on their wholesale energy purchases, by the same logic as described above for Denmark. Hours with high renewable energy production typically have low wholesale prices and hours with low renewable energy production typically have high wholesale prices. In 2020 and beyond, during the hours when California's solar generation capacity is producing a substantial amount energy, there is a significant risk that total renewable energy production will exceed electricity consumption in the California ISO. Further wholesale energy cost savings are therefore possible, if consumers are able to shift their consumption to the hours of the day where there is a significant risk this over-generation condition occurring.

A simple rule of thumb is that if the RPS share exceeds the capacity factor of renewable generation technology used to meet it, then there is potential for an over-generation condition that could be addressed by customers shifting their demand into hours when renewable energy production is likely to be the greatest. To illustrate this point suppose that demand is 100 MWh every hour of the year. To obtain the mandated 33 percent renewable energy from a technology with a 20 percent capacity factor will require at least 33 MW/0.20 = 165 MW of solar PV capacity. This means all hours in the year with an hourly capacity factor for all solar PV units over 0.60 will produce more solar energy than system demand. Taking the example of California, the capacity factor for solar photovoltaic (PV) generation units is approximately 20 percent, meaning that the potential megawatt-hours (MWh) that PV-units could produce operating at full capacity for all hours of the year —is five times larger than their mean hourly production. When solar PV capacity is used to meet the 33 percent RPS, then solar capacity will be 65% greater than mean hourly demand, this implies many hours of the year when total solar PV production exceeds total electricity consumption.

An increasing number of countries and regions have the ambitious renewable energy goals. Consequently, designing real-time pricing and information provision mechanisms to cause consumers to shift-their consumption into certain hours of the day and away from other hours of the day are part of a cost effective strategy to achieving these renewable energy goals. The popularity with customers and regulators of rebate-based dynamic pricing programs relative to pure dynamic pricing programs that charge high prices for all consumption during peak periods further emphasizes the need understand the relative effectiveness of different rebate-based dynamic pricing programs.

3. Description of Experiment and Data Collected

The experiment was conducted in collaboration with the energy company SE[1] in Denmark. Participants were recruited through e-mails sent to customers that had given SE permission to contact by through e-mail[2]. In April 2015, an e-mail informed these customers of a new SE-program called SE MOVEPOWER. In the e-mail some customers were told that they could earn a rebate on their power bill if they moved their power consumption into or away from particular time slots and that information about the relevant time slots would be signaled to them though a text to their cell phone (see an English translation of e-mail text in Appendix A1). Other customers were told that the energy company would ensure GHG-free production of the energy they moved in accordance with the text messages they received (see e-mail text in Appendix A2).

The sample of SE-customers contacted by e-mail was randomized across seven different treatments. Three treatments offered a 5%, 20%, and 50% rebate respectively on all energy moved in accordance with the text messages (calculated based on SEs wholesale power rate regardless of the rate paid by the customer). For the other four treatments, customers were promised that all energy moved in accordance with the text messages would be produced using GHG-free energy

[1] See the energy company SE, https://www.se.dk/

[2] E-mail invitations were sent to the 22,007 costumers randomly selected from SE's data base of customers who have given SE contact permission. This data base contains 40,490 of SE's more than 247,010 customers in southern Denmark.

sources (specifically SE committed to increase investments in GHG free energy production matching the amount of energy moved). The four information treatments only reflect slight differences in the wording of how this information was conveyed to the consumers. All consumers had advanced meters that measured their hourly consumption making it possible to calculate their consumption during the relevant into and away time slots.

To participate in the experiment, customers were asked to click on a link in the e-mail to a dedicated SE-website where they were asked to inform SE of the cellphone number to which text messages should be sent and given additional information (see Appendix B1-B3 for more details). Here they were also told that the program would be evaluated by researchers after the first year and that rebate payment and GHG-free energy investments for the first year would be made at that time. In total 737 customers signed up for for the rebate based program and 1,065 customers signed up for the GHG-free energy program.

The first text messages were sent on the 4th of June 2015 and the experiment was terminated on 7th of February 2016. Customers were prompted via text message to their cell phones a few hours in advance on the same day they were supposed to move power. Customers were notified an average of 1.2 times per week of three-hour time slots in which a rebate could be earned. The text message notified them of the target time slot and whether they should move power *into* or *away* from the target time slot that day in order to earn the rebate or ensure GHG-free electricity production. The text message also reminded them of the rebate percent on the standard rate that they would earn or the GHG-free production they would ensure by moving energy in accordance with the text message (see the Appendix C. for English translations of sample text messages).

Target time slots to each participating customer varied randomly across the days of the week, between different 3 hour time slots (10 am to 1 pm; 3 pm to 6 pm; 6 pm to 9 pm; 9 pm to 12 am, and 12 am to 3 am). The amount of prior notification also varied from 2 hours to 5 hours in advance of the target 3-hour time slot. Customers were also randomly assigned to moving consumption into or moving consumption away from the target 3-hour time slot.

Each month customers received an e-mail with feedback comparing their performance at moving their consumption with that of other participants (see Appendix D). However, it was not possible for the customer to deduce how much energy he had actually moved during a given month from this relative feedback. Customers were not informed of their actual rebate earnings nor of the actual quantity of power moved during the experiment. They were also not informed about precisely how SE would calculate how much power they had moved or how much rebate they had earned[3].

After the experiment was terminated on 7th of February 2016, SE calculated rebates and the amount of KWhs of GHG-free energy production due each customer. Rebates were then paid to costumers and earned GHG-free KWh reported in connection with the customer's subsequent quarterly electricity bill. We estimated energy movement for each customer using a variant of the model estimates described below. However, because these estimates for individual households

[3] Customers could contact SE's help desk who had dedicated service personal who had been instructed about the experiment who registered all questions and answers. No one contacted the help desk about the size of their earned rebates or GHG-free energy production nor how they were calculated.

are uncertain we rounded up rebate refunds and credited GHG-free KWH so that most people were actually paid or credited GHG-free energy in excess of what they rationally would have expected. However, this (positive surprise) was not announced to them before after the experiment and so cannot have affected the participant's behavior during the experiment.

All communication with customers from the initial recruitment mail to text messages and feedback was done by SE through their mail server and text message service using their letterhead and logo.[4] Customers with questions could contact SE's help desk, which had dedicated customer service personal who were familiar with the experiment. As noted above, customers were informed that the scheme would be evaluated by researchers and possibly discontinued after the first year. At the end of this period customers were informed that the MOVEPOWER program would not be continued.

Table 1 presents summary statistics on the number of households participating in the tree rebate treatments, the average number of treatment and non-treatment days and average power consumption during the 3 hour time slots for each of three different rebate level treatment groups. Average consumption is presented for treatment time slots in into/away treatment and non-treatment slots, separately. Consumption in control time slots is obtained on days without treatment for that customer. For all three rebate groups, note that the average (across customers and time periods) consumption during into treatment periods is higher than average consumption during controls. However, the time slots on days without treatment, the average consumption is roughly the same as time slots on the days with the away treatment.

Table 2 presents the same summary statistics for the four informational treatment groups. As shown in Appendices B2 and B3, these groups differ only slightly in wording of the supplementary information provided just after the initial invitation, whereas all of the initial e-mail invitations, text messages on peak days, and monthly feedback were identical for the groups 31, 34, 35, and 36. For all four of these treatment groups, average consumption during into treatment periods is higher than average consumption during the control time periods. Average consumption during time slots with away treatments is roughly the same as time slots on the days with the away treatment.

The raw data shows that the rebate and informational treatments have the intended effect of increasing electricity consumption when this is indicated in the text message. However, the raw data does not show the expected response of lower consumption during away treatment periods. To determine whether these results are due to the timing of the treatment interventions and which customers are treated, we now turn to analysis that flexibly controls for these differences across customers and time periods.

[4] All communications with SE's costumers were approved by the marketing division of SE.

Table 1. Summary Statistics for Rebate Groups.

	5% rebate	20% rebate	50% rebate
Number of customers	**326**	**183**	**121**
Average number of time slots per customer			
With into-treatment[i]	**44.81**	**44.02**	**44.21**
With away-treatment[ii]	**21.04**	**19.88**	**19.83**
With no treatment[iii]	**874.62**	**872.13**	**873.47**
Average kWh consumption per 3 hours period			
With into-treatment	**1.81**	**1.89**	**1.96**
With away-treatment	**1.58**	**1.60**	**1.62**
With no treatment	**1.53**	**1.56**	**1.57**

[1] 27% of the *into* treatments are in the time slot 10-13, 23% are 15-18, 23% are 18-21, 19% are 21-24 and 8% are 24-3.

[1] 20% of the *away* treatments are in the time slot 10-13, 30% are 15-18, 30% are 18-21, 14% are 21-24 and 6% are 24-3.

[1] All *potential* treatment periods in the timeslot 10-13, 15-18, 18-21, 21-24 and 24-3 on days with *no* treatments. To be specific, 20% of the potential treatments are in the time slot 10-13, 20% are 15-18, 20% are 18-21, 20 are 21-24 and 20% are 24-3.

Table 2. Summary Statistics for Zero-GHG Energy Groups

	Group: 31	Group: 34	Group: 35	Group: 36
Number of customers	**319**	**260**	**133**	**84**
Average number of time slots per customer				
With into-treatment(a)	**44.69**	**45.54**	**44.52**	**44.90**
With away-treatment(b)	**20.57**	**21.33**	**20.92**	**20.53**
With no treatment(c)	**882.40**	**878.29**	**888.31**	**859.64**
Average kWh consumption per 3 hours period				
With into-treatment [iv]	**1.80**	**1.71**	**1.55**	**1.82**
With away-treatment	**1.62**	**1.57**	**1.39**	**1.61**
With no treatment	**1.55**	**1.49**	**1.36**	**1.55**

(a) 27% of the *into* treatments are in the time slot 10-13, 23% are 15-18, 23% are 18-21, 19% are 21-24 and 8% are 24-3.

(b) 20% of the *away* treatments are in the time slot 10-13, 30% are 15-18, 30% are 18-21, 14% are 21-24 and 6% are 24-3.

(c) All *potential* treatment periods in the timeslot 10-13, 15-18, 18-21, 21-24 and 24-3 on days with *no* treatments.

3. Estimation Procedure and Results

In this section we estimate a number of different average treatment effects for each of the three rebate groups and the four information provision groups. These treatment effects are estimated using a difference-in-difference estimator for the sample of rebate customers and the sample of information treatment customers separately. Customers in each of the three rebate treatment groups are randomly assigned to receive treatment across and within days. Similarly, customers in each of the four information treatment groups are randomly assigned to receive treatment across and within days. This implies that customers in each of the two samples not experiencing a treatment event in that time interval or day are serving as the "control" group used to estimate the treatment effect for that day. This logic implies that our estimation procedures are recovering the average treatment effect for customers receiving rebates and the average treatment effect for customers receiving the information intervention for the population of customers that participated in the two experiments.

For the purposes of the experiment, the day is divided into 9 time periods. They are: 3 am to 6 am, 6 am to 7 am, 7 am to 10 am, 10 am to 1 pm, 1 pm to 3 pm, 3 pm to 6 pm, 6 pm to 9 pm, 9 pm to 12 am, and 12 am 3 am. Treatment events for both the rebate and informational samples were only declared during the 3-hour time periods.

For each rebate group we define six indicators, three for the into-treatment and three for away-treatment. The first variable, Away(r,i,t,d), is equal to 1 for rebate level r (r = 5 percent, 20 percent and 50 percent), if customer i in time period t, of day d received an "away" notification for that time period and day, and the variable is equal to zero for all other time periods in the sample. The second variable, BeforeAway(r,i,t,d), is equal to 1 for all time periods after an "away" notification was sent to consumer i with rebate level r and before the actual "away" time period occurred for this customer and is equal to zero for all other time periods in the sample The third variable, AfterAway(r,i,t,d), is equal to 1 for as many hours after the "away" event as the BeforeAway(r,i,t,d) variable was equal to 1 for the same "away" event and equal to zero for all other time periods in the sample. The idea of including the BeforeAway and AfterAway variables in the regression is to determine if shifting energy consumption away from a given time period during an "away" event within the day leads to higher or lower consumption immediately after being notified of the event up to the event time period and after the "away" event for a time period equal to the same length of time as the amount of advance notice the customer received for this "away" event.

Three analogous variables are defined for the "into" events. The variable, Into(r,i,t,d) is equal to 1 for rebate level r if customer i in time period t of day d received an "into" notification for that time period and day and equal to zero for all other time periods in the sample BeforeInto(r,i,t,d) is equal to 1 for all time periods after an "into" notification was sent to consumer i with rebate level r and before the actual "into" time period occured for this customer and equal to zero for all other time periods in the sample. AfterInto(r,i,t,d) is equal to 1 for as many hours after the "into" event as the BeforeInto(r,i,t,d) variable was equal to 1 for the same "into" event and equal to zero for all other time periods in the sample. Again, these variables are included to determine if shifting energy into a given time period leads to lower or higher consumption immediately after being notified of the event up to the event time and after the "into" event for a period of time equal to amount of advance notice the customer received for this "into" event.

Let y(r,i,t,d) equal the natural logarithm of electricity consumption in kilowatt-hours by customer i facing rebate level r during period t of day d. In terms of this notation, we estimate the following regression for each of the three samples of rebate customers:

$$y(r,i,t,d) = \mu(t) + \nu(i) + \eta(d) + \beta_1\mathrm{BeforeInto}(r,i,t,d) + \beta_2\mathrm{Into}(r,i,t,d) + \beta_3\mathrm{AfterInto}(r,i,t,d)$$

$$+ \alpha_1\mathrm{BeforeAway}(r,i,t,d) + \alpha_2\mathrm{Away}(r,i,t,d) + \alpha_3\mathrm{AfterAway}(r,i,t,d) + \varepsilon(r,i,t,d)$$

where the $\mu(t)$ (t=1,2,...,9) are period-of-day fixed effects, the $\nu(i)$ (i=1,2,…,I) are customer fixed effects, the $\eta(d)$ (d=1,2,..,D) are day-of-sample fixed effects, and the $\varepsilon(r,i,t,d)$ are mean zero regression disturbances. The first column of numbers in Table 3 presents the estimates of $(\beta_1,\beta_2,\beta_3,\alpha_1,\alpha_2,\alpha_3)'$ for the 5 percent rebate level intervention. The second column presents the 20 percent rebate level estimates and the third column presents the estimates for the 50 percent rebate sample. To account for possible autocorrelation in the $\varepsilon(r,i,t,d)$ over time periods in the sample for a customer and the possibility that this autocorrelation could differ across customers, we report the Arellano (1986) standard errors for these coefficient estimates. The bottom row of each column lists the total number of combined time period and customer observations used to estimate each regression.

The first result of note is the uniformly two to three time larger in absolute value coefficient on Into(r,i,t,d) versus Away(r,i,t,d). The "into" average treatment effect ranges from a roughly 8 percent to 13 percent increase in consumption during the treatment period, and is significantly larger for the 50 percent rebate relative to the 5 percent and 20 percent rebate level. The "away" average treatment effect is between 3 and 4.5 percent for all rebate levels, with the highest percentage reduction occurring for the 20 percent rebate level. A second result is the fact that both before and after an "into" event, consumption is lower relative to the control group. These two results are very encouraging for using "into" treatments to achieve targeted demand reductions as well as a targeted demand increases. For the 5 percent rebate sample, there appears to be some evidence that before and after an "away" event demand increases. The imprecisely estimated coefficients on BeforeAway and AfterAway for the 20 percent and 50 percent rebate samples could be the result of the significantly smaller samples sizes available for these regressions relative to the 5 percent rebate sample.

To investigate whether the results for the BeforeAway and AfterAway might be due a sample size issue, we also estimate a pooled version of the model which imposes the restriction that all three rebate groups have the same time-period-in-the-day fixed effects and the same day-of-sample fixed effects. Specifically, we estimate the following pooled regression across the three rebate groups:

$$y(r,i,t,d) = \mu(t) + \nu(i) + \eta(d) + \sum_{r=5,20,50} [\beta_{1r}\text{BeforeInto}(r,i,t,d) + \beta_{2r}\text{Into}(r,i,t,d)$$

$$+ \beta_{3r}\text{AfterInto}(r,i,t,d) + \alpha_{1r}\text{BeforeAway}(r,i,t,d) + \alpha_{2r}\text{Away}(r,i,t,d) + \alpha_{3r}\text{AfterAway}(r,i,t,d)]$$

$$+ \varepsilon(r,i,t,d).$$

Table 3: Separate Estimation Results for 5 Percent, 20 Percent and 50 Percent Rebate Levels

Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t			
	5 % Rebate	**20 % Rebate**	**50 % Rebate**
Regressor			
BeforeInto	**-0.0241**	**-0.0154**	**-0.0224**
	(0.0033)	**(0.0045)**	**(0.0054)**
Into	**0.0843**	**0.0909**	**0.1343**
	(0.0057)	**(0.0077)**	**(0.0099)**
AfterInto	**-0.0089**	**-0.0086**	**-0.0037**
	(0.0031)	**(0.0043)**	**(0.0051)**
BeforeAway	**0.0149**	**0.0006**	**0.0232**
	(0.0049)	**(0.0071)**	**(0,0085)**
Away	**-0.0366**	**-0.0451**	**-0.0311**
	(0.0075)	**(0.0108)**	**(0.0130)**
AfterAway	**0.0093**	**-0.0112**	**0.0072**
	(0.0045)	**(0.0064)**	**(0.0077)**
# of Observations	**694,163**	**387,170**	**255,663**

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

Table 4: Pooled Estimation results for 5 percent, 20 percent and 50 percent rebate levels

Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t			
	5 % Rebate	**20 % Rebate**	**50 % Rebate**
Regressor			
BeforeInto	**-0.0305**	**-0.0054**	**-0.0184**
	(0.0033)	**(0.0044)**	**(0.0053)**
Into	**0.0784**	**0.0959**	**0.1441**
	(0.0056)	**(0.0077)**	**(0.0098)**
AfterInto	**-0.0103**	**-0.0038**	**-0.0052**
	(0.0031)	**(0.0042)**	**(0.0051)**
BeforeAway	**0.0120**	**0.0051**	**0.0265**
	(0.0049)	**(0.0071)**	**(0.0084)**
Away	**-0.0388**	**-0.0473**	**-0.0207**
	(0.0075)	**(0.0108)**	**(0.0129)**
AfterAway	**0.0115**	**-0.0121**	**-0.0040**
	(0.0045)	**(0.0063)**	**(0.0077)**
# of Observations		**1,336,996**	

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

Table 4 reports the results of estimating this regression along with Arellano (1987) standard error estimates. The major change in the results from rebate-level-specifc regressions is the larger in absolute value coefficients on Into(r,i,t,d) for the 20 and 50 percent rebate levels and the smaller in absolute value coefficient on Away(r,i,t,d) for the 50 percent rebate level. Otherwise, the same qualitative conclusions from the results in Table 2 hold for Table 3. For the same rebate percentage, significantly larger in absolute value treatment effects hold for the "into" intervention versus the "away" intervention. A significant fraction of the energy that shifts into a treatment periods comes from reductions in consumption during periods after the customer is notified and the "into" treatment periods occurs, as well as immediately after the "into" period. To lesser extent, the energy that is shifted away from the "away" period results in increased consumption during periods after the customer has been notified and the "away" treatment period occurs, there is evidence of increased consumption after the "away" event only for the 5 percent rebate group.

Table 5: Pooled Estimates of Impact of Four Informational Treatments

Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t				
	Group 31	**Group 34**	**Group 35**	**Group 36**
Regressors				
BeforeInto	**-0.0200**	**-0.0190**	**-0.0109**	**-0.0099**
	(0.0033)	**(0.0037)**	**(0.0054)**	**(0.0061)**
Into	**0.0656**	**0.0608**	**0.0759**	**0.0824**
	(0.0057)	**(0.0061)**	**(0.0091)**	**(0.0107)**
AfterInto	**-0.0046**	**-0.0030**	**-0.0069**	**-0.0075**
	(0.0031)	**(0.0035)**	**(0.0050)**	**(0.0057)**
BeforeAway	**0.0011**	**0.0062**	**-0.0045**	**0.0047**
	(0.0051)	**(0.0056)**	**(0.0082)**	**(0.0094)**
Away	**-0.0303**	**-0.0212**	**-0.0218**	**-0.0366**
	(0.0078)	**(0.0087)**	**(0.0127)**	**(0.0146)**
Afterway	**-0.0021**	**0.0112**	**0.0085**	**0.0016**
	(0.0045)	**(0.0051)**	**(0.0074)**	**(0.0086)**
# of Observations		**1,703,242**		

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

Table 6: Restricted Estimates of Impact of Informational Treatments

Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t	
Regressor	
BeforeInto	**-0.0171**
	(0.0021)
Into	**0.0675**
	(0.0036)
AfterInto	**-0.0048**
	(0.0020)
BeforeAway	**0.0023**
	(0.0032)
Away	**-0.0265**
	(0.0050)
Afterway	**0.0045**
	(0.0029)
# of Observations	**1,703,242**

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

We now turn to the information treatment sample. We first estimate a pooled version of the model that allows for different values of $(\beta_1,\beta_2,\beta_3,\alpha_1,\alpha_2,\alpha_3)'$ for each of the four information treatments. These results are given in Table 5 along with the Arellano (1987) standard error estimates. The same qualitative results appear to hold for informational treatments as for rebates. The absolute value of the estimated impact of an "into" information treatment is significant larger than the estimated impact of an "away" event. In addition, there is stronger evidence that shifting consumption into a time period leads to lower consumption in the time periods that surround that period than there is evidence that shifting away consumption from a time period leads to higher consumption in the surrounding periods. However, because many of the coefficients in Table 5 are not very large relative to their standard errors and the point estimates for the same element of $(\beta_1,\beta_2,\beta_3,\alpha_1,\alpha_2,\alpha_3)'$ are not significantly different across the four informational treatments, in Table 6 we present estimates of this regression that impose the restriction that the elements $(\beta_1,\beta_2,\beta_3,\alpha_1,\alpha_2,\alpha_3)'$ are the same across the four informational treatments.

The estimation results in Table 6 confirm our qualitative results with significantly more statistical precision. The absolute value of the "into" treatment effect is 6.75 percent, whereas the absolute value of the "away" treatment effect is less than half that magnitude at 2.65 percent. The BeforeInto and AfterInto coefficients are negative, which is consistent with the energy shifted to the "into" period coming from these periods. Although the point estimates of the BeforeAway and Afterway coefficients are positive, which is consistent with the energy shifting from the "away" period going to these periods, these coefficients are not nearly as precisely estimated or as large in absolute value as the coefficients on BeforeInto and AwayInto.

4. Testing the Validity of the Randomization of Interventions

This section reports on the results of several placebo regressions to investigate whether our "into" and "away" interventions actually cause the consumption changes that we estimate in the previous section. We create the following two indicator variables: (1) IntoP(r,i,t,d) equals 1 in time period t of day d if this time period is immediately before notification of an "into" intervention is given to customer i with rebate level r and zero in all other time periods and (2) AwayP(r,i,t,d) equals 1 in time period t of day if this time period is immediately before an "away" intervention is given to customer i with rebate level r and zero in all other time periods.

For each rebate level sample and the pooled rebate sample, we estimate the following regression:

$$y(r,i,t,d) = \mu(t) + \nu(i) + \eta(d) + \beta \text{IntoP}(r,i,t,d) + \alpha \text{AwayP}(r,i,t,d) + \varepsilon(r,i,t,d)$$

For each regression we would not expect either α or β to be nonzero because customers have no economic or informational incentive to shift their consumption into or away from time periods when either IntroP or AwayP is equal to 1.

Table 7 reports these results with Arellano (1987) standard error estimates. In all cases, the null hypothesis $\alpha = 0$ and $\beta = 0$ cannot be rejected. The last column of Table 7 presents estimates of these coefficients that pool the data for all of the rebate levels. In this case as well, the null hypothesis that $\alpha = 0$ and $\beta = 0$ cannot be rejected. These results are consistent with our "into" and "away" indicators actually causing the consumption changes that we estimate.

Table 7: Placebo Estimates of Impact of Rebate Treatments

	Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t			
	5 Percent Rebate	**20 Percent Rebate**	**50 Percent Rebate**	**Pooled Sample**
Regressor				
IntoP	**-0.0134**	**-0.0198**	**0.0042**	**-0.0118**
	(0.0082)	**(0.0119)**	**(0.0164)**	**(0.0063)**
AwayP	**-0.0102**	**-0.0049**	**-0.0213**	**-0.0001**
	(0.0114)	**(0.0142)**	**(0.0163)**	**(0.0079)**
# of Obs	**697,077**	**388,807**	**256,734**	**1,342,618**

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

Table 8 reports the results of estimating this same regression for the pooled informational intervention sample with Arellano (1987) standard estimates. In this case as well, the null hypothesis $\alpha = 0$ and $\beta = 0$ cannot be rejected.

Table 8: Placebo Estimates of Impact of Informational Treatments

	Dependent Variable is Natural Logarithm of Customer i's Consumption in Time Period t
Regressor	
IntoP	**-0.0100**
	(0.0059)
AwayP	**-0.0006**
	(0.0071)
# of Observations	**1,710.354**

Standard errors computed using the heteroscedasticity and autocorrelation-consistent covariance matrix for two-way panel data models presented in Arellano (1987) are in parentheses below coefficient estimates.

The results in Tables 7 and 8 are consistent with the "into" and "away" consumption shifting estimates presented in the previous section being caused by our rebate and informational treatments.

4. Cost-Effectiveness of the Shifting "Into" and Shifting "Away"

This section assesses the heterogeneity in the cost-effectiveness of our experimental intervention. Using information on the total amount of rebates paid in Danish Kroner over the experiment period for each customer and the estimated treatment effects for each rebate level and both the "into" and "away" interventions, we compute the average rebate per kilowatt-hour (KWh) of energy moved for each customer. We find considerable heterogeneity across customers in the average rebate per KWh, but more than 50 percent of the customers have an average rebate per KWh less than 0.5 Kroner/KWh which at current exchange rates is 7 cents/KWh.

We compute the total amount of KWh shifted for each customer as follows. For each "into" event and rebate level, we estimate the amount energy moved during that time period as

$$\text{MoveI}(r,i,t,d) = [1 - \exp(-b_r)]C(r,i,t,d)$$

where $\exp(b_r)$ is the estimate of β_2, the average treatment effect for an "into" event for a customer with rebate level r, from the pooled estimates in Table 4 and C(r,i,t,d) is the customer's actual consumption during period t of day d. For each "away" event and rebate level, we estimate the total amount of energy moved during that time period as

$$\text{MoveA}(r,i,t,d) = [\exp(-b_r) - 1]C(r,i,t,d)$$

We then compute the sum of MoveI and MoveA over all interventions that customer i experienced during the experiment and divided that magnitude into the total amount of rebates in Kroner paid for customer i.

Figure 3 presents the histogram of customer-level average rebate per KWh in Danish Kroner. Although there are a number of customers with extremely large values of the average rebate per KWh, the vast majority of customers have average rebates per KWh less than one. More that 50 percent of the customers have values less than 0.5 Kroner/KWh, which is roughly 0.07 Dollar/KWh. Thus despite the procedure described above at the end of the experiment of rounding up of rebate payments, our implemented rebate scheme was not excessively costly.

To provide quantitative evidence of the significantly greater cost effectiveness of "into" interventions versus the "away" interventions, for each customer we compute the sum of MoveI across all "into" interventions in the experiment and divide this by the total number of number of "into" interventions experienced by the customer during the experiment. This gives the average KWh of electricity shifted for an "into" intervention for that customer. We also computed the sum of MoveA across all "away" interventions for that customer and divided this by the total number of away interventions experienced by the customer. This gives the average KWh of electricity shifted for an "away" intervention.

Figure 4(a) plots the histogram of the customer-level values of average KWh shifted per "into" intervention and Figure 4(b) plots the histogram of customer-level values of average KWh shifted per "away" intervention. The values range from zero to 0.8 KWh per "into" intervention with a median value of 0.2 KWh per "into" intervention. For the "away" interventions the numbers range from zero to 0.2 KWh per "away" intervention with a median of 0.05 KWh per "away" intervention. The four times larger average amount shifted for "into" interventions suggests that this form of consumption-shifting is likely to be a far more cost-effective way to maintain system balance in regions with significant intermittent renewable generation capacity.

5. Explaining Results Using A Model of Household Demand under Uncertainty

This section presents a model of household demand under uncertainty that rationalizes our empirical results. The model builds on the "option-to-quit" property of rebate schemes versus dynamic pricing schemes discussed in Wolak (2010). Under an away rebate scheme, if a household does not consume below the level necessary to receive a rebate, that customer only pays the usual fixed price for consumption. The same logic applies for the into scheme. If the household does not consume more than the level necessary to receive a rebate, the household pays for consumption at the usual fixed price.

Figure 5 considers the behavior of a household that has received an into signal. However, at the time the into signal occurs, the household does not know if their demand for electricity is $D_L(p)$ or $D_H(p)$, where $D_L(p) < D_H(p)$ for all prices, p. Figure 7 also shows the reference level relative to which a rebate is issued as Q_R. Figure 5(a) shows the customer's demand if it faces, P_N, the normal fixed retail price, and P_N – r, the price less the rebate amount. In this case $D_L(P_N) <$ Q_R, but $D_L(P_N\text{-}r) > Q_R$, so the household would receive a rebate in the low demand state for consuming more than Q_R.

Figure 5(b) repeats Figure 5(a), for $D_H(p)$. In this case the household would receive a rebate because $D_H(P_N\text{-}r) > Q_R$, Figure 5(c) presents the average treatment effect for the customer by computing the difference between the household's consumption in the low demand state if an into event has been declared less the household's consumption if an into event has not been declared times the probability of the low demand state plus the same difference for the high demand state times the probability of the high demand state. In this case, ATE = $Prob_L(D_L(P_N\text{-}r) – D_L(P_N)) + Prob_H(D_H(P_N\text{-}r) – D_H(P_N))$.

Figure 6 repeats Figure 5 for the case of an away event. If Figure 6(a), the customer will receive a rebate under the low demand state, because $D_L(P_N+r) < Q_R$. However, the customer will not receive a rebate under the high demand state at the price, (P_N+r), because $D_H(P_N+r) > Q_R$ in Figure 6(b). Here is where the option to quit comes into play. The customer can obtain a higher level of utility in the high demand state by continuing the consume at P_N and purchase $D_H(P_N)$. Figure 6(b) shows what this utility-maximizing action under the rebate scheme does to the average treatment effect of an away event. It becomes, ATE = $Prob_L(D_L(P_N) – D_L(P_N+r)) + Prob_H(D_H(P_N) – D_H(P_N)) = Prob_L(D_L(P_N) – D_L(P_N+r))$.

Figure 7(a) compares the into and away average treatment effects in Figures 5 and 6 and shows that because of the option to quit being exercised in the high demand state under the away rebate scheme, the absolute value of the ATE under the away rebate mechanism is significantly smaller than the absolute value of the ATE for the into rebate scheme. Figure 7(b) shows that if the reference level is increased, this result could be ambiguous because the away customer will not get a rebate under the low demand state and will therefore find it utility-maximizing to consumer $D_L(P_N)$ under the low demand state, so that the away average treatment effect becomes, $Prob_H(D_H(P_N\text{-}r) – D_H(P_N))$.

However, because the away event ATE in Figure 7(b) is based on change in demand in the low demand state under P_N versus P_N+r, and the into ATE in Figure 7(b) is based on the change in demand in the high demand state under P_N-r and P_N, it seems very likely that the absolute value of the ATE for the into event will still be higher than the ATE for the way event. Consequently, the differential impact of the option to quit under the into rebate dynamic pricing plan versus the away dynamic pricing plan rationalizes the significantly smaller in absolute value average treatment effect for into versus away interventions that we find in our empirical work.

6. Conclusions

The results of this experiment suggest an alternative more cost-effective mechanism for active participation of the final consumers in managing the real-time supply and demand balance in regions with significant intermittent renewable generation. For the same rebate percentage, load-shifting into a time period induced a two to three times larger percent increase in demand than that rebate percent induced for load-shifting away from that time period. A significant amount of the energy that shifted into the time period also resulted in reductions in consumption during time periods before and after this time period. The evidence for load-shifting away from the period finds mixed evidence that this led to increased consumption in neighboring time periods.

For purely informational interventions produced analogous results: Significantly larger in absolute value average load-shifting into time periods relative to shifting away from time periods and evidence that load-shifting into a time period led to lower consumption during neighboring time periods, but load-shifting away from a time period did not consistently lead to increases in consumption in neighboring periods.

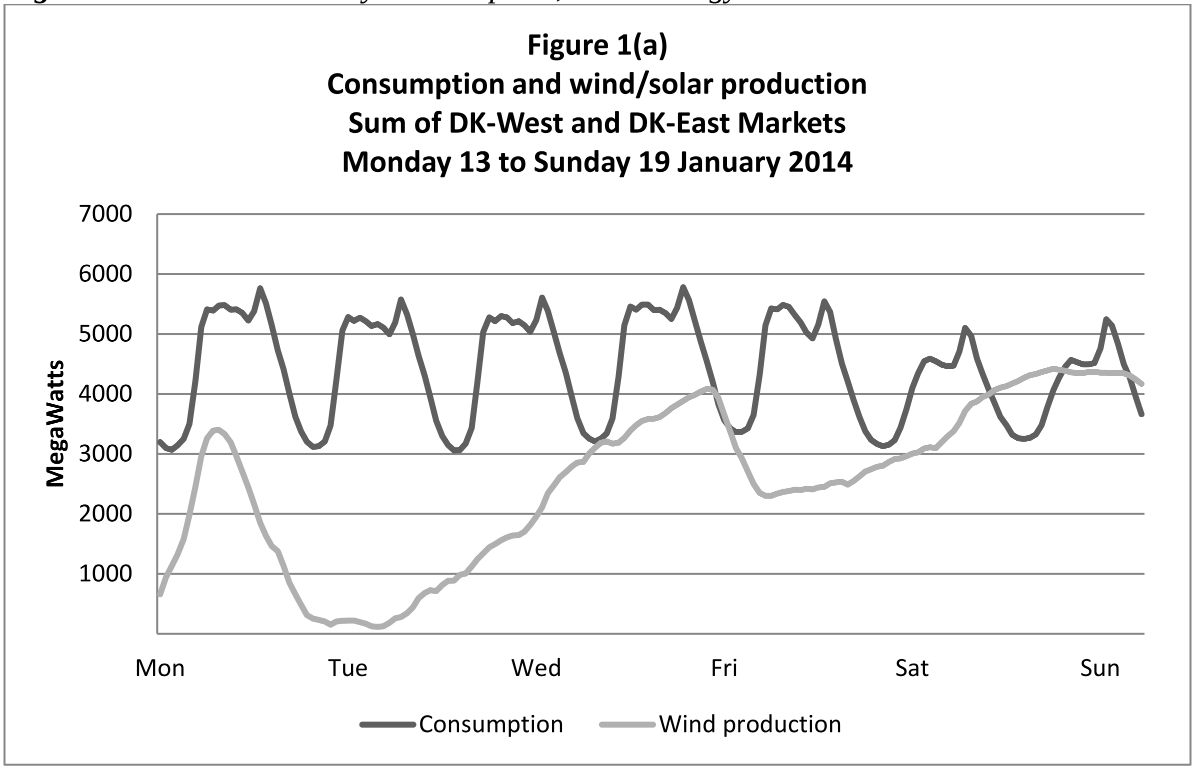
Given popularity of rebate-based dynamic pricing programs with consumers and regulators, a more cost-effective approach to implementing these programs may be the as into versus away schemes, particularly in regions with significant intermittent renewable generation capacity shares.

References

Arellano, M. (1987) "Practioner's Corner Computing Robust Standards Errors for Within-Groups Estimators. Oxford Bulletin of Economics and Statistics, 49(4):431-34.

Wolak, Frank A. (2010) "An Experimental Comparison of Critical Peak and Hourly Pricing: The PowerCentsDC Program," available at http://www.stanford.edu/~wolak

Figure 1. Danish Electricity Consumption, Wind Energy Production and Short-term Prices



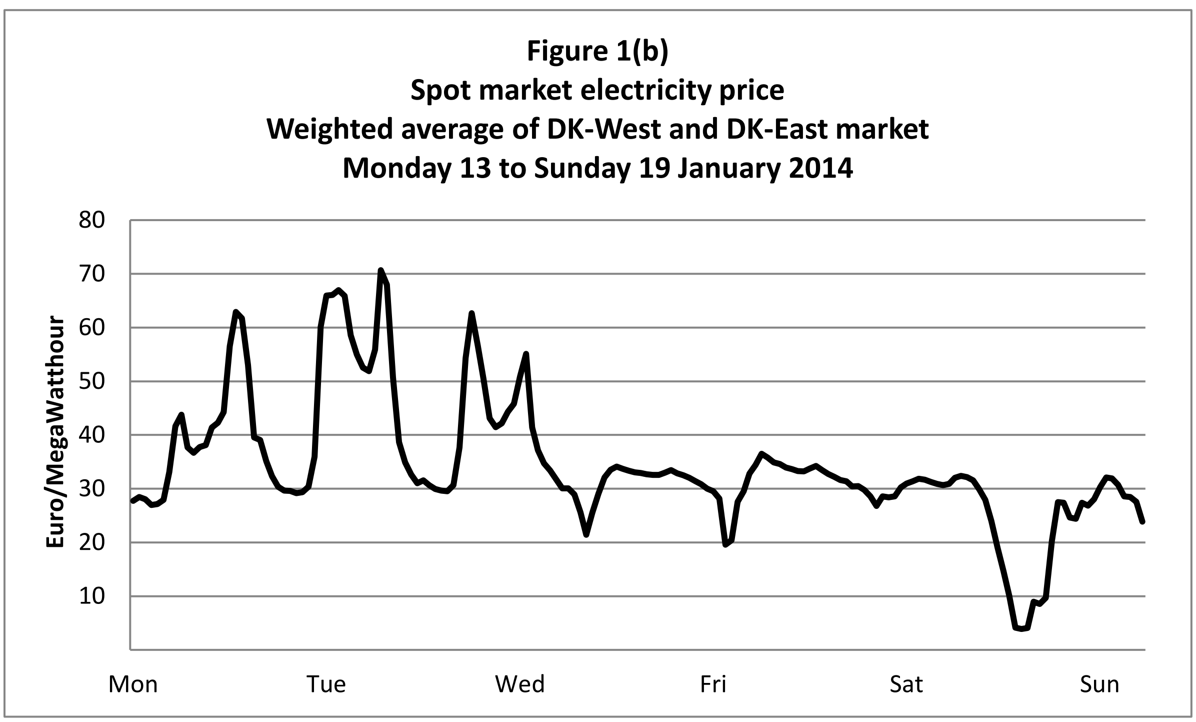


Figure 2: *The Impact of Solar Generation Deployment on Net Load in California*

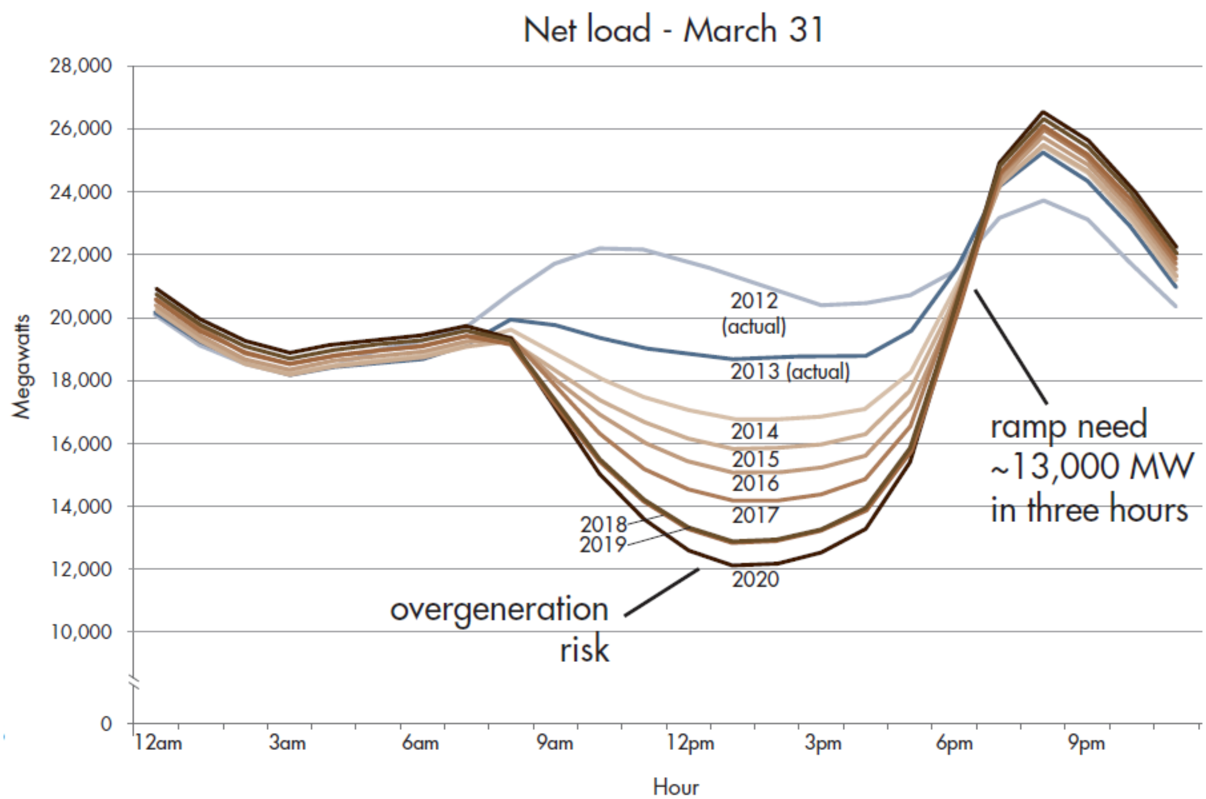


Figure 3: Histogram of Average Rebate Paid Per KWh Moved

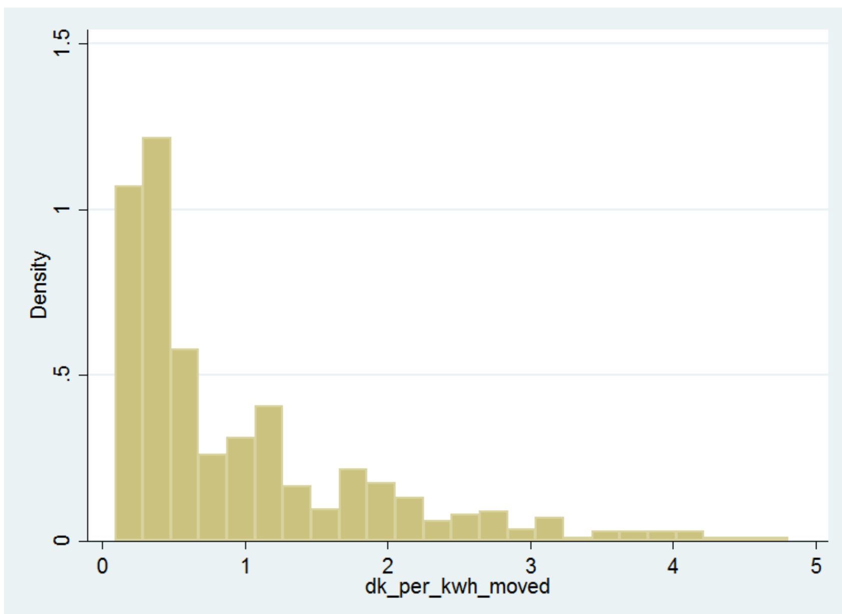


Figure 4(a): Histogram of Customer Level Average KWh Shifted per "Into" Intervention

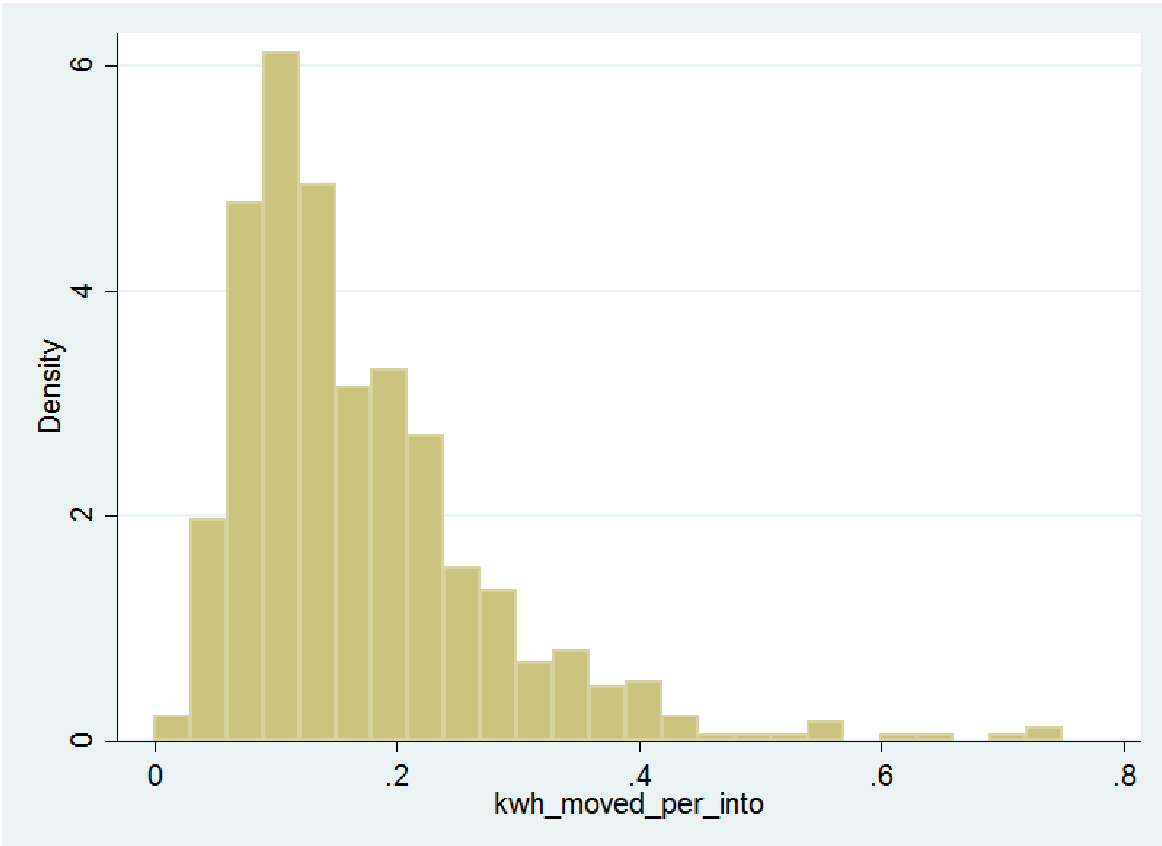


Figure 4(b): Histogram of Customer-Level Average KWh Shifted per "Away" Intervention

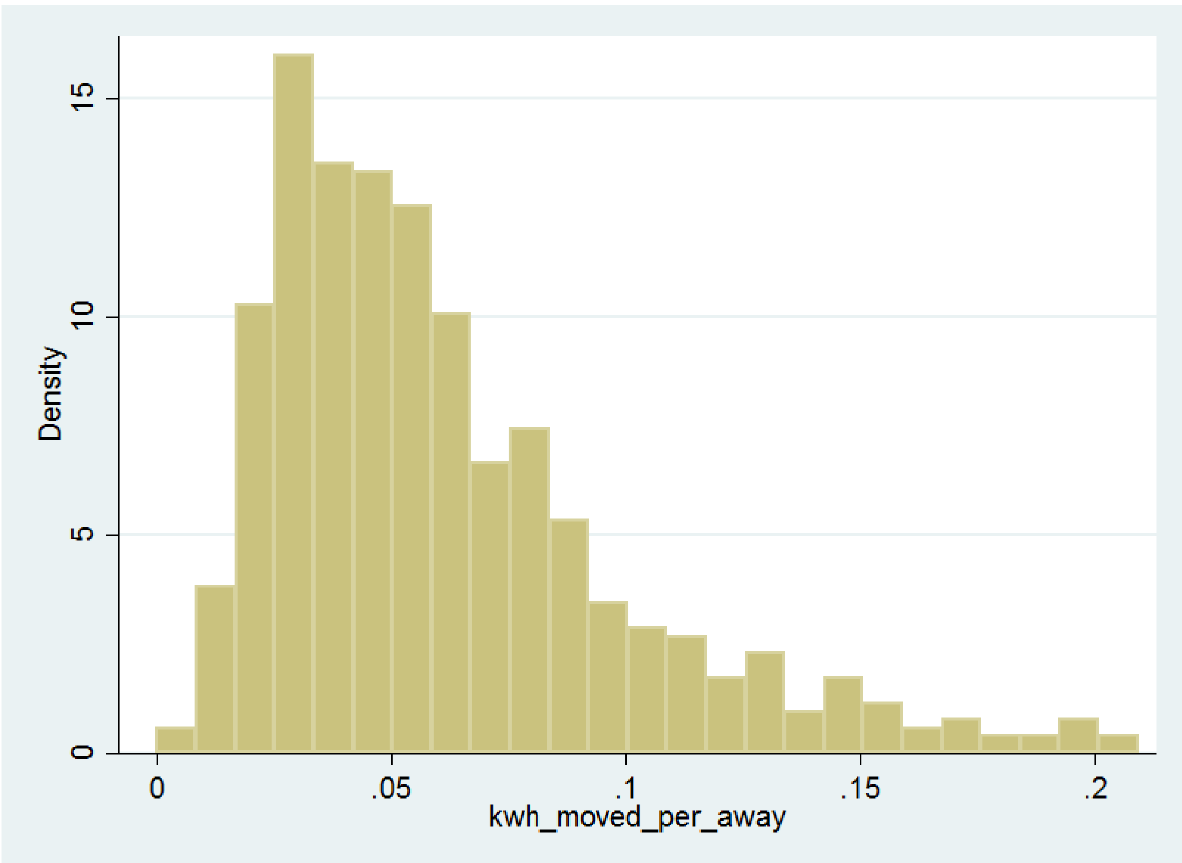


Figure 5(a): Into Rebate Pricing with Uncertain Demand

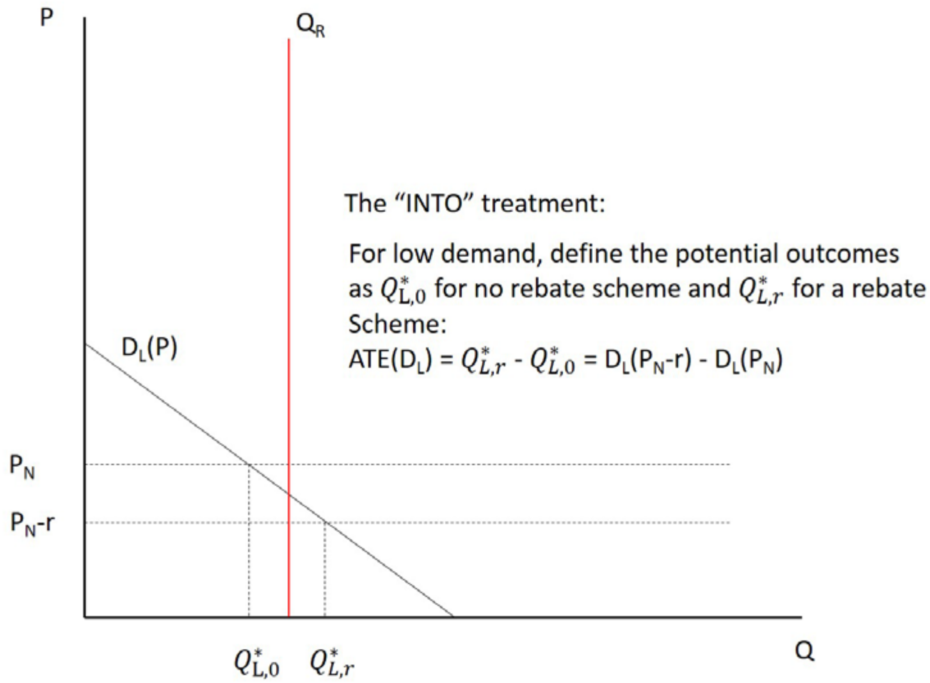


Figure 5(b): Into Rebate Pricing with Uncertain Demand

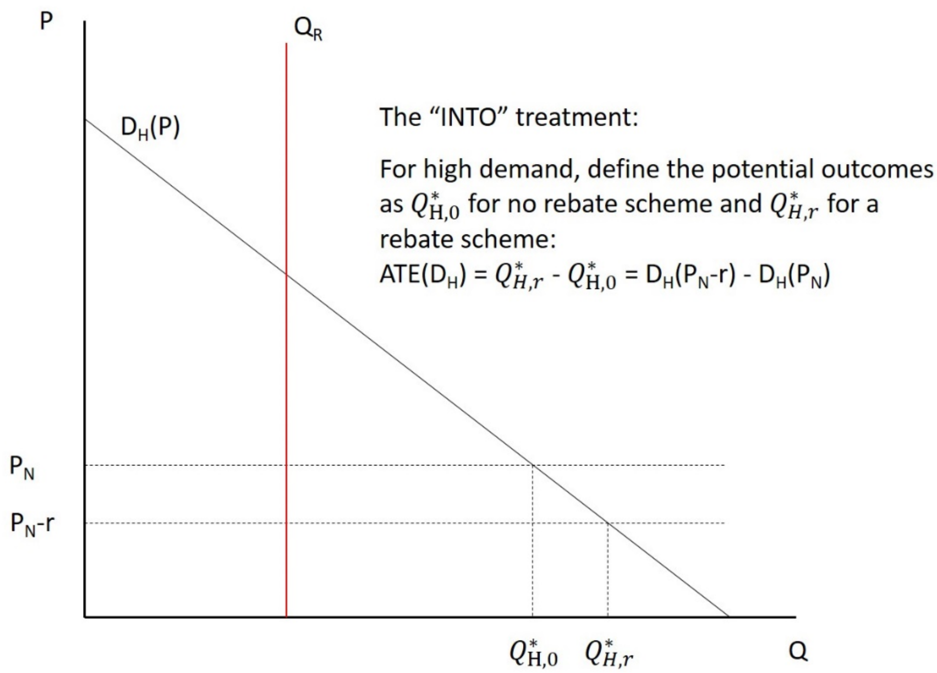


Figure 5(c): Into Rebate Pricing with Uncertain Demand

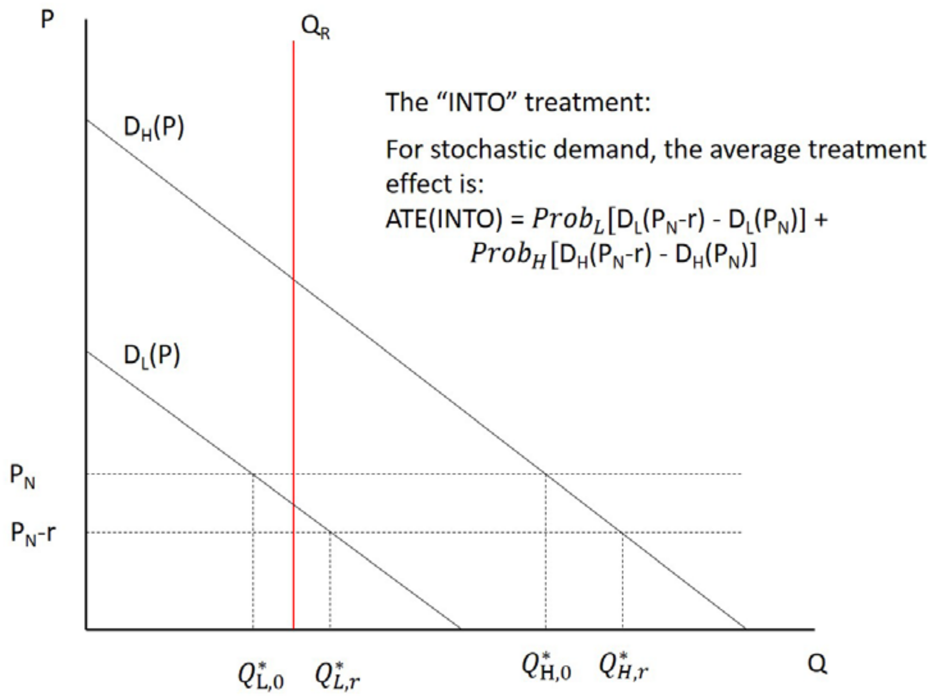


Figure 6(a): Away Rebate Pricing with Uncertain Demand

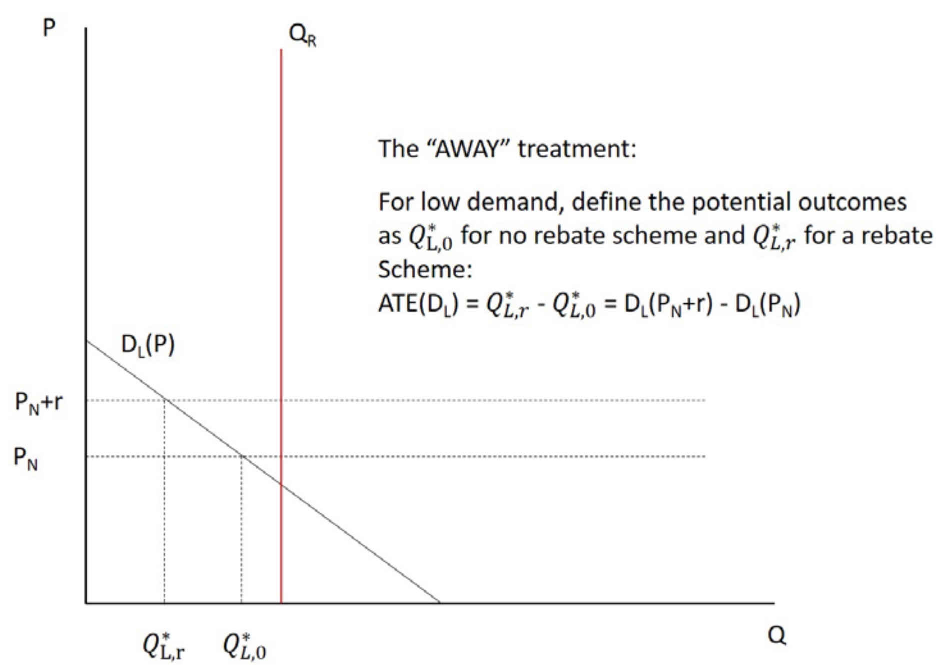


Figure 6(b): Into Rebate Pricing with Uncertain Demand

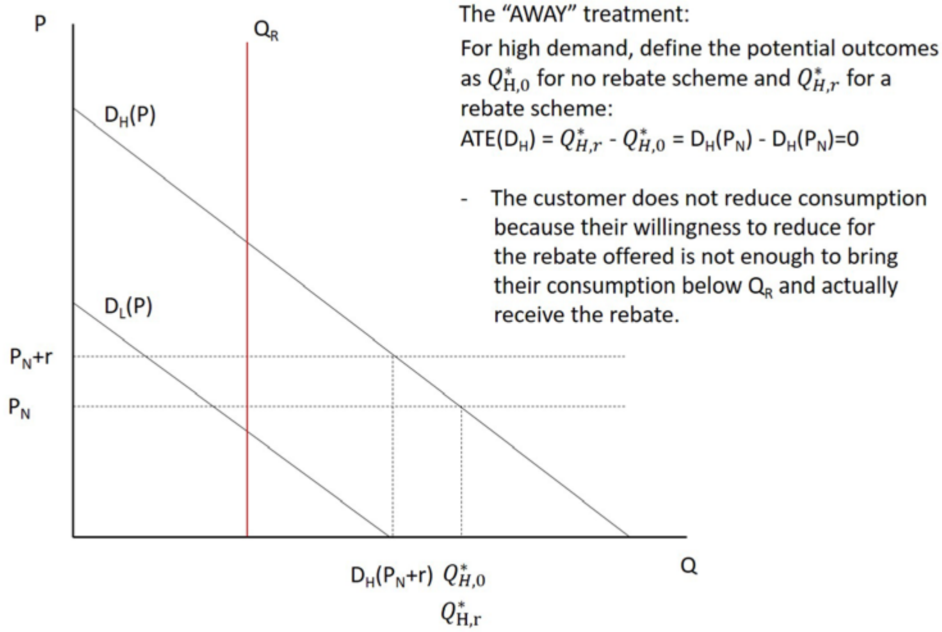


Figure 6(c): Into Rebate Pricing with Uncertain Demand

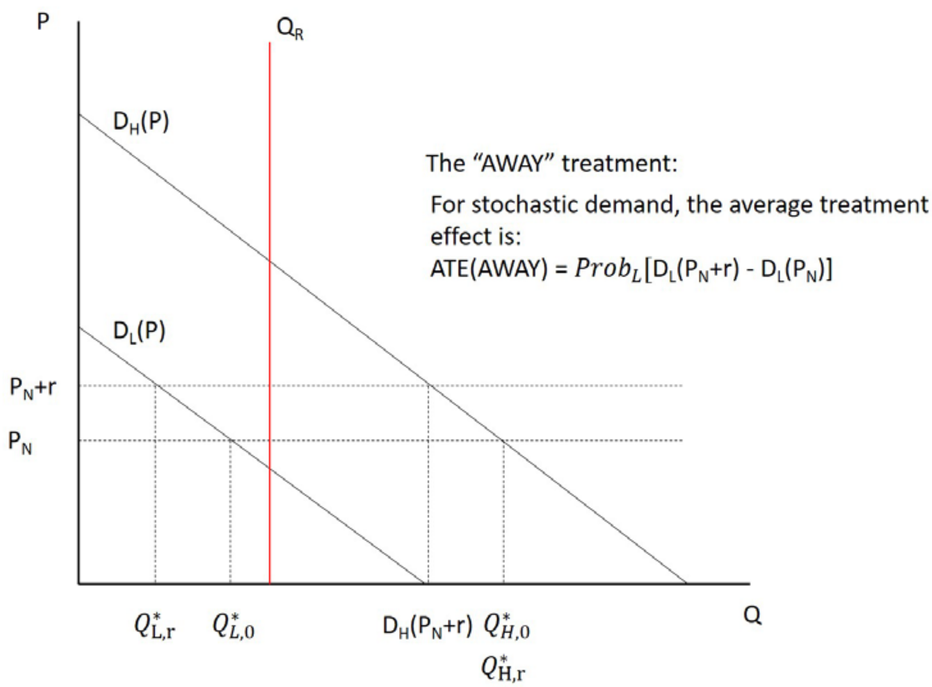


Figure 7(a): Comparison of Rebate Pricing with Uncertain Demand

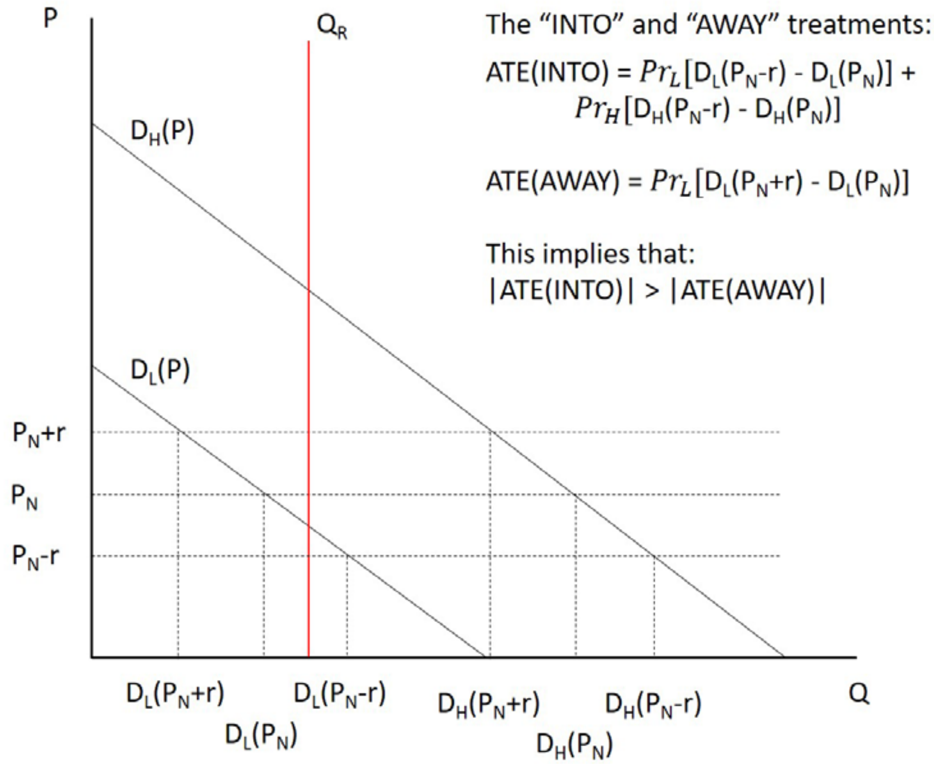
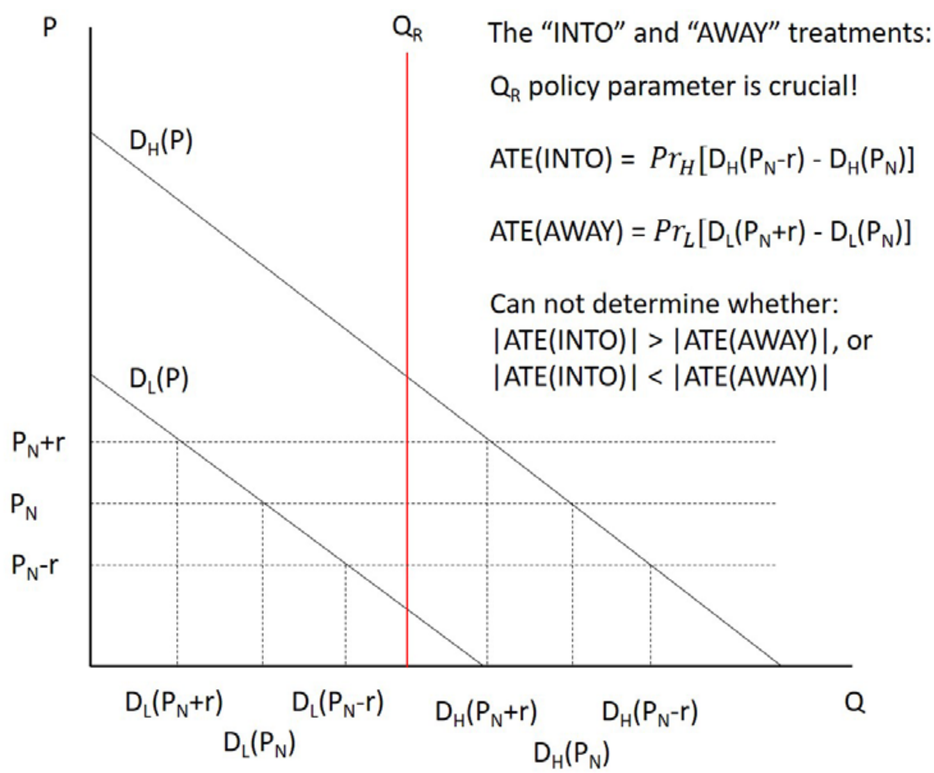


Figure 7(b): Comparison of Rebate Pricing with Uncertain Demand



Appendix

Appendix A1. E-mail invitation offering rebates* to costumers)

Read this newsletter online

April 2015
Like us on facebook

Dear Name

Get 5% off each time you move the power

Among our customers there is a clear demand for better use of weather-dependent wind power. We want to meet this demand with a new scheme, called MOVEPOWER. MOVEPOWER is initially offered to a limited number of customers in a one-year trial period.

You have been selected because we believe that you will be able to benefit from the scheme. MOVEPOWER is free and without obligation to you so we hope you find the system attractive. Of course it is your choice whether to participate or not.

During the trial period, you will receive text messages at the time of day it is best to use power. For example, you move the time when you wash clothes, or turn the dishwasher off and so on. Of course it is not intended that you should make roast pork at 3:00 in the morning. But if you can move just a little of your power consumption, it will be an advantage.

What's MOVEPOWER?

- You will receive text messages at the time of day it is best to use power.
- It is optional whether to respond to the text messages you receive.
- You save money* every time you move power as recommended.
- MOVEPOWER is free and without obligation and does not affect your current electricity contract.

If you want to participate in MOVEPOWER, proceed HERE

If you do not wish to participate, please click HERE

Yours sincerely
SE

PS. If you have questions about MOVEPOWER, please feel free to contact us at XXXXXXXX.

*You get 5% off your power you move. This is calculated based on the price of "basic electricity" for January 2015, which was 2.04 DKK per kWh, no matter what price you pay cf. your electricity agreement.

*) In the invitation there are three rebate levels 5% rebate, 20% rebate and 50% rebate.

Appendix A2. E-mail invitation offering GHG-free production to costumers*)

Read this newsletter online

April 2015
Like us on facebook

Dear name

Get 100% sustainability every time you move power

Among our customers there is a clear demand for better use of weather-dependent wind power. We want to meet this demand with a new scheme, called MOVEPOWER. MOVEPOWER is initially offered to a limited number of customers in a one-year trial period.

You have been selected because we believe that you will be able to benefit from the scheme. MOVEPOWER is free and without obligation to you so we hope you find the system attractive. Of course it is your choice whether to participate or not.

During the trial period, you will receive text messages at the time of day it is best to use power. For example, you move the time when you wash clothes, or turn the dishwasher off and so on. Of course it is not intended that you should make roast pork at 3:00 in the morning. But if you can move just a little of your power consumption, it will be an advantage.

What's MOVEPOWER?

- You will receive text messages at the time of day it is best to use power.
- It is optional whether to respond to the text messages you receive.
- You save money* every time you move power as recommended.
- MOVEPOWER is free and without obligation and does not affect your current electricity contract.

If you want to participate in MOVEPOWER, proceed HERE

If you do not wish to participate, please click HERE

Yours sincerely
SE

PS. If you have questions about MOVEPOWER, please feel free to contact us at XXXXXX.

*SE moves electricity generated by conventional power plant to sustainable wind energy equivalent to the amount of power you move.

*) The e-mail invitation is identical to all GHG groups 31,34, 35 and 36.

Appendix B1. Suplementary information provided after accepting rebate invitations: Terms of conditions to costumers offered rebate.*)

These are the conditions in MovePower:

- During the week you will receive text messages that states the hour of the day in which it is best for you to use power.
- If you choose to move some of your power consumption, as recommended in the text messages, you will earn a discount percentage that is stated in the text messages. You will earn the percentage discount for every kWh you move. The discount is minimum the percentage you have been promised in the initial MovePower offer. The discount is calculated as a percentage of the list price for ”Basis el” in January 2015 (2.04 kr. pr. kWh) no matter which tariff you pay stated in your power contract. In this way you save money.
- It is voluntary for you to choose to move some of your power consumption as recommended in the text messages.
- To give you an overview you will once a month receive a message stating how much of your power consumption you have moved, as suggested in the text messages.
- MovePower initially includes a limited number of customers in a one-year trial scheme. You will get a notice when the scheme begins and when it ends.
- If you earn a discount, you will receive the money after one year when the trial scheme ends.
- The MovePower scheme applies only for one address (your daily place of living). If you move from this address within the one-year trial scheme, you will automatically be unsubscribed to MovePower and your earned discount will be cancelled.

If you want to know more about how you can move your power consumption, visit: www.se.dk/FlytStroem.

*) The terms of conditions are identical for the rebate groups 5%, 20% and 50%.

Appendix B2. Suplementary information provided after accepting GHG-free invitations: Terms of conditions for costumers offered GHG-free production.(group 35 and 36) *)

These are the conditions in MovePower:

- During the week you will receive text messages that states the hour of the day in which it is best for you to use power.
- If you choose to move some of your power consumption when you can secure sustainability, the power you move will be 100 % sustainable as stated in the text messages. You will secure 100 % sustainability for every kWh you move. The sustainability is secured because SE (SydEnergi) will move the power production from traditional power stations to sustainable windmills corresponding to the amount of power you move. In this way you help to reduce the environmental impact.
- It is voluntary for you to choose to move some of your power consumption as recommended in the text messages.
- To give you an overview you will once a month receive a message stating how much of your power consumption you have moved, as suggested in the text messages.
- MovePower initially includes a limited number of customers in a one-year trial scheme. You will get a notice when the scheme begins and when it ends.
- If you help moving power SE will increase the windmill capacity corresponding to the amount of power you have moved.
- The MovePower scheme applies only for one address (your daily place of living). If you move from this address within the one-year trial scheme, you will automatically be unsubscribed to MovePower and your earned discount will be cancelled.

If you want to know more about how you can move your power consumption, visit: www.se.dk/FlytStroem.

*) In the terms of conditions for the group 35 and 36, it was not implied that implied that the costumers were part of a team effort, which is in contrast to group 31 and 34 where this was implied.

Appendix B3. Suplementary information provided after accepting GHG-free invitations: Terms of conditions for costumers offered GHG free production (group 31 and 34*)

These are the conditions in MovePower:

- You are part of a MovePower team together with people who are similar to you. You and the other people on your team will during the receive text messages that states the hour of the day in which it is best for you to use power.
- If you and your team choose to move some of your power consumption as stated in the text messages, the power you move will be 100 % sustainable as stated in the text messages. You and your team will thereby secure 100 % sustainability for every kWh you move. The sustainability is secured because SE (SydEnergi) will move the power production from traditional power stations to sustainable windmills corresponding to the amount of power you move. In this way you help to reduce the environmental impact.
- It is voluntary for you to choose to move some of your power consumption as recommended in the text messages.
- To give you an overview you and your team will once a month receive a message stating how much of your power consumption you have moved, as suggested in the text messages.
- MovePower initially includes a limited number of customers in a one-year trial scheme. You will get a notice when the scheme begins and when it ends.
- If you and your team help moving power SE will increase the windmill capacity corresponding to the amount of power you have moved.
- The MovePower scheme applies only for one address (your daily place of living). If you move from this address within the one-year trial scheme, you will automatically be unsubscribed to MovePower and your earned discount will be cancelled.

If you want to know more about how you can move your power consumption, visit: www.se.dk/FlytStroem.

*) It the terms of conditions for the group 31 and 34 it was implied that the costumers were part of a team effort , which is in contrast to group 35 and 36 where this was not implied.

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Appendix Table C. Text Message Variations.

Motive in text message	Move INTO/AWAY text message treatment	Description of text message
Rebate	INTO	Dear SE client. Get a 5% rebate[1)] on electricity you move INTO 3pm-6pm.[2)] This is true today, Monday.[3)]. Sincerely, SE
	AWAY	Dear SE client. Get a 5% rebate[1)] on electricity you move AWAY from 3pm-6pm.[2)] This is true today, Monday.[3)] Sincerely, SE
GHG free production	INTO	Dear SE client. Get 100% sustainability on electricity you move INTO 3pm-6pm.[2)] This is true today, Monday.[3)] Sincerely, SE
	AWAY	Dear SE client. Get 100% sustainability[4)] on electricity you move AWAY from 3pm-6pm.[2)] This is true today, Monday.[3)] Sincerely, SE

1) Treatment rebate groups 5 %, 20 % and 50 %.
2) Treatment hours varied across time slots (10 am to 1 pm; 3pm to 6 pm; 6 pm to 9 pm; 9 pm to 24 pm, and 12 am to 3 pm).
3) Treatment day variations (Monday, Tuesday, Wednesday Thursday Friday, Saturday and Sunday)
4) The text messages to the GHG groups (31, 34, 35 and 36 are identical.

Appendix Table D. An example of the monthly e-mail feedback

Page 1:

In June you have moved less than 3 % of the power consumption that is typical potentially possible to move during the month.

If you wish to see how you have done compared to others, in the figure on the next page you can see that you have done below average.

Click "Next to move on.

Page 2:

*Your neighborhood comprises selected households that are comparable with you and that live in SE's utility area.