Can Incentives to Increase Electricity Use Reduce Emissions, Lower Customer Bills, and Increase Retailer Profits?[1]

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Abstract

Intermittent wind and solar energy can reduce greenhouse gas emissions from electricity generation, but it also increases the challenge of balancing supply and demand throughout the day. We investigate the potential for household demand adjustments to address this challenge through a field experiment that sent text messages to Danish consumers a few hours in advance asking them to shift consumption *into* or *away* from certain hours of the day. Household-level demographic information for all customers randomly invited to participate in the experiment is used to obtain selection-corrected estimates of the impact of these interventions. We estimate a two to three times larger consumption shift for an *into* compared to an *away* request while consumption before and after *into* requests is reduced. The selection-corrected estimates imply that appropriately designed *Into* requests during periods of excess supply of renewable electricity can simultaneously reduce Denmark's greenhouse gas emissions, reduce customer bills, and increase retailer profits.

JEL Classifications: C93, L51, L94, Q41

Key words: Dynamic electricity pricing, Intermittent renewables integration

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1. Introduction

Successfully shifting electricity production from fossil fuels to renewable sources that do not emit greenhouse gases is critical for reducing global greenhouse gas (GHG) emissions. In the United States, electricity production contributes 25.2 percent of GHG emissions (Table 2-10, EPA, 2021). A substantially increased supply of renewable electricity is required if GHG emissions from the transportation and residential heating sectors, which are responsible for 34 percent of US emissions, are to be reduced by converting to electric vehicles and electric residential heating.

An increasing number of jurisdictions have implemented policies to increase significantly the share of intermittent renewable energy, primarily from wind and solar resources, serving their electricity demand. This implies that an increasing share of electricity is produced when the wind blows or when the sun shines, not necessarily when it is in demand by consumers. Depending on availability of the underlying wind or solar resource, the amount of electricity produced by these generation units can change dramatically throughout the day. In contrast, the aggregate demand for electricity typically 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 of the year. This difference between the pattern of aggregate demand and the pattern of renewable energy production throughout the day can create substantial positive and negative imbalances between the instantaneous supply of renewable energy and the demand for electricity, particularly as the share of intermittent renewable energy in a region increases.

If not properly addressed, these imbalances can result in substantial economy-wide costs from the abrupt curtailment of electricity supply and the resulting blackout or brownouts. These outcomes are typically avoided by keeping dispatchable generation units operating at or near their minimum safe operating levels and by investments in storage capacity, both which of have significant economic and environmental costs. Consumers can provide to a lower cost solution to this problem by adjusting their electricity demand in response to financial or environmental signals.

Historically, the role of consumer demand response actions was to ensure that system demand was always below the amount of available generation capacity. However, in regions with significant intermittent renewable generation capacity, there can be many hours when the amount of energy produced by 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 produced may need to be curtailed or exported outside the region in order to maintain system balance. Even a region like California that relies on solar energy that produces during the high demand hours of the day could face the same challenge if there is enough solar generation capacity in the state relative to system demand. These reliability challenges imply a new role for active demand-side participation in shifting demand from hours with less renewable energy production to hours with more renewable energy production.

We provided residential consumers from SE, a large Danish retailer, with dynamic price and environmental signals aimed at causing them to shift their consumption *into* certain hours of the day or *away* from certain hours of the day. Consumers were notified of these price and environmental signals through text messages to their cell phones with prior notification varying from 2 hours to 19 hours. 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 hours or shift *into* the target hours. For the purely environmental motivation signals, customers were promised that SE would invest in additional wind generation capacity equal to the amount of power that they shifted during the experiment period, but were not promised any explicit financial compensation.

Although a random sample of SE's residential consumers were invited to participate in each of the experiment treatments, only those that accepted the invitation actually participated in the experiment. Different from previous dynamic pricing experiments, we take advantage of rich demographic data from Statistics Denmark to account for the decision of invited households to participate. We employ a version of the Ahn and Powell (1993) semiparametric estimator of the single index selection model to account for the joint determination of a customer's decision to participate in the experiment and their willingness to shift their demand in response to text messages during the experiment period. This provides estimates of the expected effects of a randomly selected SE customer responding to a given *Into* or *Away* intervention.

Accounting for the decision of each invited SE household to accept the invitation to participate in the experiment yields slightly smaller absolute magnitudes for each of the *Into* and *Away* effects that are generally statistically different from the ordinary least squares estimates of the same magnitudes. This outcome is consistent with the logic that the households that accepted the invitation to participate in the experiment are those among the population of invited households that expected to be more responsive to our *Into* and *Away* interventions.

Both the empirical analysis that conditions on participation in the experiment and the one that accounts for self-selection into the experiment finds that the same marginal price signal has 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. We also find strong statistical evidence that load shifts *into* a set of target hours significantly reduces consumption in the hours before and after these target hours. For the *away* target hours, we find limited evidence of slight increases in consumption in hours of the day that surround the target hours. The purely environmental signals produced qualitatively similar results. The absolute value of the *Into* effect is significantly larger in absolute value than the *Away* effect and there is stronger evidence that shifting consumption *into* a time interval reduced consumption in surrounding time periods than is the evidence that shifting consumption *away* from a time interval increased consumption in hours surrounding the target hours.

We perform a counterfactual analysis using our selection-corrected estimates to answer the question posed in the title of the paper. Using data on hourly market outcomes in Nordic electricity market from January 1, 2016 to June 30, 2020, we demonstrate the potential for *Into* events to: (1) reduce the wholesale energy costs of SE, (2) increase its profits from electricity retailing after accounting for the rebates paid, (3) lower the electricity bills of customers, and (4) reduce GHG emissions in Denmark. To demonstrate this result, we focus on the small number of days with surplus renewable electricity production in Denmark during the 2016 through 2020 time period.

During a surplus renewable production period in Denmark, the demand increase caused by an *Into* event can be satisfied by reducing exports of renewable energy. Before and after a surplus production period, the marginal supply is satisfied by fossil fuel units at substantially higher costs. By declaring an *Into* event for the surplus renewable production period Denmark's fossil fuel electricity production is reduced because of the reduction in consumption we estimate before and after an *Into* event. Depending on wholesale prices during the *Into* period and before and after the *Into* period, SE's daily wholesale energy costs could also be reduced by shifting demand from before and after the surplus renewable production period into that period. If the daily wholesale cost reduction is large enough to offset the rebates paid for customers and reduction in daily retail revenues, the profits of retailer can increase. If the rebates paid to customers are sufficiently large relative to the increase in retailer revenues, the electricity bills of customers can fall.

We also investigate the effects of appropriately timed *Into* and *Away* events associated with the daily morning and evening consumption and wholesale price peaks in order to shift consumption into other parts of the day. Such consumption shifts are unlikely to reduce Denmark's GHG emissions because its renewable capacity is primarily wind-powered, which typically produces in the morning and evening. Nevertheless, we investigate this price-based consumption shifting because there is such a potential in other jurisdictions where renewable production is primarily solar powered like in California where declaring *Into* events during low-prices hours in the middle of the day can yield environmental benefits, consumers benefits and profit increases for electricity retailers. We find many instances where an appropriately timed *Into* event based on the daily pattern of prices can simultaneously yield significant daily wholesale cost savings and profit increases for SE and lower bills for customers.

Taken together these consumption shift results for excess renewable energy supply periods and for daily morning and evening price peaks emphasize the cost-effectiveness of incentives to increase electricity consumption used during certain times of the day to maintain real-time system balance in regions with significant intermittent renewable generation units.

Finally, we present a simple model of household electricity demand under uncertainty that can explain the significantly larger in absolute value demand response to *Into* versus *Away* events. 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 an *Away* period then she can still pay for all of the electricity she consumes at the standard fixed retail price. In contrast, a customer on a traditional dynamic pricing plan pays the higher dynamic price for all consumption during an *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, and as the model demonstrates, this difference can explain the larger in absolute value treatment effect for *Into* events versus *Away* events for both the price and environmental motivation treatments.

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 intermittent renewable generation resources. Section 3 places the paper in the context of the existing literature on dynamic pricing. Section 4 describes the experimental design and the data collection process for the experiment. Section 5 presents our econometric modeling framework and estimation results for our ordinary least squares model and our selection-corrected model. Section 6 presents the results of the counterfactual analysis using our selection-corrected estimates demonstrating that paying customers to increase their electricity consumption during certain periods can benefit consumers, the retailer that serves them, and reduce GHG emissions in the region. Section 7 presents our simple model of customer demand under uncertainty that rationalizes the difference in our empirical results for *Into* versus *Away* events. Section 8 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 motivates our experiment by describing two examples, one from Denmark and one from California, of how significant amounts of intermittent 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. As we demonstrate in Section 6, different from the case of regions with only dispatchable thermal generation, increasing electricity consumption during certain hours of the day can reduce daily wholesale energy costs if this increase in consumption also reduces consumption during other hours of the day, as we show below is the case with our *Into* events.

Figures 1(a) and 1(b) illustrate the challenges facing Denmark in managing a grid with

Figure 1(a). *Danish Electricity Consumption and Wind Energy Production in MWh per hour*

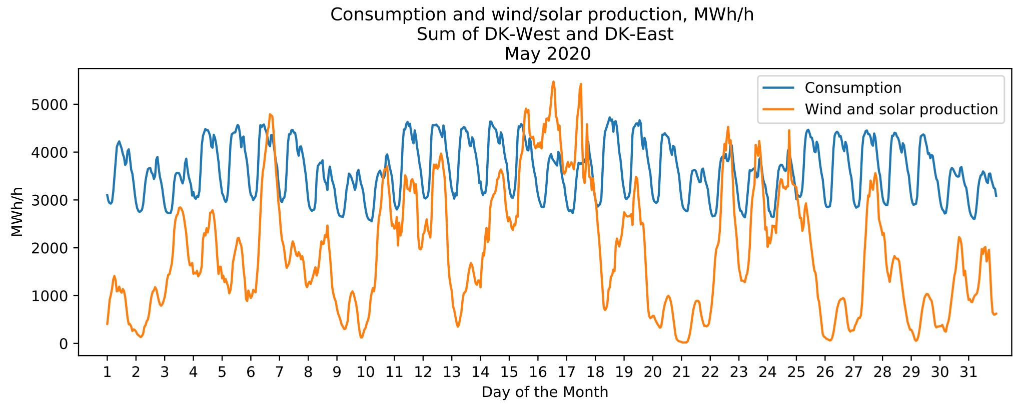
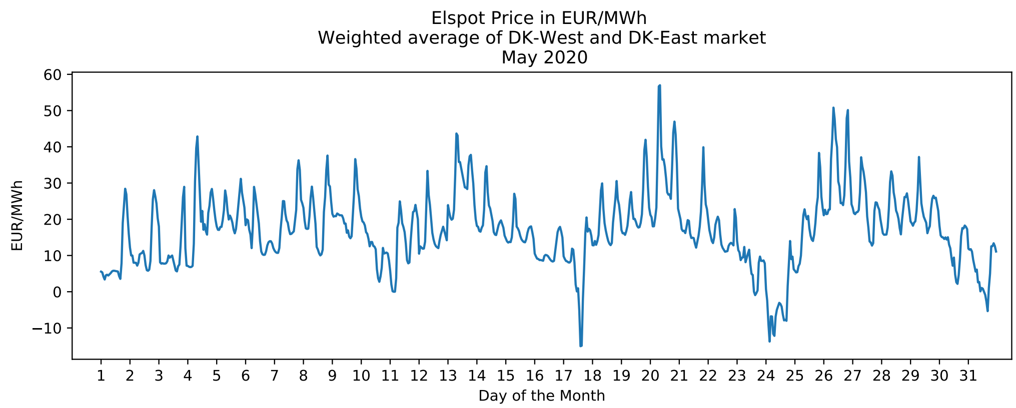


Figure 1(b). *Day-Ahead Short-Term Prices (Zonal Average) in Euros per MWh*



almost 50 percent of the electricity coming from intermittent wind generation units.[2] Figure 1(a) displays the pattern of wind generation and aggregate electricity consumption and Figure 1(b) the Danish wholesale price in Euros per megawatt-hour (MWh) for the entire month of May 2020.[3] Figure 1(a) shows the smooth pattern of aggregate consumption throughout the day and across days of the month. In contrast, the total output of wind generation units is extremely irregular both within the day and across days of the month. There are hours when almost no wind energy is produced and hours when wind energy production exceeds Denmark's electricity consumption.

[2]In 2019, 47 percent of electricity consumption in Denmark came from wind generation. See https://www.statista.com/statistics/991055/share-of-wind-energy-coverage-in-denmark/

[3]Denmark is composed to two pricing zones in Nord Pool market, DK1 and DK2. Demand in Denmark is the sum of consumption in these two zones. The price in Figure 1(b) is the consumption-weighted average price for these two zones.

As shown in Figure 1(b), hourly day-ahead wholesale prices in Denmark are negatively correlated with the amount of wind energy produced. This relationship occurs because the difference between total consumption and renewable energy production must be met with dispatchable generation that is costly to operate, typically because it requires burning an input fossil fuel to produce electricity. This logic implies that increasingly expensive fossil fuel-fired generation units must operate the larger the difference is between system demand and renewable energy production. Therefore, shifting demand *into* hours with high levels of wind generation and *away* from hours with low wind generation has the potential to reduce wholesale energy purchase costs because customers would be buying more energy in low-priced hours and less energy in high-priced hours.

An extreme version of this opportunity occurs on May 17 when the price is negative for a few hours of day that wind production exceeded system demand. These negative prices could have allowed a retailer to pay customers to consume more energy during this hour of the day. Our counterfactual analysis reported in Section 6 finds that both *Into* and *Away* actions can yield wholesale energy purchase cost savings for the retailer as well as variable profit increases after accounting for the rebates paid to customers.

Volatility in the difference between total electricity consumption and total renewable energy production is not unique to Denmark. California has a renewables portfolio standard (RPS) that requires 33 percent of the state's electricity consumption to come from qualified renewable sources—solar, wind, biomass, geothermal, and small hydro—by 2020. This share is required to increase to 60% by 2030. Solar generation capacity is currently thought to be the primary technology that will be used to meet these renewable energy goals. There is currently more than 12,000 MW of grid-scale solar photovoltaic (PV) and solar thermal capacity in California, almost 8,000 MW of distributed solar PV capacity, and almost 7,000 MW of grid-scale wind capacity.[4] This amount of solar capacity has given rise to Figure 2(a), which shows the actual load and the net-of-renewables load curve (total system demand less total renewable energy output) in the California wholesale electricity market for each hour of the day for February 23, 2020. This net-of-renewables load curve is called the "Duck Curve" because of its shape within the day relative to the shape of demand within the day. Both the morning ramp up and evening ramp down of solar production have become increasingly steep as the amount of solar generation capacity in the state has

[4]https://www.energy.ca.gov/data-reports/energy-almanac/california-electricity-data/electric-generation-capacity-and-energy

increased.

Figure 2(a): *System Load and Net Load in MWh in California on February 23, 2020*

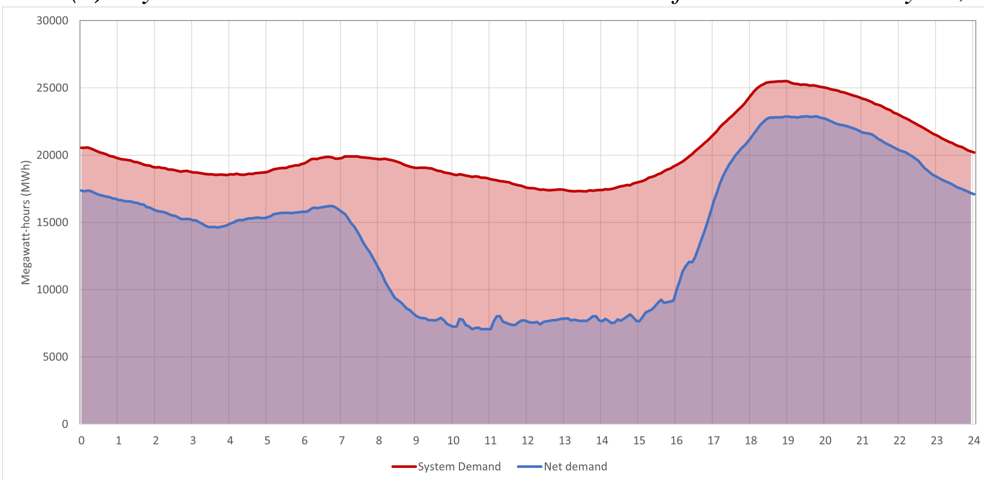


Figure 2(b): *Day-Ahead Prices for California's Three Large Retailers in $ /MWh on February 23, 2020*

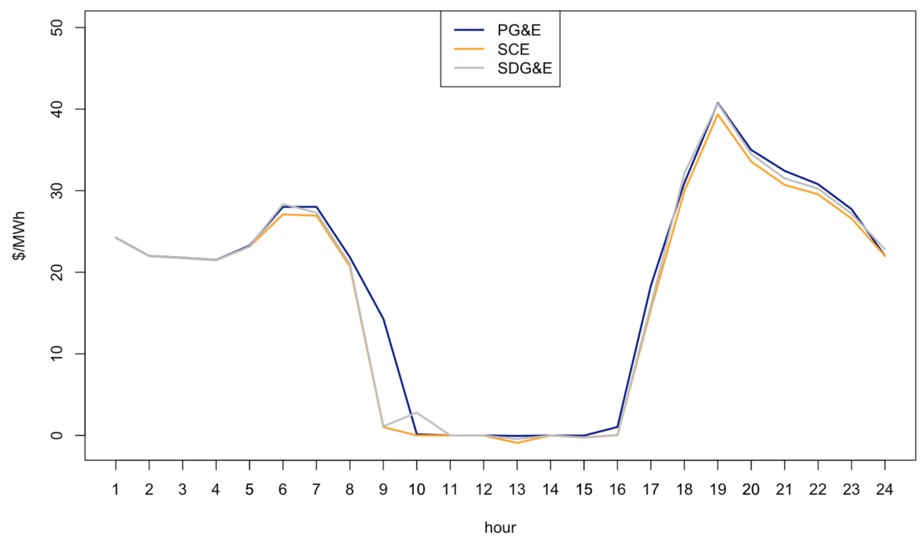


Figure 2(b) shows hourly pattern of day-ahead wholesale prices for the three large investor-owned utilities–Pacific Gas and Electric, San Diego Gas and Electric and Southern California Edison–for February 23, 2020.[5] Prices from 10 am to 3 pm are extremely

[5]The California market is operated by the California Independent System Operator (ISO) which runs a day-ahead forward energy market and real-time energy market where differences between day-ahead purchases and sales and real-time production and consumption are traded.

low, even slightly negative in a few hours during this time period. This figure implies a growing economic benefit from shifting consumption *into* the 10 am to 3 pm time period as California continues to increase its solar generation capacity. According to the results of our experiment, shifting consumption *into* these hours will reduce consumption during the early morning and late evening hours when prices are 20 to 40 times higher, and this can save consumers and their retailer on their daily wholesale energy purchase costs, by the same logic as described above for Denmark.

In 2020 and beyond, during the hours when California's solar generation capacity is producing a substantial amount of energy, there is a significant risk that total renewable energy production in California will exceed its electricity consumption. When this happens, real-time prices are likely to be negative. Consequently, further wholesale energy cost savings are possible if consumers are able to shift their consumption *into* the hours of the day when this over-generation condition occurs. Sustained periods of solar energy production in excess of system demand are very likely to occur in California given its ambitious renewable energy goals. A simple rule of thumb is that if the renewable energy share exceeds the capacity factor of the renewable generation technology used to meet it, then there is a 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 highest.[6] The fleet-wide capacity factor for solar photovoltaic (PV) generation units in California is approximately 25 percent. This implies that if solar energy is the major renewable generation source used to meet the 60 percent RPS, then without significant investments in storage capacity there will be many hours of the year when total solar PV production exceeds total electricity demand in California.[8]

To conclude, three major factors motivate our real-time pricing and information provision experiment to shift consumption with short notice via text messages. First, an increasing number of countries and regions have the ambitious renewable energy

[6]To illustrate this point suppose that demand in a region is 100 MWh every hour of the year. Obtaining a 33 percent annual renewable energy share in a region using solar PV technology that has 25 percent annual capacity factor will require at least 33 MW/0.25 = 132 MW of solar PV capacity, assuming no curtailment of renewable energy production during the year.[7] This means during all hours of the year with an hourly capacity factor for all solar PV units greater than 0.757 (100 MWh = 132 MWh x 0.757), will have more solar energy produced than system demand.

[8]California has substantial interconnection capacity with the rest of the western United States, so it can export energy if in-state demand is less than in-state energy production up to the amount of this transmission capacity.

goals. Real-time pricing and information provision mechanisms that cause consumers to shift-their consumption both *into* certain hours of the day and *away* from other hours of the day are likely to be part of a cost-effective strategy for achieving these renewable energy goals. Second, because the amount of energy produced by wind and solar generation units can change with little advance notice, to manage most effectively the supply and demand imbalances caused by intermittent renewable energy production, customers on dynamic pricing or other load-shifting plans must respond with short notice. Text messages are an ideal mechanism for providing price and environmental motivation information with short notice. Third, the popularity of rebate-based dynamic pricing plans with customers and regulators emphasizes the need to understand the relative effectiveness of different rebate-based dynamic pricing programs.

3. Relation to Existing Research on Dynamic Pricing and Load-Shifting

A number of studies have used randomized controlled experiments to investigate the effects of various dynamic pricing schemes (e.g. Ito et al. (2018), Jessoe and Rapson (2014), Allcott (2011), Wolak (2010), Herter (2007), Lijesen (2007), Wolak (2006) and the studies reviewed in Kessels et al. (2016) and Faruqui and Sergici (2010)). The main focus of this literature is on lowering peak demand and the consensus is that critical peak pricing (CPP) schemes are effective at achieving this goal. There are six ways that we believe our experiment adds to this research.

First, all previous research that we are aware of has conditioned the experimental results obtained on the customers that self-selected to participate. Building on a preliminary investigation of our data in Møller et al. (2019) the present study uses detailed household-level demographic data from Statistics Denmark for all SE customers invited to participate in our experiment to recover estimates of our *Away* and *Into* interventions that accounts for the propensity of households to participate in our experiment as a function of these demographic characteristics.

Second, most previous research studied day-ahead notifications of the need to reduce demand, with Jessoe and Rapson (2014) being an exception where 30-minute prior notice is used. Our experiment uses text messages provided via a cell phone with short notice and so adds to the literature on short notice effects. As noted above, short notice effects are especially relevant for evaluating the potential of demand response to mitigate imbalances caused by variations in intermittent renewable energy production.

Third, we focus on explicit incentives to consume more electricity during certain time periods. Virtually all previous research on dynamic pricing focuses on reducing demand during certain critical time periods. We are not aware of any other studies of incentives to increase electricity consumption during certain time periods. As discussed in Section 2, and demonstrated empirically in Section 6, this approach to dynamic pricing and load-shifting is directly relevant to addressing periods of excess supply of renewable energy likely to occur because of large amounts of intermittent renewable generation capacity in a region.

Fourth, we study the question of how incentives to move electricity consumption *into* and *away* from target hours affects consumption in neighboring hours both between the time a customer is notified of an intervention and the target time period, as well as during the same length of time after the target period. This pre- and post-event load-shifting turns out to be important for calculating the overall benefits and costs of *Into* and *Away* approaches to managing renewable energy supply and system demand imbalances during the day.

Fifth, peak period rebate schemes are popular with consumers and utilities as an alternative to traditional dynamic pricing schemes, most likely because of the fear among regulators that dynamic pricing schemes can imply substantial wealth transfers among electricity consumers (Borenstein, 2007). Yet, only a few studies have investigated rebate schemes (e.g. Wolak (2006) and Wolak (2010)). Our experiment implements load-shifting (both increases and decreases) incentives using rebates. Ito (2015) studies the asymmetries in rebate schemes for the case of energy efficiency investments.

Finally, we consider both financial incentive and environmental motivation interventions to move electricity consumption *into* and *away* from the target time intervals. We add to the literature where Ito et al. (2018) compares the effects of financial incentives on electricity demand with the effects of an environmental motivation.

4. Description of Experiment and Data Collected for Empirical Analysis

The experiment was conducted in collaboration with the energy company SE[9] one of the largest electricity retailers in Denmark. Participants were recruited through e-mails sent

[9] SE, https://www.se.dk/

to customers that had given SE permission to contact them by e-mail[10]. In April 2015, these customers were notified of the existence of a new SE program called MOVEPOWER. A randomly selected set of customers were told that they could earn a rebate if they moved their energy consumption *into* or *away* from particular time slots and that information about the relevant time slots would be sent to them though a text to their cell phone (see an English translation of the e-mail text in Appendix B-2). The remaining randomly selected customers were told that SE would invest in additional GHG emissions-free energy production equal to the amount of energy customers moved in accordance with the text messages they received (see an English translation of e-mail text in Appendix B-3).

The SE-customers contacted were randomized across seven different treatments. The customers receiving the financial incentive e-mail were randomly offered a 5%, 20%, or 50% rebate on all energy moved in accordance with the text messages (calculated based on SE's retail electricity price regardless of the price paid by the customer). Customers receiving the GHG emissions-free production e-mails, were randomly assigned to four types of messages promising that all energy moved in accordance with the text messages led to a commitment by SE to increase investments in GHG emissions-free energy production that matched the amount of energy moved. The four environmental motivation treatments only reflect slight differences in the wording of how this information was conveyed to the consumers. Consequently, which of the three rebate groups or the four environmental motivation treatments a customer is assigned to is the result of the initial invitation to participate in the experiment they were sent and their decision to accept or reject this invitation.

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 B-4 to B-6 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, 735 customers signed up for the rebate-based program and 1,061 customers signed up for the GHG emissions-free energy program.

[10] For this part of the experiment, e-mail invitations were sent to the 23,935 customers randomly selected from SE's database identified as residential households. This e-mail contact database contains 36,083 residential households out of SE's more than 247,000 residential customers in southern Denmark.

The first text messages were sent on the June 4, 2015 and the experiment was terminated on February 7, 2016.[11] Customers were prompted via text messages to their cell phones a few hours in advance on the same day they were supposed to move energy. Customers were notified an average of 1.2 times per week of the 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 energy *into* or *away* from the target time slot that day in order to earn the rebate or ensure GHG emissions-free electricity production. The text message also reminded them of the rebate percent on the standard rate that they would earn or the GHG emissions-free energy production they would ensure by moving energy in accordance with the text message (see the Appendix C for English translations of sample text messages).

The target time slots for *into* and *away* from events for each participating customer varied randomly across the days of the week, between different three-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 typically varied from 2 hours to 19 hours in advance of the target 3-hour time slot. All interventions were randomly assigned to require moving consumption *into* or moving consumption *away* from the target 3-hour time slot. All consumers had interval meters that recorded their hourly consumption each day, making it possible to calculate their consumption during the relevant *Into* and *Away* time slots.

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 customers to deduce how much energy they had actually moved during a given month from this relative feedback. Customers were not informed of their actual rebate earnings or of the actual quantity of energy moved prior to February 7, 2016. They were also not informed about precisely how SE would calculate how much energy they had moved or how much rebate they had earned.[12]

After the experiment was terminated, rebates were calculated and the amount of kWhs of GHG emissions-free energy production due for each customer. Rebates were then paid to customers and earned GHG emissions-free kWhs reported. We estimated energy movement

[11]The part of the experiment we report results for here was terminated at this date and the dataset used in our empirical analysis ends on this date.

[12]Customers could contact SE's help desk which 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 or how these magnitudes were calculated.

that each customer would be compensated for using a variant of the model estimates described below. However, because these estimates for individual households were based on a statistical model, we rounded up rebate refunds and credited GHG emissions-free kWhs so that most customers were actually paid or credited GHG emissions-free energy in excess of what they rationally would have expected. However, this positive surprise was not announced to them before or during the experiment and so it could not have affected the participant's behavior during the experiment. All communication with customers from the initial recruitment e-mail to text messages and feedback was done by SE through their mail server and text message service using their letterhead and logo.[13]

Because of our focus on recovering selection-corrected estimates of the impact of *Into* and *Away* interventions, we perform all of our empirical analyses with electricity consumption data from customers that we were able to match with Statistics Denmark demographic data. This enables us to attribute the difference between our ordinary least squares and the selection-corrected estimates of the impact of our *Into* and *Away* interventions to the self-selection of SE customers to participate in our experiment. For both the rebate and environmental inventions we lose very few experiment participants by excluding customers we were unable to match with the Statistics Denmark demographic data. The number of participants in the rebate treatments–624–is lower than the 735 who signed up because we randomly selected some of these customers for other interventions involving rebates combined with other treatments. However, out of these 624 customers, 611 could be matched with demographic data from Statistics Denmark. The number of participants in the environmental motivation treatments–792–is lower then the 1,061 who signed up because we randomly assigned some of these customers to other interventions involving environmental motivations combined with other treatments. However, out of these 792 customers, 784 could be matched with demographic data from Statistics Denmark.

Table 1 presents summary statistics on the number of households with matching demographic data from Statistics Denmark participating in the three rebate treatments and the environmental motivation treatment and the average number of treatment and

[13]All communications with SE's customers were approved by the marketing division of SE. Customers with questions could contact SE's help desk, which had dedicated customer service personal 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.

non-treatment days for each group.[14]

Table 1: Summary Statistics for Participants

	5% rebate	20% rebate	50% rebate	Envr.
Number of customers	318	179	114	784
Average number of time slots per customer				
With *Into* treatment[i]	45.71	45	44.97	45.6
With *Away* treatment[ii]	21.45	20.28	20.17	21.1
With no treatment[iii]	911.21	913.75	922.20	912.4

[i] 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.

[ii] 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.

[iii] All *potential* treatment periods in the timeslot 10-13, 15-18, 18-21, 21-24 and 24-3 on days with *no* treatments. Twenty percent of the potential treatments are in the time slots 10-13, 15-18, 18-21, 21-24, and 24-3.

5. Estimation Procedure and Empirical Results

In this section we estimate a number of average treatment effects for each of the three rebate groups and the environmental motivation group. We first estimate the average treatment effect for the population of customers that decided to participate in our experiment. We then examine the extent to which our results change when we account for the self-selection of SE customers to participate in the experiment using the semimparametric Ahn and Powell (1993) estimator. We estimate both models separately for the sample of rebate customers and the sample of environmental motivation customers that we were able to match to demographic data from Statistics Denmark.

The average treatment effect for the population of customers that decided to participate in our experiment can be recovered from a difference-in-difference estimator because customers in each of the treatment groups are randomly assigned to receive treatments

[14]There are four environmental motivation treatment groups. As shown in Appendices B-5 and B-6, the four environmental motivation groups differ only slightly in wording of the supplementary information provided just after the initial invitation, whereas all of the initial e-mail invitations were identical for the four groups. In Supplementary material appendix SA we estimate the treatment effect model presented later in the paper for each group and find no statistical difference between parameter estimates for each group. In the rest of the paper we present pooled regressions for the environmental motivation treatments.

(via text messages) across and within days. This implies that customers in our sample 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 these difference-in-difference estimation procedures are recovering the average treatment effect for customers receiving rebates and the environmental motivation intervention for the population of customers that participated in the experiment.

To estimate the selection-corrected estimates of the treatment effects for the population of SE residential customers for an *Into* or *Away* event for the rebate and environmental treatment groups we estimate a flexible model for the conditional mean of the binary decision of an invited household to participate in the experiment as a function of the characteristics of the invitation given to that household and a variety of household-level demographic characteristics compiled by Statistics Denmark. Following the procedure outlined by Ahn and Powell (1993), we use the fitted value of this conditional mean function and the assumption of continuity of the underlying selection function that depends on the conditional mean of the decision to participate in the experiment to estimate six *Into* and *Away* coefficients nonparametrically controlling for the selection mechanism. As discussed in the following section, these six coefficients are the *Away* and *Into* effects and the *Before* and *After* effects for both *Away* and *Into* events.

5.1. Treatment Effects for the Experiment Population

Because we are interested in quantifying whether *Into* events led to reduced consumption in periods that surround a treatment period and whether *Away* events cause increased consumption in periods that surround a treatment period, for each treatment group we define six indicators, three for the *Into* treatment and three for the *Away* treatment. The first variable, $Away_{ritd}$, is equal to 1 for incentive r (r = 5 percent, 20 percent, 50 percent and environmental motivation), 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, $BeforeAway_{ritd}$, is equal to 1 for all time periods after an *Away* notification was sent to consumer i with incentive 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, $AfterAway_{ritd}$, is equal to 1 for as many hours after the *Away* event as the associated $BeforeAway_{ritd}$ variable is equal to 1 and it is equal to zero for all other time periods in the sample. The idea of including the $BeforeAway_{ritd}$ and $AfterAway_{ritd}$ 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 length of time equal to the advance notice the customer received for this *Away* event.

Three analogous variables are defined for the *Into* events. The variable, $Into_{ritd}$ 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. $BeforeInto_{ritd}$ 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 occurred for this customer and is equal to zero for all other time periods in the sample. $AfterInto_{ritd}$ is equal to 1 for as many hours after the *Into* event as the $BeforeInto_{ritd}$ variable was equal to 1 for the same *Into* event and is 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 the length of time equal to amount of advance notice the customer received for this *Into* event.

For the purposes of the experiment, the day is divided into 9 time periods, $t = 1, 2, ..., 9$. 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 environmental motivation samples were only declared during the 10 am to 1 pm period and the last four 3-hour time periods.

Let y_{itd} equal the natural logarithm of electricity consumption in kilowatt-hours (kWh) *per hour* by customer i during period t of day d.[15] In terms of this notation, we estimate the following regression for each of the four samples of customers, r = 5%, 20%, 50%, and environmental motivation:

[15]We normalize the energy consumption in each of the nine time periods by the number of hours in that time period to account for differences in the number hours in these time periods of the day. This normalization makes it possible to apply our treatment effects estimates to counterfactual *Into* and *AWay* events of shorter and longer time periods than the length of the *Before*, *During*, and *After Into* and *Away* events in our experiment period.

$$y_{itd} = \mu_t + \nu_i + \eta_d + \beta_1 BeforeInto_{ritd} + \beta_2 Into_{ritd} + \beta_3 AfterInto_{ritd}$$
$$+ \alpha_1 BeforeAway_{ritd} + \alpha_2 Away_{ritd} + \alpha_3 AfterAway_{ritd} + \varepsilon_{itd}$$

where the μ_t (t=1,2,...,9) are period-of-day fixed effects, the ν_i (i=1,2,... ,I) are customer fixed effects, the η_d (d=1,2,..,D) are day-of-sample fixed effects, and the ε_{itd} are mean zero regression disturbances that are independently distributed of the regressors, $BeforeInto_{ritd}$, $Into_{ritd}$, $AfterInto_{ritd}$, $BeforeAway_{ritd}$, $Away_{ritd}$, and $AfterAway_{ritd}$, because both *Away* and *Into* events are draw randomly both across customers and over time.

Table 2: Estimation Results for 5%, 20%, 50% Rebate and Environmental Motivation

	Dependent variable: log(kWh per hour)			
	5% Rebate	20% Rebate	50% Rebate	Envr.
Regressor				
BeforeInto	-0.0082	-0.0082	-0.0066	-0.0055
	(0.0016)	(0.0025)	(0.0029)	(0.0012)
Into	0.0320	0.0319	0.0496	0.0236
	(0.0029)	(0.0039)	(0.0062)	(0.0017)
AfterInto	-0.0033	-0.0041	0.0019	-0.0010
	(0.0013)	(0.0020)	(0.0021)	(0.0010)
BeforeAway	0.0038	-0.0001	0.0026	-0.0003
	(0.0023)	(0.0032)	(0.0036)	(0.0015)
Away	-0.0147	-0.0122	-0.0137	-0.0095
	(0.0029)	(0.0038)	(0.0044)	(0.0017)
AfterAway	0.0026	-0.0014	-0.0007	0.0013
	(0.0020)	(0.0030)	(0.0034)	(0.0013)
N	707,346	389,880	253,179	1,743,167

Note: Robust standard errors (in parentheses) computed as in Arellano (1987).

The first column of numbers in Table 2 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, the third column presents the estimates for the 50 percent rebate sample and the fourth column presents the estimates for the envihronmental motivation sample. To account for arbitrary forms of autocorrelation in the ε_{itd} across time periods and days in the sample for each customer and the possibility that this pattern of autocorrelation could differ across customers, we report the Arellano (1987) standard errors that are robust to this form of heteroscedasticity and autocorrelation in the values of ε_{itd}. The bottom row of each column lists the total number of combined time period, day, and customer observations used to estimate each regression.

Looking at the three rebate treatments the first result of note is the uniformly two to three times larger in absolute value coefficient on $Into_{ritd}$ versus $Away_{ritd}$. The *Into* average treatment effect for rebates ranges from a 3.20 = 100*(exp(0.0319)-1) percent to 5.08 = 100*(exp(0.0496)-1) percent increase in consumption during the treatment period, and is significantly larger for the 50 percent rebate level relative to the 5 percent and 20 percent rebate level. The *Away* average treatment effect is between -1.21 = 100*(exp(-0.0122)-1) and -1.46 = 100*(exp(-0.0147) -1) percent for all rebate levels, with the highest percentage reduction occurring for the 5 percent rebate level. In Supplementary material appendix SC we present a simple theoretical model of household-level demand under uncertainty that rationalizes the divergence between the *Into* and *Away* coefficient estimates for the rebate and the environmental treatments.

A second result is the fact that both before and after an *Into* event, consumption is significantly lower relative to the control group. These results are very encouraging for using *Into* treatments to achieve targeted demand increases surrounded by demand reductions. Only for the 5 percent *Away* treatment is there some evidence that consumption is higher relative to the control before and after an *Away* event.

Turning to the environmental motivation treatment sample in the last column of Table 2, the same qualitative results hold as for the rebate treatments. The absolute value of the *Into* treatment effect is 2.39 = 100*(exp(0.0236)-1) percent, whereas the absolute value of the *Away* treatment effect is almost one-third that magnitude in absolute value at -0.95 = 100*(exp(-0.0095)-1) percent. 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 consumption *away* from a time period leads to higher consumption in the surrounding periods.

To investigate whether the estimation results for the $BeforeAway_{ritd}$ and $AfterAway_{ritd}$ for the different rebate levels is due to the sample size differences shown in Table 2, 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:

$$
\begin{aligned}
y_{itd} = \mu_t + \nu_i + \eta_d + \sum_{r=5,20,50} \Big[& \beta_{1r} BeforeInto_{ritd} + \beta_{2r} Into_{ritd} + \beta_{3r} AfterInto_{ritd} \\
& + \alpha_{1r} BeforeAway_{ritd} + \alpha_{2r} Away_{ritd} + \alpha_{3r} AfterAway_{ritd} \Big] + \varepsilon_{itd}
\end{aligned}
$$

Table 3 reports the results of estimating this regression along with Arellano (1987) standard error estimates. The major change in the results from rebate-level-specific regressions is the larger in absolute value coefficient on $Into_{ritd}$ for the 50 percent rebate levels and the smaller in absolute value coefficient on $Away_{ritd}$ 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, the absolute value of the treatment effects for the *Into* interventions are two to three times larger than the corresponding value for the *Away* interventions. A significant fraction of the energy that shifts *into* a treatment period 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.

We now report the results of several placebo regressions to investigate whether our *Into* and *Away* interventions actually caused the consumption changes presented in Tables 2 and 3. We create the following two indicator variables, both covering periods which were *not* treated, and therefore should have no effect: $IntoP_{itd}$ equals 1 in time period t of day d if this time period is immediately before notification of an *Into* event given to customer i with any rebate level and zero in all other time periods and (2) $AwayP_{itd}$ equals 1 in time period t of day if this time period is immediately before an *Away* notification is presented to customer i with any rebate level and zero in all other time periods.

For each rebate level sample and the pooled rebate sample, we add the variables $IntoP_{itd}$ and $AwayP_{itd}$ to the regression. For each regression we would not expect the coefficient

Table 3: Pooled Estimation Results for 5%, 20%, and 50% Rebate Levels

	Dependent variable: log(kWh per hour)		
	5% Rebate	20% Rebate	50% Rebate
Regressor			
BeforeInto	-0.0097	-0.0056	-0.0060
	(0.0019)	(0.0030)	(0.0034)
Into	0.0307	0.0319	0.0534
	(0.0031)	(0.0042)	(0.0064)
AfterInto	-0.0036	-0.0030	0.0013
	(0.0015)	(0.0024)	(0.0027)
BeforeAway	0.0029	0.0013	0.0033
	(0.0024)	(0.0034)	(0.0038)
Away	-0.0152	-0.0145	-0.0086
	(0.0031)	(0.0044)	(0.0051)
AfterAway	0.0032	-0.0021	-0.0010
	(0.0020)	(0.0030)	(0.0036)
N		1,350,405	

Note: Robust standard errors (in parentheses) computed as in Arellano (1987).

on either variable to be nonzero because customers have no economic or environmental incentive to shift their consumption *into* or *away* from time periods when either $IntroP_{itd}$ or $AwayP_{itd}$ is equal to 1. Table 4 reports these two coefficient estimates along with Arellano (1987) standard error estimates. With the exception of the $IntoP_{itd}$ for the 5% rebate and the $AwayP_{itd}$ variable for the 50% rebate, a size 0.05 test of the the null hypothesis that the coefficient on each of these two variables is zero cannot be rejected. The second to last column of Table 4 presents estimates of these coefficients that pool the data for all of the rebate levels. In this case as well, a size 0.05 test of the null hypothesis that the coefficient on each of these two variables is zero cannot be rejected.

The last column of Table 4 reports the results of estimating this same regression for the environmental motivation intervention sample with Arellano (1987) standard estimates. The variable $IntoP_{itd}$ now equals 1 in time period t of day d if this time period is immediately before notification of an *Into* event is given to customer i for any

Table 4: Placebo Estimates of Impact of Treatments

	Dependent variable: log(kWh per hour)				
	5% Rebate	20% Rebate	50% Rebate	Pooled Rebate Sample	Envr.
Regressor					
IntoP	-0.0047	-0.0046	0.0052	-0.0028	-0.0019
	(0.0020)	(0.0030)	(0.0040)	(0.0016)	(0.0014)
AwayP	0.0020	-0.0025	-0.0089	-0.0013	0.0009
	(0.0026)	(0.0036)	(0.0032)	(0.0018)	(0.0016)
N	707,346	389,880	253,179	1,350,405	1,743,167

Note: Robust standard errors (in parentheses) computed as in Arellano (1987).

environmental motivation treatment and zero in all other time periods and $AwayP_{itd}$ equals 1 in time period t of day if this time period is immediately before an *Away* intervention is given to customer i for any environmental motivation treatment and zero in all other time periods. In this case as well, a size 0.05 test of the null hypothesis that each of these two coefficients are zero cannot be rejected.

The results in Table 4 are broadly consistent with the *Into* and *Away* consumption shifting estimates presented in the previous section being caused by our rebate and environmental motivation treatments.

5.2. Selection Corrected Estimates of Experimental Results

This section presents estimates of the models in Tables 2 to 4 that account for the decision of invited SE households to participate in the experiment. The first step in computing selection-corrected estimates is to estimate the conditional probability of participating in the experiment as a function of characteristics of the invitation sent to the customer and demographics and home characteristics for the customer obtained from Statistics Denmark. The next step takes the value of this conditional probability of participating in the experiment for each customer and uses it to construct a nonparametric (in the sense described below) selection-corrected estimate of the parameters of the models presented in Tables 2 to 4.

The first-step in estimating the semiparametric selection model is an estimate of the conditional mean of the decision of a customer to participate in the experiment. To do this, we first match each SE customer that was invited to participate in our experiment to its demographic and home characteristics from Statistics Denmark. Out of the 23,935 customers invited, 22,658 could be matched with data from Statistics Denmark, which implies our estimation sample size is 22,658.[16]

Empirical evidence that selection may be an issue can be obtained from comparing the mean characteristics of the invitation for those that participated in the experiment and those that did not. Table 5 gives these sample means, the difference between these sample means, and the estimated standard error of the difference.[17] Supplementary material Appendix SB gives the variable definitions for each variable in Table 5. For the majority of the variables, the means are statistically different between customers that did and did not participate in the experiment. For instance, customers offered higher rebates were more likely to participate in the experiment. We also performed a multivariate difference of means test for the joint null hypothesis that all nine means are equal and obtained a test statistic equal to 151.6, which is substantially larger than the critical value for virtually any nonzero size test of this null hypothesis.[18]

Appendix B-1 reports the same four magnitudes for each of the customer demographic and home characteristics variables for customers that participated in the experiment and those that did not. Supplementary material Appendix SB gives the variable definitions for each variable listed in Appendix B-1. For virtually all of the variables, the mean for those who participated is statistically different from mean of those who did not participate. A joint test that all 31 means are equal yields a test statistic equal to 554.6, which is much larger than the critical value for virtually any nonzero size test of the null hypothesis.

[16]Recall that this process resulted in 611 of 624 customers that participated in the rebate portion of the experiment and 784 of 792 customers that participated in the environmental motivation portion of the experiment in our estimation sample.

[17]The estimated standard error of the difference in means is equal to SE(Diff) = $\sqrt{\frac{(s_{Participate})^2}{N_{Participate}} + \frac{(s_{Not\ Participate})^2}{N_{Not\ Participate}}}$, where $(s_k)^2$ is the sample variance of the variable and N_k is the number of observations used to compute this sample variance for group k = Participate or Not Participate.

[18]The test statistic is equal to $(\bar{X}_{Participate} - \bar{X}_{Not\ Participate})'[\frac{\hat{\Sigma}_{Participate}}{N_{Participate}} + \frac{\hat{\Sigma}_{Not\ Participate}}{N_{Not\ Participate}}]^{-1}(\bar{X}_{Participate} - \bar{X}_{Not\ Participate})$, where $\bar{X}_k$ is the sample mean and $\hat{\Sigma}_k$ is the sample covariance matrix of the vector X for group k = Participate or Not Participate. This statistic is asymptotically distributed as a χ^2_j, where j is the dimension of X, under the null hypothesis.

Table 5: Summary Statistics for Invitation Variables

	Mean (Participate=0)	Mean (Participate=1)	Diff.	Std. Error
Second Wave	0.5044	0.4516	0.0529	0.0123
5% Rebate	0.1694	0.2385	-0.0691	0.0105
20% Rebate	0.0756	0.1025	-0.0269	0.0075
50% Rebate	0.0400	0.0652	-0.0252	0.0060
Environmental Signal	0.7150	0.5938	0.1213	0.0121
Foot in the Door with Price Motive	0.1407	0.2147	-0.0740	0.0101
Foot in the Door with Envi. Motive	0.3567	0.3025	0.0542	0.0114
Offered Device	0.3305	0.3320	-0.0015	0.0117

Note: There are 1,765 individuals who participated, and 20,893 who did not.

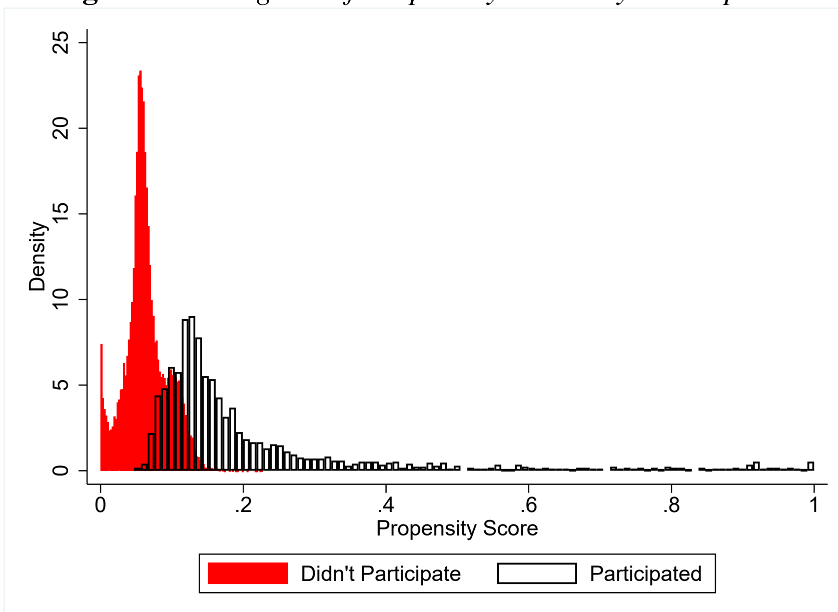
A joint test that the means of all 40 invitation and customer demographic and home characteristics are jointly equal yields a test statistic 713.0, which is larger than the critical value for virtually any size test of the null hypothesis. The results in Tables 5 and 6 provide strong evidence that selection into the experiment was not independent of the values of invitation variables and demographic and home characteristics variables.

Let g_i equal $E(D_i = 1|w_i)$ where $D_i = 1$ if customer i chose to participate in the experiment and w_i is a K-dimensional vector of invitation and demographic and dwelling characteristics for customer i listed in Tables 5 and 6. Although we focus on rebates for energy moved and green energy investment commitments for energy moved during *Into* and *Away* events, our conditional mean of participation estimation procedure accounts for all possible inducements. We employ a multivariate kernel regression to estimate g_i:

$$E(D_i = 1|w_i) = g_i = \frac{\sum_{j=1}^{N} D_j \mathbf{k}_H(w_i - w_j)}{\sum_{j=1}^{N} \mathbf{k}_H(w_i - w_j)}$$

where $\mathbf{k}_H(s)$ is the multivariate normal kernel $\mathbf{k}_H(s) = (2\pi)^{-K/2}|H|^{-1/2}exp(-\frac{1}{2}s'H^{-1}t)$ for $s \in \mathbb{R}^K$ and H is a $(K \times K)$ diagonal matrix of smoothing parameters that we estimate using cross-validation. Let $\hat{g}_i$ equal the estimated value of this conditional mean from our kernel regression estimation for the cross-validated value of H. Figure 3 plots the histogram of values $\hat{g}_i$ for $D_j = 1$ and $D_j = 0$. There is overlap in the supports of the histograms of the $\hat{g}_j$ for $D_j = 1$ and $D_j = 0$. As a robustness check of our kernel regression procedure, we also estimated a flexible probit including w_i and squares and interactions of the elements of w_i and obtained histograms of $\hat{g}_j$ for $D_j = 1$ and $D_j = 0$ with more support in common, although the selection-corrected estimation results reported in this section did not change significantly if we used this estimate of $\hat{g}_j$ instead of the one obtained from our kernel regression.

Figure 3: *Histogram of Propensity Scores by Participation*



The Ahn and Powell (1993) estimator relies on continuity of the selection function $\lambda(\cdot)$ in the conditional mean function, g_i, to difference out the unknown selection function in the regression equation. Selection-corrected estimates of the coefficients of the original model are obtained from a regression involving all pairwise differences of observations.

To operationalize this intuition consider the following observation for time period t of day d of the selection-corrected equation for our rebate sample:

$$y_{itd} = \mu_t + \nu_i + \eta_d + X'_{itd}\Gamma + \lambda_{td}(g_i) + u_{itd} \tag{1}$$

where X_{itd} contains the six *Into* and *Away* regressors. The vector Γ is the associated vector regression coefficients. The function is $\lambda_{td}(\cdot)$ is unknown, but is assumed to be continuous in its argument, g_i. Note that this function is allowed to vary across both time periods, t, and days in the sample, d, to account for the fact that the dependence between a customer's decision to participate in the experiment and their consumption during the experiment can differ across time periods and days.

To account for the presence of customer specific fixed-effects we compute the mean of each variable over all time periods and days in the sample to obtain:

$$\bar{y}_i = \bar{\mu} + \nu_i + \bar{\eta} + \bar{X}_i{}'\Gamma + \overline{\lambda(g_i)} + \bar{u}_i \tag{2}$$

where $\bar{Z} \equiv \frac{1}{9D}\sum_{d=1}^{D}\sum_{t=1}^{9} Z_{td}$ for any variable Z_{td} to account for the fact that there are D days in our sample and 9 consumption periods in each day. Subtracting equation (2) from (1) yields:

$$(y_{itd} - \bar{y}_i) = (\mu_t - \bar{\mu}) + (\eta_d - \bar{\eta}) + (X_{itd} - \bar{X}_i)'\Gamma + (\lambda_{td}(g_i) - \overline{\lambda(g_i)}) + (u_{itd} - \bar{u}_i) \tag{3}$$

Define $y^*_{itd} \equiv (y_{itd} - \bar{y}_i)$. Equation (3) can be re-written in this notation as:

$$y^*_{itd} = \mu^*_t + \eta^*_d + X^{*\prime}_{itd}\Gamma + \lambda_{td}(g_i)^* + u^*_{itd} \tag{4}$$

Taking the difference between the observations of equation (4) for the same day and period of the day for customer i and customer j, for individuals with $g_i \approx g_j$ yields:

$$\begin{aligned} y^*_{itd} - y^*_{jtd} &= (X^{*\prime}_{itd} - X^{*\prime}_{jtd})\Gamma + [\lambda_{td}(g_i)^* - \lambda_{td}(g_j)^*] + [u^*_{itd} - u^*_{jtd}] \\ &\approx (X^*_{itd} - X^*_{jtd})'\Gamma + [u^*_{itd} - u^*_{jtd}] \end{aligned}$$

The second $\approx$ follows from the fact that the $\lambda_{td}(g)$ are assumed to be continuous in g, that if $g_i = g_j$ then $\lambda_{td}(g_i)^* = \lambda_{td}(g_j)^*$ for all t and d. As discussed by Ahn and Powell (1993), this result is also the reason that the estimator provides a nonparametric selection correction, because the functional form for λ_{td} does not need to be specified, in order to obtain a consistent estimate of Γ. The estimator of the elements of Γ assigns weights to each pair of observations in the sample that participated in the experiment, with a smaller weight given to pairs of observations with larger values of $|\hat{g}_i - \hat{g}_j|$. Let the weight assigned to the (i, j) pair of observations equal

$$\hat{\omega}_{ij} \equiv \frac{1}{h_S}K\left(\frac{\hat{g}_i - \hat{g}_j}{h_S}\right)D_iD_j$$

where $K(s) = \frac{3}{4}(1 - s^2)$ for $|s| \leq 1$ is the Epanechnikov kernel, and $h_S > 0$ is a smoothing parameter. The smoothing parameter, h_S, is chosen to be consistent with the rate restrictions in Assumption 3.6 in Ahn and Powell (1987). We experimented with values h_S that were one-half to twice the value used and found that our estimates of the elements of Γ only changed in the second and third significant digits.

Our estimate of Γ is equal to:

$$\hat{\Gamma} = [\hat{S}_{xx}]^{-1}\hat{S}_{xy},$$

where the $(K \times K)$ matrix

$$\hat{S}_{xx} = \frac{1}{9D}\sum_{d=1}^{D}\sum_{t=1}^{9}\hat{S}_{xx}(t,d)$$

and the $(K \times 1)$ vector

$$\hat{S}_{xy} = \frac{1}{9D}\sum_{d=1}^{D}\sum_{t=1}^{9}\hat{S}_{xy}(t,d),$$

where K is the dimension of the Γ vector for the regression. These components of $\hat{\Gamma}$ depend on:

$$\hat{S}_{xx}(t,d) = \binom{n_{td}}{2}^{-1}\sum_{i=1}^{n_{td}-1}\sum_{j=i+1}^{n_{td}}\hat{\omega}_{ij}(X^*_{itd} - X^*_{jtd})(X^*_{itd} - X^*_{jtd})'$$

$$\hat{S}_{xy}(t,d) = \binom{n_{td}}{2}^{-1}\sum_{i=1}^{n_{td}-1}\sum_{j=i+1}^{n_{td}}\hat{\omega}_{ij}(X^*_{itd} - X^*_{jtd})(y^*_{itd} - y^*_{jtd}),$$

where n_{td} is the total number of customers in our sample during time period t of day d. Following the logic of Ahn and Powell (1993), we can prove that $\sqrt{n}(\hat{\Gamma} - \Gamma)$ converges in distribution to a $N(0, \Sigma_{xx}^{-1}\Omega_{xx}[\Sigma_{xx}^{-1}]')$ random variable where $n = \sum_{d=1}^{D}\sum_{t=1}^{9} n_{td}$, the total number of observations in our sample. Appendix A derives expressions for consistent estimates of Σ_{xx} and Ω_{xx} that are used to construct our standard error estimates. We estimate the models in Tables 2 to 4 using this selection-corrected estimator and the values of $\hat{g}_i$ from our kernel regression estimate of $E(D_i = 1|w_i) = g(w_i)$.

A general result across all of the selection-corrected estimates in Tables 6 to 8 is slightly smaller in absolute value coefficient estimates for the three *Into* coefficients and the three *Away* coefficients relative to the corresponding coefficients in Tables 2 to 4. This result is consistent with the logic that those customers invited to participate in the experiment that accepted are those likely to be more responsive to our *Into* and *Away* interventions.

Table 6: Replication of Table 2 (Separate Estimation Results for 5%, 20%, 50% Rebate Levels and Environmental Motivation) using censored selection method

	Dependent variable: log(kWh per hour)			
	5% Rebate	20% Rebate	50% Rebate	Envr.
Regressor				
BeforeInto	-0.0080	-0.0100	-0.0077	-0.0048
	(0.0018)	(0.0027)	(0.0031)	(0.0013)
Into	0.0310	0.0308	0.0502	0.0230
	(0.0031)	(0.0042)	(0.0074)	(0.0021)
AfterInto	-0.0019	-0.0025	0.0028	0.0018
	(0.0013)	(0.0022)	(0.0026)	(0.0010)
Bef.Away	0.0046	0.0009	0.0035	0.0009
	(0.0025)	(0.0034)	(0.0038)	(0.0017)
Away	-0.0105	-0.0092	-0.0068	-0.0038
	(0.0030)	(0.0040)	(0.0047)	(0.0020)
AfterAway	0.0028	-0.0019	-0.0010	0.0025
	(0.0021)	(0.0032)	(0.0043)	(0.0015)
N	707,346	389,880	253,179	1,743,167

Notes: Standard errors (in parentheses) computed as described in Appendix A. For each rebate-level, the Wu-Hausman test statistic of the null hypothesis that $\hat{\Gamma}^{\text{OLS}} = \hat{\Gamma}^{\text{Ahn-Powell}}$ is asymptotically $\chi^2(6)$. The realized test statistic is 147.637 for the 5%-rebate group, 12.784 for the 20%-rebate group, and 17.980 for the 50%-rebate group, corresponding to p-values of 0.000, 0.047, and 0.006 respectively.

There is also a remarkable degree of agreement between our original results and the selection-corrected results for both the three rebate levels and the environmental motivation treatment both in terms of the relative magnitude and precision of the three *Into* parameter estimates relative to the *Away* parameter estimates.

Table 7: Replication of Table 3 (Pooled Estimation Results for 5%, 20%, and 50% Rebate Levels) using censored selection method

	Dependent variable: log(kWh per hour)		
	5% Rebate	20% Rebate	50% Rebate
Regressor			
BeforeInto	-0.0097	-0.0080	-0.0062
	(0.0021)	(0.0035)	(0.0036)
Into	0.0292	0.0312	0.0554
	(0.0035)	(0.0046)	(0.0075)
AfterInto	-0.0015	-0.0021	0.0007
	(0.0015)	(0.0026)	(0.0029)
BeforeAway	0.0031	0.0018	0.0066
	(0.0027)	(0.0037)	(0.0042)
Away	-0.0128	-0.0101	0.0013
	(0.0032)	(0.0048)	(0.0055)
AfterAway	0.0033	-0.0020	-0.0022
	(0.0021)	(0.0032)	(0.0043)
N		1,350,405	

Notes: Standard errors (in parentheses) computed as described in Appendix A. The Wu-Hausman test statistic of the null hypothesis that $\hat{\Gamma}^{\text{OLS}} = \hat{\Gamma}^{\text{Ahn-Powell}}$ is asymptotically $\chi^2(18)$. The realized test statistic is 1,812.609, corresponding to a p-value of 0.000.

The *Into* coefficient estimates for both the price and environmental treatments are at least two to three times the absolute value of the *Away* coefficient estimates for the same rebate level or environmental incentive. For both treatments, the *BeforeInto* and *AfterInto* coefficient estimates are significantly larger in absolute value and more precisely estimated than the *BeforeAway* and *AfterAway* coefficient estimates.

The notes below each table report the results of the Durbin-Wu-Hausman test of the null hypothesis $plim(\hat{\Gamma}^{OLS} - \hat{\Gamma}^{Ahn-Powell}) = 0$. For the rebate-level models, pooled rebate model, and the environmental motivation model this null hypothesis is rejected for a size 0.05 test. Different from the results in Table 4, for all of our selection-corrected placebo estimates of the coefficients on the variables *IntoP* and *AwayP*, a size 0.05 test of null hypothesis of a zero coefficient associated with each variable in the table cannot be rejected.

Table 8: Replication of Table 4 (Placebo Estimates of Impact of Treatments) using censored selection method

	Dependent variable: log(kWh per hour)				
	5% Rebate	20% Rebate	50% Rebate	Pooled Rebate Sample	Envr.
Regressor					
IntoP	-0.0021	-0.0011	0.0060	-0.0003	0.0017
	(0.0023)	(0.0032)	(0.0040)	(0.0017)	(0.0015)
AwayP	0.0015	-0.0010	-0.0051	-0.0007	0.0017
	(0.0028)	(0.0039)	(0.0034)	(0.0020)	(0.0021)
N	707,346	389,880	253,179	1,350,405	1,743,167

Notes: Standard errors (in parentheses) computed as described in Appendix A.

These results demonstrate that self-selection of customers into the experiment results in statistically different estimates of the impacts of our *Into* and *Away* interventions. However, our major empirical result that *Into* interventions imply two to three times larger in absolute value movements of electricity consumption relative to *Away* events is preserved. Different from the case of our OLS results, the placebo estimates in Table 8 provide no empirical evidence against the hypothesis that the estimated impacts in Tables 6 and 7 are caused by our experimental interventions.

6. Customer, Firm and Environmental Benefits of *Into* versus *Away* Events

To demonstrate how both *Into* and *Away* events can provide economic benefits electricity retailers and consumers and reduce GHG emissions in Denmark, we first present the empirical distribution of net impacts of *Into* and *Away* events for our selection-corrected estimates in Table 6 during our sample period. We compute the net impact of each intervention during our sample period as well the decomposition of this net impact into the *Before*, *During*, and *After* periods. These results reveal that for a majority customers and rebate levels, *Into* events imply net increases in daily electricity consumption. For *Away* events there is typically a modest reduction in daily consumption. However, the largest daily consumption reductions are from *Into* events, because the total consumption reduction before and after the *Into* events is significantly larger than the increase in consumption during the *Into* event.

For all *Into* events, our parameter estimates imply that both *Before* and *After* periods experience reductions in consumption, particularly for the 5% and 20% rebate levels. This suggests that with careful timing and the appropriate amount of advance notice, the declaration of *Into* events can shift consumption into time periods with over-supply of renewable electricity production that otherwise would be exported from Denmark or curtailed. If the reduction in consumption comes from time periods when a marginal increase in electricity consumption is served by fossil fuel units, an *Into* event could also yield a reduction in daily GHG emissions. This *Into* event also could save SE wholesale energy costs if, as shown in Figure 2, wholesale electricity prices during time periods with an over-supply of renewable energy to Denmark are significantly lower than prices during surrounding periods. Finally, SE customers responding to the *Into* event could benefit from a lower bill if the difference between the increase in their payments for retail electricity from moving their consumption throughout the day minus the rebates they receive for these actions is negative.

We investigate whether the simultaneous combination of customer benefits, retailer benefits, and environmental benefits could occur using our selection-corrected parameter estimates to compute the effects on electricity production, wholesale energy costs and net revenues to SE from implementing *Away* and *Into* events for all of its customers. Using hourly supply and demand data from Nordpool, the wholesale electricity market operating in the Nordic countries, we identify isolated renewable oversupply events in Denmark between January 1, 2016 and June 30 2020. We simulate the effect on SE's electricity demand before and after renewable energy oversupply periods from an appropriately timed *Into* or *Away* event for all of its customers. We then calculate the effect of these events on SE's daily demand, its daily wholesale energy costs and profits, and the bills of its customers.

We also investigate the use of appropriately timed *Into* and *Away* events to shift consumption away from the morning and evening wholesale price peaks and into other parts of the day. These actions do not systematically affect fossil fuel electricity production in Denmark because renewable electricity is primarily from wind energy, which is typically produced in the early morning and early evening. However, as shown Figure 2, declaring *Into* events to shift consumption away from the morning and evening pricing peaks could deliver economic benefits to consumers and retailers and reduce GHG emissions in California where renewable electricity production is primarily solar powered. We show that for the case of Denmark there are *Into* and *Away* events that can both reduce customer bills and increase the retailer profits.

6.1. Net Impacts of Into versus Away Events

To estimate the net impacts of the *Into* and *Away* treatments during our sample period, we need to compute what the customer's consumption would have been had the intervention not occurred and subtract it from the customer's actual consumption which was subject to the intervention. For the net impact of *Into* treatments, we compute

$$\phi_{1id} = \sum_{t \in BeforeInto} (1 - \exp(-\gamma_{BeforeInto}))C_{itd}$$

$$\phi_{2id} = \sum_{t \in Into} (1 - \exp(-\gamma_{Into}))C_{itd}$$

$$\phi_{3id} = \sum_{t \in AfterInto} (1 - \exp(-\gamma_{AfterInto}))C_{itd}$$

for each consumer i where C_{itd} is customer's i's actual consumption during time period t of day d. γ_z is the coefficient on the regressor z, estimated from the selection-corrected models described above. Note that although summations over time periods in *Before* and *After* an event can be over multiple periods, depending on the length of these time periods, *Into* is for a single time period in the day. For each customer, i, the net impact of an *Into* event at day d is then $\phi_{2id} + (\phi_{1id} + \phi_{3id})$.

For the net impact of the *Away* treatments, we compute

$$\psi_{1id} = \sum_{h \in BeforeAway} (1 - \exp(-\gamma_{BeforeAway}))C_{itd}$$

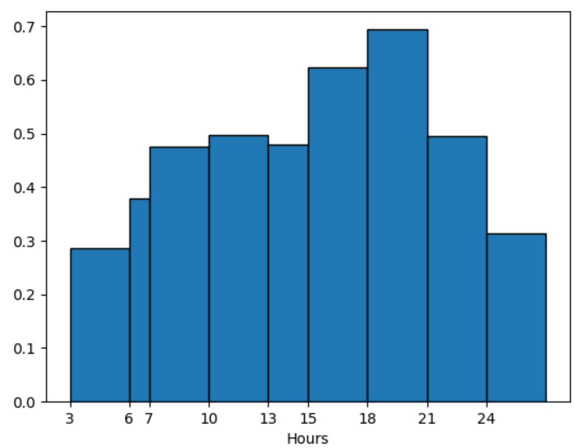
$$\psi_{2id} = \sum_{h \in Away} (1 - \exp(-\gamma_{Away}))C_{itd}$$

$$\psi_{3id} = \sum_{h \in AfterAway} (1 - \exp(-\gamma_{AfterAway}))C_{itd}$$

for each consumer i. The net impact for each i is then $\psi_{2id} + (\psi_{1id} + \psi_{3id})$.

Figure 4 plots the average hourly consumption in kWhs for each of the nine daily time periods for SE customers in our experiment. Appendix E Figures E1 to E3 plot the histogram of the kilowatt-hour net impacts for *Into* and *Away* treatments for samples with a 5%, 20%, and 50% rebate, respectively. Figure E4 plots the histogram of kilowatt-hour impacts for *Before* these two types of events for a 5% rebate. Figure E5 plots the histogram of kilowatt-hour *During* impacts for these two types of events for a 5% rebate. Figures E6 plots the histogram of kilowatt-hour *After* impacts for these two types of events for a 5% rebate.

Figure 4: Average Period-Level Energy Consumption in kWh per Hour for SE Customers



The support of the *Before* impacts of the *Into* kilowatt-hour changes in Figure H3 is significantly larger than the support for *Away* kilowatt-hour changes. This same result–a larger support for the impacts of *Into* consumption changes–holds to a lesser extent for the *After* events in Figure E6. Finally, the *During* impacts in Figure E5 demonstrate the often more than three times larger in absolute value *Into* response relative to the *Away* response, consistent with the absolute values of the *Away* and *Into* coefficients estimates in Table 6.

The 20% and 50% rebate levels produce qualitatively similar results in the sense that the absolute value of the *During* events tend to be three times larger for *Into* versus *Away* events and the absolute values of the *Before* and *After* coefficients are also larger in absolute value for *Into* versus *Away* events.

6.2. *Into versus Away Events and Periods of Over-Supply of Renewable Powered Electricity*

The results of the previous subsection suggest that it may be possible to both reduce GHG emissions in Denmark, increase retailer profits and reduce customer electricity bills from *Into* and *Away* events. However, there are variety of parameters that the retailers must set correctly to achieve this outcome. First, shifting consumption from a period when a marginal increase in demand from SE comes from fossil fuel generation to one with excess renewable energy production in Denmark holds the potential to reduce daily GHG emissions in the country. Second, how far in advance an *Into* or *Away* event is declared influences the total amount of electricity moved during the *Before* and *After* periods associated with these events. Third, the length of time an *Into* or *Away* event is declared influences the total amount of energy moved during the event. Fourth, the prices of wholesale electricity during the *Before*, *During*, and *After* periods influences the magnitude of wholesale cost savings to SE from an *Into* or *Away* event. Finally, the rebate paid to consumers determines amount of energy moved during these events and also influences whether the retailer profits from declaring an *Into* or *Away* event and whether customers benefit from lower bills.

A retailer that wants to reduce GHG emissions, increase its profits, and benefit customers with lower bills must set the features of the rebate scheme to balance a number of trade-offs. First, higher rebates are more likely to lead to lower bills for consumers, but this increases the likelihood of lower profits for the retailer. Second, less advance notice for an *Into* event may not reduce daily demand enough before and after the *Into* event to reduce the customer's bill, but this outcome increases the retailer's profits. The retailer must provide incentives for customers to shift their demand throughout the day to reduce the retailer's daily cost of wholesale energy. If this is done without a significant increase in daily demand by customers, then the retailer can benefit consumers with lower bills by sharing a portion of this reduction in daily wholesale energy costs through a rebate. The remainder of the daily wholesale energy costs can go to increase the retailer's profits. If the *Into* action takes place during a period with excess renewable energy, then it is also likely to reduce GHG emissions in the region.

For this reason, our first counterfactual analysis focuses on isolated two to three hours periods of excess renewable energy production in Denmark during the January 1, 2016 to June 30, 2020 time period. We also assume all of our counterfactual *Into* and *Away* events have the mean length of advance notice during our experiment. For *Into* events, it is 5 hours 39 minutes and for *Away* events it is 5 hours on 55 minutes. We also only use rebate amounts equal to the three used in our experiment. For these reasons, our counterfactual analysis can be thought of as providing a conservative estimate of the potential for *Into* and *Away* events to simultaneously deliver benefits to retailers, customers and the environment.

During our counterfactual time period, we found fifteen durations of two-hour or three-hour isolated renewable oversupply periods between 10 am and 8 pm, the time interval during the day that we felt it was plausible for SE to declare an *Into* event given the times of the day that these events were declared during our experiment.[19] For each two-hour oversupply period we simulate the effect of a two-hour *Into* event targeting this period and we simulate effects of a two-hour *Away* event targeting the two hours prior to this period and a two-hour *Away* event right after this period. For any three-hour oversupply period we simulate the effects of a three-hour *Into* event targeting this period, a three-hour *Away* event targeting the three hours prior to the excess renewable energy period and a three-hour *Away* event for the three hours after the excess renewable energy period.

Using the estimates of the impact of *Into* and *Away* events from the parameter estimates in Table 6, we can estimate what would happen to aggregate hourly demand if the SE population of customers all received an *Into* or *Away* signal. The change in demand during the two or three hour oversupply period is equal to:

$$\sum_{h=1}^{H(E)} C_{SE}(new, h) - C_{SE}(actual, h)$$

where $C_{SE}(actual, h)$ is the consumption of SE customers in hour h and $C_{SE}(new, h)$ is the consumption of SE customers with the impact of the *Into* or *Away* event accounted for and $H(E)$ is the length in hours of the renewable over-supply period. The change in demand before and after the oversupply period is calculated in the same way where $H(E)$ is the number of hours impacted by the *Into* or *Away* event before and after the oversupply period.[20]

[19] All of these two-hour or three-hour periods were surrounded by a number of hours with renewable energy production less than the demand for electricity in Denmark, consistent with fossil fuel generation being the marginal source of electricity during these time periods.

[20] For example, if notification occurs five hours before an *Into* or *Away* event that occurs within a two-hour period, the total number of hours of the day impacted is 13 hours and 18 minutes: 5 hours and 39 minutes before the event, 2 hours during the event, and 5 hours and 39 minutes after the event. Note that because the

Because any increase in demand by SE's customers during a renewables over-supply period would most likely be met from reduced exports of renewable energy from Denmark and any demand reduction in the surrounding periods by SE's customer is likely to be met by a reduction in fossil fuel generation in Denmark, this allows us to estimate the effect of *Into* and *Away* events on Denmark's GHG emissions.

The change in SE's gross profits from announcing *Into* and *Away* events is equal to increase in retail income from selling electricity to its customers less the total rebates paid to customers plus the reduction in the cost of purchasing wholesale electricity to serve these customers:

$$\Delta Gross\ Profit = \Delta Retail\ Income\ -\ Rebates\ Paid\ -\ \Delta Wholesale\ Cost.$$

To calculate the effect on wholesale costs, we plug these estimated demand changes into a model for setting wholesale prices in the Nord Pool each impacted hour and we re-compute the hourly price for each hour that is impacted by the event. Because SE's demand is a very small fraction of the total demand in the Nord Pool, there is little change in the market-clearing price from the change in SE's demand due to the *Away* or *Into* event. The total change in wholesale energy costs associated with this price and demand change is equal to:

$$\sum_{h=1}^{H(E)} PW(new, h) \times C_{SE}(new, h) - PW(actual, h) \times C_{SE}(actual, h)$$

where $PW(actual, h)$ is the Nordpool wholesale price during hour h and $PW(new, h)$ is the Nordpool price during hour h accounting for the impact of the *Into* or *Away* event during that hour, and $H(E)$ is the number of hours impacted by the *Into* over *Away* event. The effect on SE's income from sales to its retail customers before the cost of the rebates paid to customers is calculated in the same way except the Nordpool wholesale price is replaced with the fixed retail price paid by customers:

$$\sum_{h=1}^{H(E)} PR \times (C_{SE}(new, h) - C_{SE}(actual, h))$$

dependent variable of all our models is the logarithm of energy consumption in kWhs per hour during that time interval, it is straightforward to handle fractions of the hour in computing counterfactual consumption values before and after the intervention.

where *PR* is the retail price paid to SE by its customers. We assume the same retail price of electricity that prevailed during our experiment period of 27.35 Euro cents per kWh. The rebate is paid per kWh of energy moved for an *Into* or *Away* event is based on this same average residential price. For example, a 5% rebate would pay 1.37 Euro cents per kWh moved, 20% rebate would pay 5.47 Euro cents per kWh moved and finally a 50% rebate would pay 13.68 Euro cents per kWh. Note that the payment is made only for the amount moved *into* the designated period for an *Into* event and the amount moved *away* from the designated period for *Away* event.

We should note that computing the precise profit implications of *Into* and *Away* events to electricity retailers is considerably more complex than the approach we take because of the significant amount and number of taxes assessed on electricity consumption in Denmark. These taxes comprise roughly half of a customer's bill. In addition, it is unclear how rebates paid under a dynamic pricing tariff involving *Into* and *Away* would be taxed, if such a tariff was ultimately implemented. Nevertheless, the same mechanism would operate for realizing our three goals of environmental benefits, increased retailer profits, and reduced customer bills. Specifically, the wholesale cost savings from shifting consumption within the day to periods with surplus wind energy and from periods with fossil fuel resources producing energy would have to be large enough to finance the rebates paid to customers and still leave net wholesale cost reductions to increase the profits of the retailer. If there is little change in the total consumption by customers during the day, then retailer revenues for the day would be largely unchanged. The total rebates paid would need to be less than the total savings in wholesale electricity costs to the retailer in order for customer bills to be reduced and retailer profits to increase.

For the 5% rebate parameter estimates in Table 6, Appendix F Table F1 presents information on each excess renewables supply period including the date, time, and length of the period, SE's demand change during the *Into* event and SE's total demand change before and after the *Into* event, SE's wholesale cost savings using hourly day-ahead wholesale prices from these changes in consumption before, during, and after the event, the change in gross retail profits computed as described above, and the change in the total bills (including rebates) of its customers. Appendix F Table F4 presents the same information using the 5% rebate estimates in Table 6 for an *Away* event of the same length before each excess renewables supply period. Appendix F Table F7 repeats this same information for an *Away* event of the same length after each excess renewables supply period. The advance notice for the *Into* events is the sample mean of *Into* events for our experiment and advance notice for the *Away* events is sample mean for *Away* events for our experiment.

Because of how these excess renewable production periods were selected as isolated consecutive hours of excess renewable production, an *Into* event should reduce GHG emissions in Denmark, because of the consumption reduction *Before* and *After* the *Into* event. The results in Tables F1, F4 and F7 demonstrate the challenges facing retailers in designing rebate schemes for *Into* and *Away* events that achieve all three desired outcomes. There are a number of events that increase retailer profits and there are number events that reduce customer bills, but only one event achieves that outcome for the same event. A two-hour *Into* event at 2 pm on September 17, 2019 would have reduced customers' bills by 345.01 Euros, increased SE's profits by 43.61 Euros, and reduced Denmark's GHG emissions by 13.5 tonnes by applying a 0.5 tonne per MWh marginal GHG emissions rate to the 27.17 MWh reduction in generation before and after the *Into* event. Because there is virtually no change the total consumption for the day, a 27.81 MWh increase and a 27.17 MWh decrease as result of the *Into* event, retailer revenues for the day would be largely unchanged. If the taxes paid by the retailer depended only on revenues from retailer energy sales, the total rebates paid would need to be less than the total savings in wholesale electricity costs to the retailer in order for customer bills to be reduced and retailer profits to increase. For the *Into* event on September 17, 2019, total rebates paid are in fact less than total wholesale energy cost savings.

There are a number of events where the increase in the retailer's profits is more than the increase in customer bills which implies that a lump-sum transfer from the retailer to consumers would yield an outcome that benefits both parties. For example, the event on April 8, 2017 implies a 688.65 Euros increase in retailer profits, but only a 636.53 Euros increase in customer bills, so that a transfer of more than 636.53 Euros from the retailer to consumers would make both parties better off. Similarly, there are events where the reduction in customer bills is larger in absolute value than the reduction in retailer profits. For example, an event on March 18, 2017 finds that customer bills fall by 439.81 Euros, but retailer profits fall by 143.98 Euros, so a transfer of more than 143.98 Euros from consumers to the retailer would make both parties better off.

For the *Away* events in Table F4, none of the excess renewables periods achieves the desired outcome. Consumption is typically reduced during the *Away* period, which implies reduced wholesale energy costs for the retailer. The increase in consumption *Before* and *After* the *Away* period increases customer bills more than the amount of rebates paid for the modest amount of energy moved during the *Away* event. This higher bill increases the retailer's profits. However, there are still a few instances where transfers from the retailer to consumers could yield an outcome that benefits both parties. For example, on December 26, 2016 the retailer's profits increase by 799.44 Euros whereas the customer bills increase by only 742.17 Euros.

The *Away* results in Table F7 are similar to the results in Table F4 for wholesale energy costs, retailer profits, and customer bills. Again, there are a few instances where transfers from the retailer to consumers could yield an outcome that benefits both parties. For example, on February 22, 2017 the retailer's profits increase by 286.44 Euros whereas the customer bills increase by only 275.68 Euros.

For the 20% and 50% rebate levels, none of the excess renewables periods achieve the desired outcome for *Into* events. These results are shown in Tables F2 and F3 in Appendix F. Both rebate levels imply reductions in Denmark's GHG emissions for all of the excess renewables periods because of the pattern of the *Before*, *During*, and *After* coefficient estimates for *Into* events in Table 6. For the 20% rebate, the *Into* results imply significant wholesale energy purchase cost savings for a number of the excess renewables events because the *Into* and *BeforeInto* and *AfterInto* coefficient estimates are larger in absolute value than the corresponding values for the 5% rebate. However, the larger wholesale energy savings is not large enough to overcome a per kWh rebate that is four times the value of the 5% rebate, which makes the net savings to the retailer from declaring an *Into* event negative. Consumers benefit from lower electricity bills as a result of these events, primarily because of the substantial rebates they receive. Again, there are instances when transfers from customers to the retailer could benefit both parties, because the reduction in customer bills is larger in absolute value than the reduction in retailer profits.

For the case of the 50% rebate level, the wholesale cost savings are smaller and often negative because the *BeforeInto* and *AfterInto* coefficients are small in absolute value relative to the size of the *Into* coefficient in Table 6. The customer bills are substantially lower because of the large rebates paid for the energy moved under the *Into* event.

For *Away* events for the 20% and 50% rebate levels the magnitudes of the *Away* coefficient is small relative to the magnitude of the rebates paid. Once again, there are instances when transfers from customers to the retailer could yield benefits to both parties, because the reduction in customer bills is larger in absolute value than the reduction in retailer profits. These results are shown in Tables F2,F3,F5,F6,F8 and F9 of Appendix F.

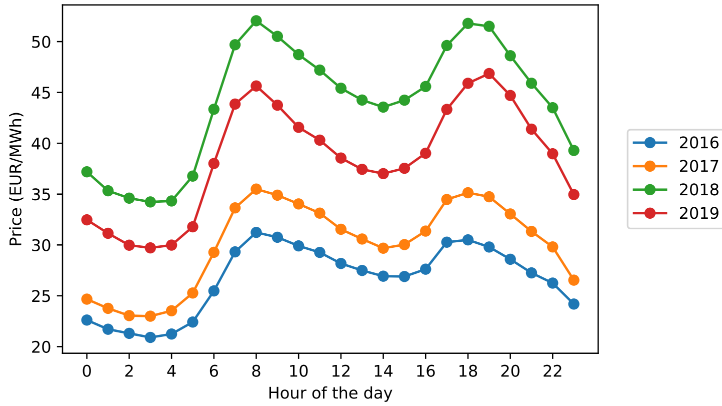
Summing up, we have shown that the 5% rebate applied with the sample mean of advance notice during renewable oversupply periods for an *Into* event can reduce GHG emissions in Denmark while lowering consumer bills and increasing retailer profits. In addition, these results show that with appropriate design of the rebate amount and advance notice, it would be possible to achieve the benefits of reduced GHG emissions, higher retailer profits and lower customer bills from *Into* and *Away* events during excess renewable generation periods.

6.3. Into versus Away Events in Connection with Morning and Evening Demand Peaks

We now investigate the potential benefits to retailers and consumers from declaring *Into* and *Away* events that shift consumption away from the morning and evening price peaks and into other parts of the day where wholesale prices are systematically lower. We focus on the potential wholesale cost saving because declaring these events is unlikely to reduce Denmark's fossil fuel electricity production.

For the *Into* simulations, a notification is assumed to be sent at 5:00 asking all customers to shift usage shift *Into* the hours of 14:00 to 16:00 for a 5%, 20%, or 50% rebate. The nine hours preceding that window constitute the *Before* period, and the nine hours following it constitute the *After* period. We chose this time period for our *Into* event and this amount of advance notice based on the pattern of annual average hourly wholesale prices within the day in Figure 5 for 2016 through 2019. The time period 14:00 to 16:00 persistently has the lowest average wholesale prices during the daylight hours across these four years and the large amount of advance notice ensures that the negative *BeforeInto* and *AfterInto* effects reduce demand during the high priced periods early and late in the day. This means that consuming more during the 14:00 to 16:00 time interval is unlikely to significantly increase wholesale energy costs, but consuming less during the 9 hours before and after this *Into* period should significantly reduce daily wholesale energy costs, resulting in a net reduction in wholesale energy purchase costs for SE.

Figure 5: Daily Average Hourly Wholesale Energy Prices in SE's Zone in Nordpool (2016-2019)



Our hypothetical *Away* events are also based on the pattern of daily average hourly wholesale prices in Figure 5. We chose the time period 8:00 to 10:00 for *Away* events because it has the highest average wholesale prices relative to other two-hour periods in the day. In this case, we assumed the event was called 2 hours before at 6:00. We also examined the period 18:00 to 20:00 for an *Away* event because of high average demand and high average prices during this period. The event was assumed to be called 2 hours in advance at 16:00.[21]

There were 89 instances of *Into* events with the 5% rebate that produced lower customer bills and higher retailer profits. Appendix G Table G1 lists the 15 instances with the largest increase in retailer profits. Appendix G Table G2 list the 15 instances with the largest decrease in customer bills. For the 20% and 50% rebate levels there were no instances when these two events occurred together, although there were many instances where transfers between customers and the retailer could have produced an outcome that benefits both parties.

For the case of *Away* events, there were 13 instances for the 50% rebate when the event at 18:00 produces higher retailer profits and lower customer bills shown in Appendix G Table G3. For the *Away* event at 8:00, there were no instances where this outcome occurred for any rebate level. Again, there were many instances when transfers between the retailer and customers could have produced an outcome that benefitted both parties.

[21] Because either the *BeforeAway* or *AfterAway* or both point estimates were positive for each rebate level, longer advance notice typically decreased wholesale cost savings.

The results of this analysis are very encouraging for the potential for *Into* events to deliver benefits for both retailers and customers in markets with predictable hourly prices differences throughout the day. The graphs in Figure 2 provides strong evidence for substantial economic benefits from *Into* events to retailers and customers in California. The approximately 20,000 MW of grid-scale and distributed solar generation capacity in California suggests that the pattern of net demand (system demand less the production of intermittent wind and solar generation) during the day can yield wholesale prices that are significantly lower during the middle of the day when the solar facilities in California are producing significant amounts of energy and higher in the early morning hours and late evening when there is no solar energy being produced. This result implies that declaring *Into* events for customers in California during the middle of the day with sufficient advance notice is likely to yield larger percent purchase cost savings than those found for Denmark, which implies the potential for larger benefits to retailers and customers from *Into* and *Away* events. Moreover, the high correlation between low prices and solar production in the middle of the day implies, a high likelihood that *Into* events in the middle of the day will also reduce GHG emissions in California.

7. 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 the same rebate percentage 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 the event period. The evidence for load-shifting *away* from the period finds mixed evidence that this led to increased consumption in neighboring time periods.

The purely environmental motivation 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.

When we account for the decision of invited SE customers to participate in the experiment, both sets of qualitative results continue to hold for the *Into* and *Away* treatment effect estimates, although the quantitative magnitude of all of these coefficient estimates are typically slightly smaller in absolute value than the corresponding estimates that condition on the sample of experiment participants. This result is consistent with the logic that the SE customers that selected to participate in the experiment are those that expected to be the most responsive to *Into* and *Away* interventions.

A counterfactual experiment with these selection-corrected estimates shows that there is a potential for simultaneously reducing fossil fuel electricity production in Denmark, increasing retailer profits and reducing customers bills from declaring *Into* events in connection with periods of over-supply of renewable electricity in Denmark. Given popularity of rebate-based dynamic pricing programs with consumers and regulators, a more cost-effective approach to implementing these programs may be to use *Into* rather than *Away* rebate schemes, particularly in regions with significant intermittent renewable generation capacity shares such as California where incentive to increase consumption during low-priced hours in the middle of the day will also lead to reduced consumption during high-priced periods early in the day and early in the evening. Thus, giving incentives to increase electricity use in certain time periods is a pricing strategy that could reduce the cost of integrating are larger share wind and solar electricity production.

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On line Appendix

Appendix A: Standard Error Computation

Appendix B: Differences in Demographic and Home Variables for non-participants and participants, and E-mail invitations for different groups

Appendix C: Text Message Variations

Appendix D: An example of the monthly e-mail feedback

Appendix E: Descriptives and net impacts for *Into* and *Away* treatments for different groups

Appendix F: *Into* and *Away* events During with Periods of Excess Renewable Electricity in Denmark

Appendix G: Effects of *Into* versus *Away* events in Connection with Morning and Evening Demand Peaks

Appendix A: Standard Errors

We have the following asymptotically normal distribution for our selection-corrected estimates of Γ:

$$\sqrt{n}(\hat{\Gamma} - \Gamma) \xrightarrow{d} N(0, \Sigma_{xx}^{-1}\Omega_{xx}[\Sigma_{xx}^{-1}]')$$

$\frac{1}{2}\hat{S}_{xx}$ consistently estimates Σ_{xx}, where $\hat{S}_{xx} = \frac{1}{9D}\sum_{d=1}^{D}\sum_{t=1}^{9}\hat{S}_{xx}(t,d)$ and

$$\hat{S}_{xx}(t,d) = \binom{n_{td}}{2}^{-1}\sum_{i=1}^{n_{td}-1}\sum_{j=i+1}^{n_{td}}\hat{\omega}_{ij}(X_i(t,d)^* - X_j(t,d)^*)(X_i(t,d)^* - X_j(t,d)^*)'$$

where n is the number of observations in the data, n_{td} is the number of observations in time period t of day d, $X_i(t,d)^*$ is a vector of mean-differenced regressors for customer i during time period t of day d. We define $\hat{\omega}_{ij}$ as

$$\hat{\omega}_{ij} = \frac{1}{h}k\Big(\frac{\hat{g}_i - \hat{g}_j}{h}\Big)$$

where $k()$ is the Epanechnikov kernel defined earlier, h is the bandwidth chosen as described earlier, and $\hat{g}_i$ the propensity score of individual i (which does not vary with t).

An estimator of Ω_{xx} is $\hat{W}_{xx} = \frac{1}{9D}\sum_{d=1}^{D}\sum_{t=1}^{9}\hat{W}_{xx}(t,d)$:

$$\hat{W}_{xx}(t,d) = \frac{1}{n_{td}}\sum_{i=1}^{n_{td}}[\hat{\psi}_i(t,d) + \hat{\xi}_i(t,d)\hat{e}_i][\hat{\psi}_i(t,d) + \hat{\xi}_i(t,d)\hat{e}_i]'$$

where

$$\hat{\psi}_i(t,d) = \frac{1}{n_{td}-1}\sum_{j=1}^{n_{td}}\hat{\omega}_{ij}(\hat{v}_i(t,d) - \hat{v}_j(t,d))(X_i(t,d)^* - X_j(t,d)^*)$$

$$\hat{v}_i(t,d) = y_i(t,d)^* - X_i(t,d)^{*\prime}\hat{\Gamma}$$

$$\hat{e}_i = 1 - \hat{g}_i$$

$$\hat{\xi}_i(t,d) = \frac{1}{n_{td}}\frac{1}{n_{td}-1}\sum_{j=1}^{n_{td}}\sum_{l=1}^{n_{td}}\left[\Big(\frac{1}{h}\Big)^2 k'\Big(\frac{\hat{g}_i - \hat{g}_j}{h}\Big)(\hat{v}_j(t,d) - \hat{v}_l(t,d))(X_j(t,d)^* - X_l(t,d)^*)\right]$$

and $k'(s)$ is the derivative of $k(s)$.

The matrix $\hat{W}_{xx}$ takes the following form if we are willing to allow arbitrary autocorrelation in the $v_i(t,d)$ over time periods and days and differences in this autocorrelation across customers.

$$\hat{W}_{xx} = \frac{1}{9D}\frac{1}{n_C}\sum_{i=1}^{n_C}\Big[\sum_{d=1}^{D}\sum_{t=1}^{9}\hat{\psi}_i(t) + \hat{\xi}_i(t)\hat{e}_i\Big]\Big[\sum_{d=1}^{d}\sum_{t=1}^{9}\hat{\psi}_i(t) + \hat{\xi}_i(t)\hat{e}_i\Big]'$$

Where n_C is the number of distinct individuals. These results imply that the approximately normal distribution of $\hat{\beta}$ is $N(\beta, \frac{\Sigma_{zx}^{-1}\Omega_{zz}[\Sigma_{zx}^{-1}]'}{n})$.

Appendix B-1: Differences in Demographic and Home Variables for non-participants and participants

Table: Summary Statistics for Demographic and Home Variables

	Mean (Participate = 0)	Mean (Participate = 1)	Diff.	Std. Error
# of men 21+ in HH	0.8991	0.8754	0.0238	0.0103
# of women 21+ in HH	0.8720	0.9003	-0.0283	0.0091
# of kids 0-6 in HH	0.2095	0.1173	0.0923	0.0109
# of kids 7-14 in HH	0.2714	0.1875	0.0839	0.0132
# of kids 15-20 in HH	0.2025	0.1722	0.0302	0.0116
HH disposable income	7.7620	7.5644	0.1977	0.0906
HH Income < 0	0.0013	0.0006	0.0007	0.0006
HH Income $\in [0, 50K)$	0.0036	0.0023	0.0014	0.0012
HH Income $\in [50K, 150K)$	0.0572	0.0431	0.0142	0.0051
HH Income $\in [150K, 250K)$	0.2017	0.2017	0.0000	0.0099
HH Income $\in [250K, 350K)$	0.2058	0.2334	-0.0277	0.0105
HH Income $\in [350K, 450K)$	0.1953	0.2198	-0.0245	0.0102
HH Income $\in [450K, 550K)$	0.1622	0.1558	0.0064	0.0090
farmhouse	0.0408	0.0385	0.0023	0.0048
terraced_or_double_house	0.1180	0.1292	-0.0111	0.0083
storey_bld	0.1389	0.0737	0.0652	0.0067
single_fam_house	0.7005	0.7569	-0.0564	0.0107
# of rooms	4.5242	4.6079	-0.0837	0.0368
Total area of home	135.2672	138.2499	-2.9826	1.1616
Construction Year	1954.1901	1956.2159	-2.0258	1.1050
district_heat	0.5572	0.5246	0.0326	0.0124
Central heating	0.3380	0.3314	0.0066	0.0117
Electric oven	0.0626	0.0895	-0.0269	0.0070
Heating pump	0.0278	0.0425	-0.0147	0.0049
Individual Owns Home	0.7103	0.7819	-0.0716	0.0103
# of employed	1.0978	0.9292	0.1686	0.0221
hh_unemployed	0.3125	0.4113	-0.0988	0.0121
# of retired in HH	0.4331	0.6272	-0.1941	0.0192
# of high-skill employees in HH	0.1641	0.1411	0.0230	0.0099
# of mid-skill employees in HH	0.2162	0.1830	0.0332	0.0106
# of low-skill employees in HH	0.4532	0.3756	0.0775	0.0151
HH state scholarship funds	4596.3533	2380.8374	2215.5160	313.1692
HH pension income	96134.1740	145885.1870	-49751.0130	4243.7483
Married couple in HH	0.5641	0.6187	-0.0546	0.0121
# of immigrants in HH	0.1487	0.1042	0.0444	0.0116

Note: There are 1,765 individuals who participated, and 20,893 who did not.

Appendix B-2. E-mail invitation offering rebates of either 5%, 20% or 50% to customers

Read the newsletter on the Internet

APRIL 2015

Find us on Facebook

Dear [First name] [Last name]

Get [Rebate]% off every time you shift power

Among our customers, there is a clear desire to see an improved use of weather-dependent wind power. We want to achieve this with a new program that we call MovePower. Initially, MovePower will only be offered to a limited number of customers for a one-year trial period.

You have been selected because we believe that you will be able to benefit from the program. MovePower is free and without obligation for you, so we hope you will find the program attractive. Whether you participate or not is, of course, up to you.

During the course of the program, you will receive text messages that tell you at what time of day it is best to use power. You can, for example, shift the timing of when you wash clothes or start the dish washer, etc. Of course, it doesn't mean that you have to cook roast pork at 3 in the morning. But shifting just a little of your power consumption will be an advantage.

What is MovePower?

- 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 act on the text messages you receive.
- You will save money* every time you shift power as recommended.
- MovePower is free and without obligations and it will not affect your current electricity agreement.

If you would like to take part in MovePower, you should continue [HERE]

If you do not wish to participate, please opt out [HERE]

Kind regards

SE

PS. If you have any questions about MovePower, you are welcome to contact us on xxxx xxxx.

* You get [Rebate]% off the power consumption that you shift. Your rebate is calculated on the basis of the price of 'basic electricity' for January 2015, which was 2.04 DKK per kWh, regardless of the price you pay according to your electricity agreement.

Appendix B-3. E-mail invitation offering GHG-free production to costumers in group 31, 34, 35 and 36

Read the newsletter on the Internet

APRIL 2015

Find us on Facebook

Dear [First name] [Last name]

Get 100% sustainability every time you shift power

Among our customers, there is a clear desire to see an improved use of weather-dependent wind power. We want to achieve this with a new program that we call MovePower. Initially, MovePower will only be offered to a limited number of customers for a one-year trial period.

You have been selected because we believe that you will be able to benefit from the program. MovePower is free and without obligation for you, so we hope you will find the program attractive. Whether you participate or not is, of course, up to you.

During the course of the program, you will receive text messages that tell you at what time of day it is best to use power. You can, for example, shift the timing of when you wash clothes or start the dish washer, etc. Of course, it doesn't mean that you have to cook roast pork at 3 in the morning. But shifting just a little of your power consumption will be an advantage.

What is MovePower?

- 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 act on the text messages you receive.
- You will get 100% sustainability* every time you shift your energy consumption as recommended.
- MovePower is free and without obligations and it will not affect your current electricity agreement.

If you would like to take part in MovePower, you should continue [HERE]

If you do not wish to participate, please opt out [HERE]

Kind regards

SE

PS. If you have any questions about MovePower, you are welcome to contact us on xxxx xxxx.

* SE will move electricity production from traditional power stations to sustainable wind energy corresponding to the amount of energy consumption you move.

Appendix B-4. Supplementary information provided after accepting rebate invitations:

Terms of conditions to customers offered rebate (identical for all rebate levels.)

https://www.se.dk/vilkaar1501

MovePower terms and conditions

These are the terms and conditions of MovePower:

- During the course of the week, you will receive text messages that specify at what time of the day it is best to use electricity.
- If you decide to shift some of your electricity consumption in line with the recommendations in the text messages, you will earn the percentage rebate stated in the text message for every kWh you shift. The rebate will be at least the rate you were promised in the MovePower offer. The rebate is calculated as a percentage of the list price for 'Base electricity' from January 2015 (2.04 DKK per kWh) regardless of the rate you pay based on your electricity contract. In this way, you'll save money.
- Whether you decide to shift some of your electricity consumption as recommended in the text messages is up to you.
- In order to give you an overview, every month, you will receive a message with details of how much electricity consumption you have shifted in line with the suggestions in the text messages.
- Initially, MovePower will involve a limited number of customers for a one-year trial period. You will receive a message when the scheme starts and when the trial period is over.
- If you have earned a rebate, you will receive the money once the one-year trial period has ended.
- The MovePower program only applies to one address (where you live on a daily basis). If you move address during the one-year trial period, you will automatically leave MovePower and the rebate you have earned will be null and void.
- MovePower is conducted in collaboration with Copenhagen University. Carsten Jensen is responsible for the data. The aim is to investigate whether private households can play a role in the utilisation of weather-dependent wind energy. The project has been reported to the Danish Data Protection Agency in line with the Personal Data Protection Act. The Danish Data Protection Agency has established terms and conditions for the project in order to protect the participants' privacy. Participation in MovePower is voluntary. Consent to participate in MovePower can be withdrawn at any time.

If you would like to know more about how you can shift your electricity consumption, you can visit: www.se.dk/FlytStroem

Appendix B-5. Supplementary information provided after accepting GHG-free invitations:

Terms of conditions for costumers offered GHG-free production (group 35 and 36). *)

https://www.se.dk/vilkaar1503

MovePower terms and conditions

These are the terms and conditions of MovePower:

- During the course of the week, you will receive text messages that specify at what time of the day it is best to use electricity.
- If you decide to shift some of your electricity consumption in line with the recommendations in the text messages, the power you move will become 100% sustainable as specified in the text messages. Therefore, you will ensure 100% sustainability for every kWh you shift is. Sustainability will be ensured by SE shifting the electricity production from traditional power stations to sustainable wind turbines corresponding to the amount of electricity you shift. In this way you will help reduce the environmental impact.
- Whether you decide to shift some of your electricity consumption as recommended in the text messages is up to you.
- In order to give you an overview, every month, you will receive a message with details of how much electricity consumption you have shifted in line with the suggestions in the text messages.
- Initially, MovePower will involve a limited number of customers for a one-year trial period. You will receive a message when the scheme starts and when the trial period is over.
- If you help to shift power, SE will increase the wind turbine capacity corresponding to the total amount of power you have shifted during the one-year trial period.
- The MovePower program only applies to one address (where you live on a daily basis). If you move address during the one-year trial period, you will automatically leave MovePower and the rebate you have earned will be null and void.
- MovePower is conducted in collaboration with Copenhagen University. Carsten Jensen is responsible for the data. The aim is to investigate whether private households can play a role in the utilisation of weather-dependent wind energy. The project has been reported to the Danish Data Protection Agency in line with the Personal Data Protection Act. The Danish Data Protection Agency has established terms and conditions for the project in order to protect the participants' privacy. Participation in MovePower is voluntary. Consent to participate in MovePower can be withdrawn at any time.

If you would like to know more about how you can shift your electricity consumption, you can visit: www.se.dk/FlytStroem

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

Appendix B-6. Supplementary information provided after accepting GHG-free invitations: Terms of conditions for costumers offered GHG free production (group 31 and 34*)

https://www.se.dk/vilkaar1504

MovePower terms and conditions

These are the terms and conditions of MovePower:

- You are a member of a MovePower team with others who are like you. You and the others on your team will receive text messages that specify at what time of the day it is best to use electricity.
- If you and your team decide to shift some of your electricity consumption in line with the recommendations in the text messages, the power you shift will be 100% sustainable as specified in the text messages. Therefore, you and your team will ensure that every kWh you shift will be 100% sustainable. Sustainability will be ensured as SE will shift electricity production from traditional power stations to sustainable wind turbines corresponding to the amount of electricity you shift. In this way, you will help to reduce the environmental impact.
- Whether you decide to shift some of your electricity consumption as recommended in the text messages is up to you.
- In order to give you an overview, every month, you and your team will receive a message with details of how much electricity consumption you have shifted in line with the suggestions in the text messages.
- Initially, MovePower will involve a limited number of customers for a one-year trial period. You will receive a message when the scheme starts and when the trial period is over.
- If you and your team help to shift power, SE will increase the wind turbine capacity corresponding to the total amount of power you have shifted during the one-year trial period.
- The MovePower program only applies to one address (where you live on a daily basis). If you move address during the one-year trial period, you will automatically leave MovePower and the rebate you have earned will be null and void.
- MovePower is conducted in collaboration with Copenhagen University. Carsten Jensen is responsible for the data. The aim is to investigate whether private households can play a role in the utilisation of weather-dependent wind energy. The project has been reported to the Danish Data Protection Agency in line with the Personal Data Protection Act. The Danish Data Protection Agency has established terms and conditions for the project in order to protect the participants' privacy. Participation in MovePower is voluntary. Consent to participate in MovePower can be withdrawn at any time.

If you would like to know more about how you can shift your electricity consumption, you can 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 C: Text Message Variations.

[X]: Treatment rebate groups 5%, 20% and 50%.

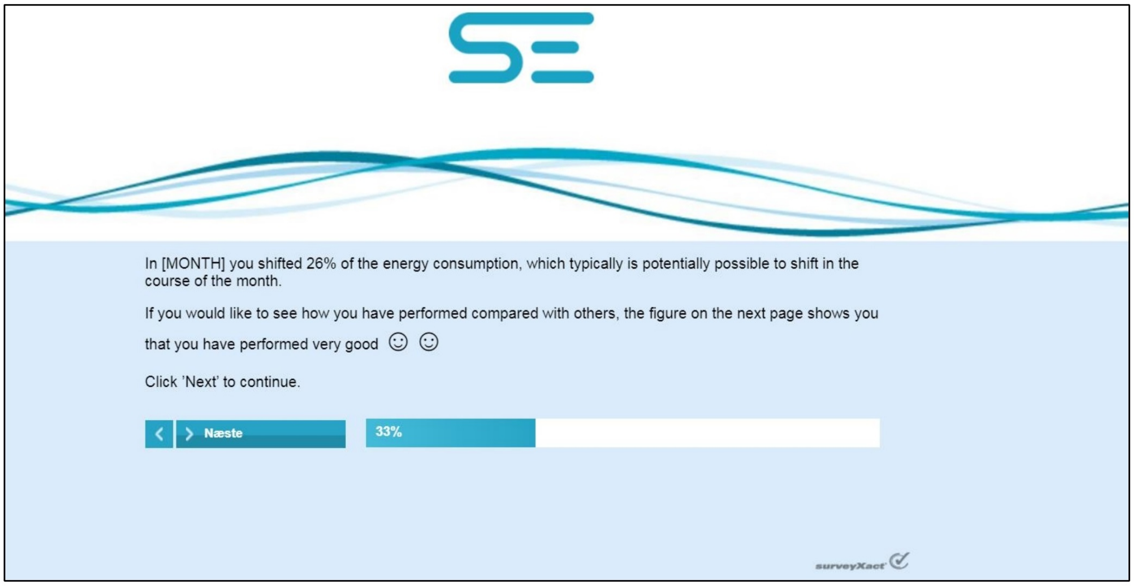
- Treatment hours varied across time slots (10 am to 1 pm; 3pm to 6 pm; 6 pm to 9 pm; 9 pm to 24 pm, and 12 am to 3 pm).

- Treatment day variations (Monday, Tuesday, Wednesday Thursday Friday, Saturday and Sunday)

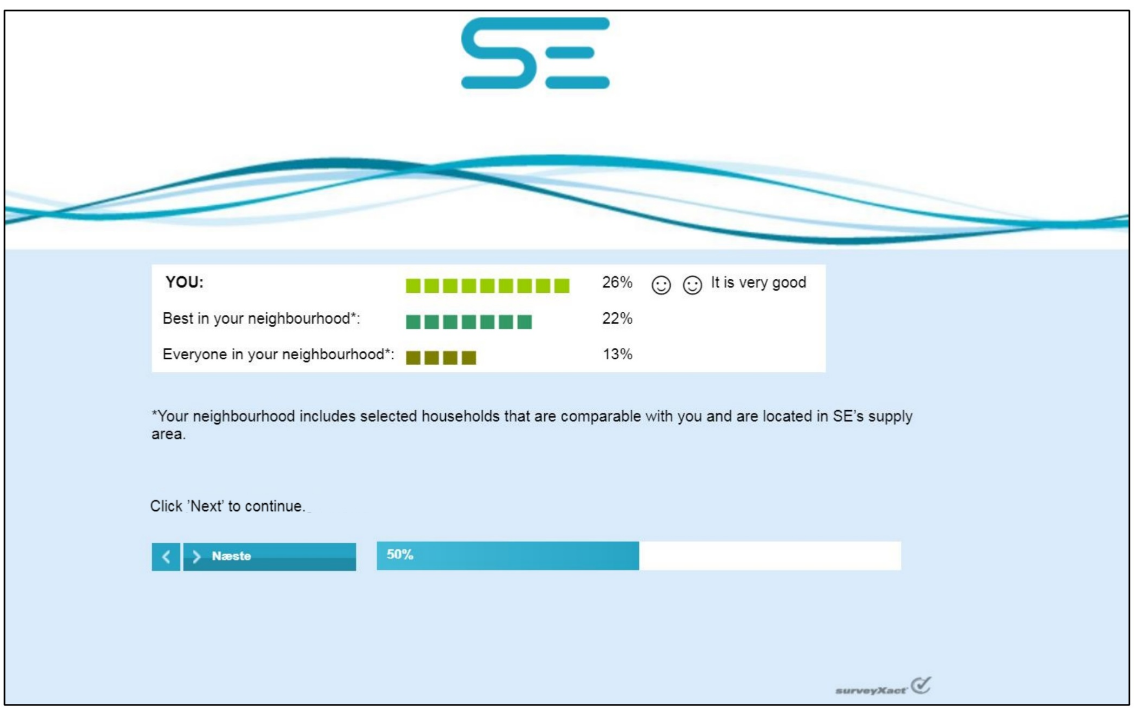
- The text messages to the GHG groups (31, 34, 35 and 36) are identical.

Appendix D: An example of the monthly e-mail feedback

Page 1:



Page 2:



Appendix E. Net Impacts of Into versus Away Events

Figure E1: Net Impact using Coefficients from Table 6 (with censored selection) and a 5% rebate

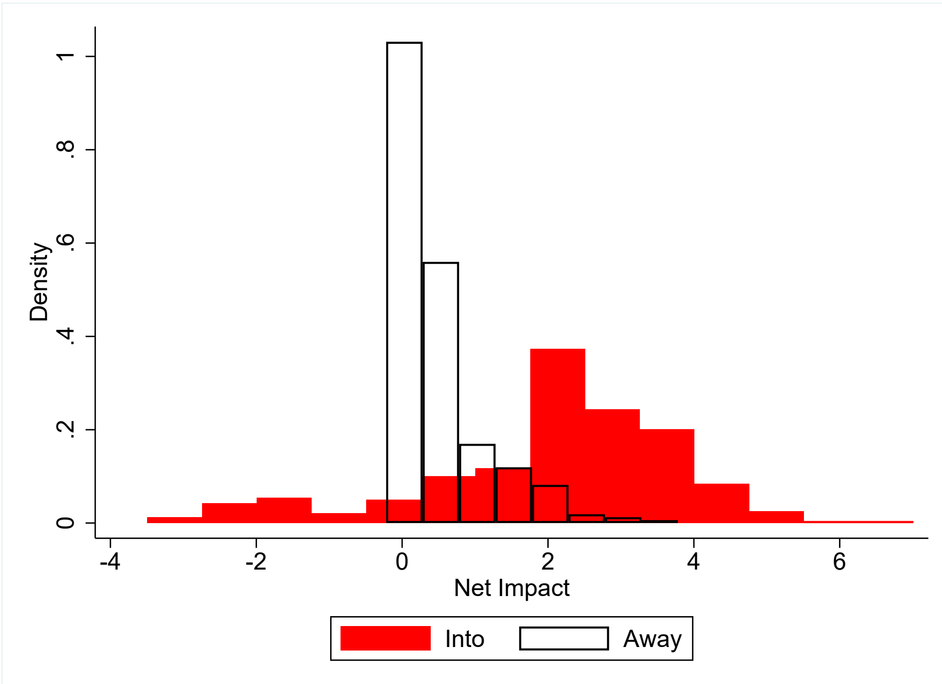


Figure E2: Net Impact using Coefficients from Table 6 (with censored selection) and a 20% rebate

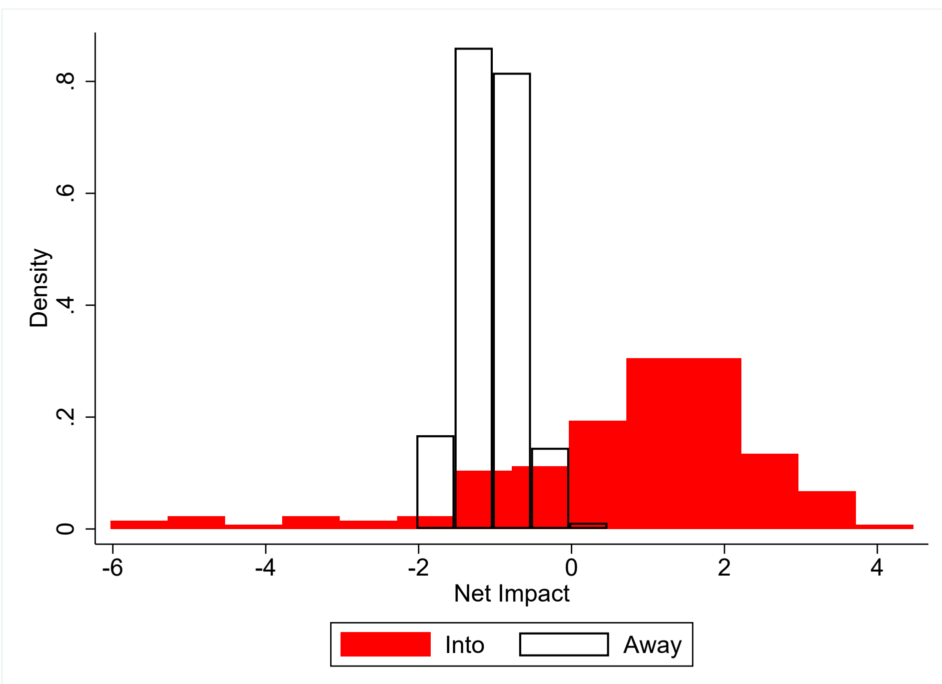


Figure E3: Net Impact using Coefficients from Table 6 (with censored selection) and a 50% rebate

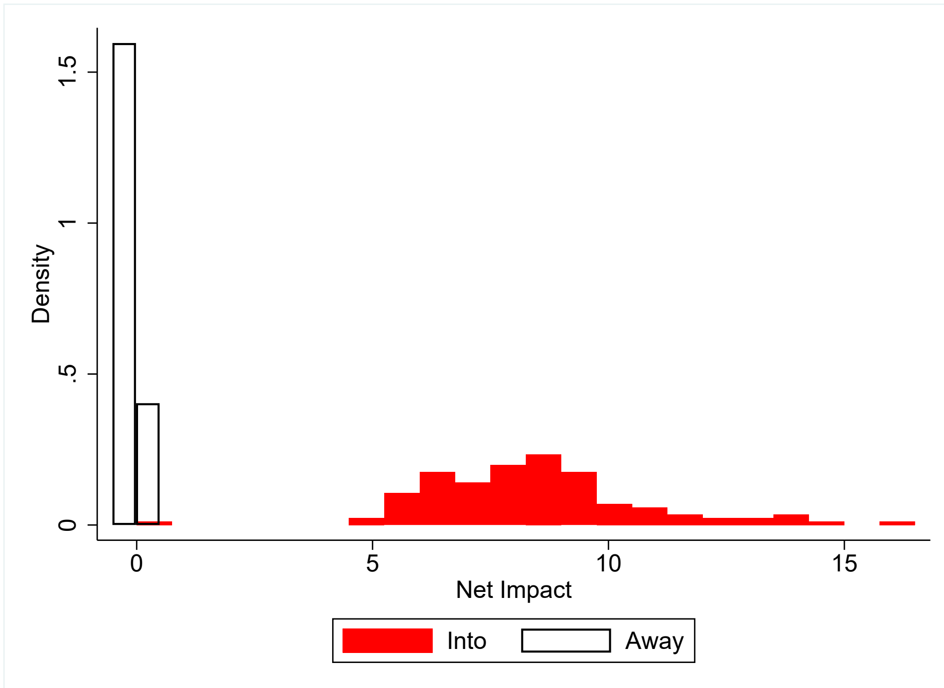


Figure E4: ϕ_1 and ψ_1 using Coefficients from Table 6 (with censored selection) and a 5% rebate

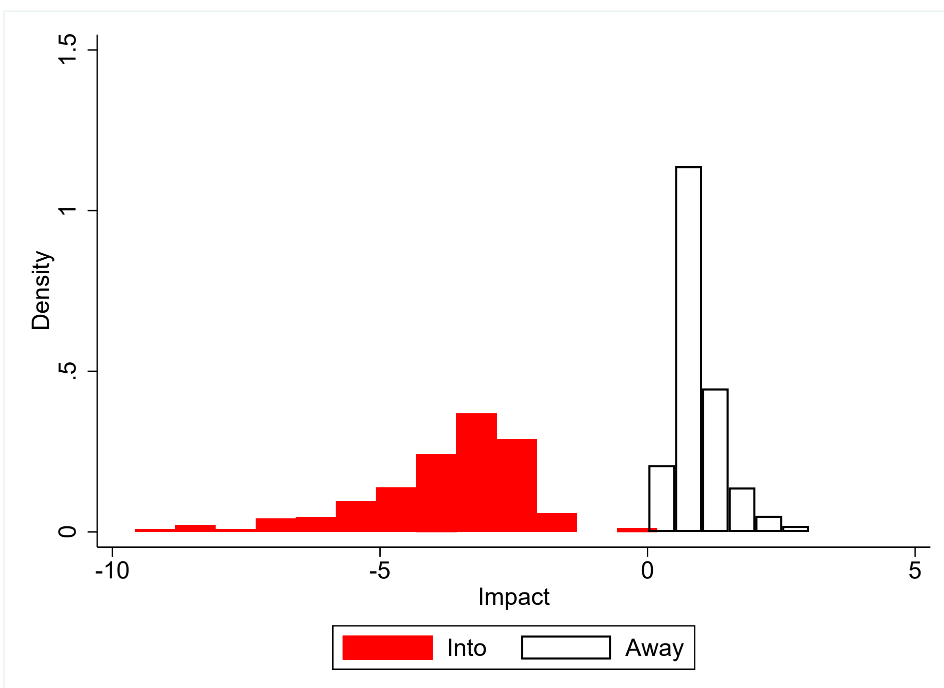


Figure E5: ϕ_2 and ψ_2 using Coefficients from Table 6 (with censored selection) and a 5% rebate

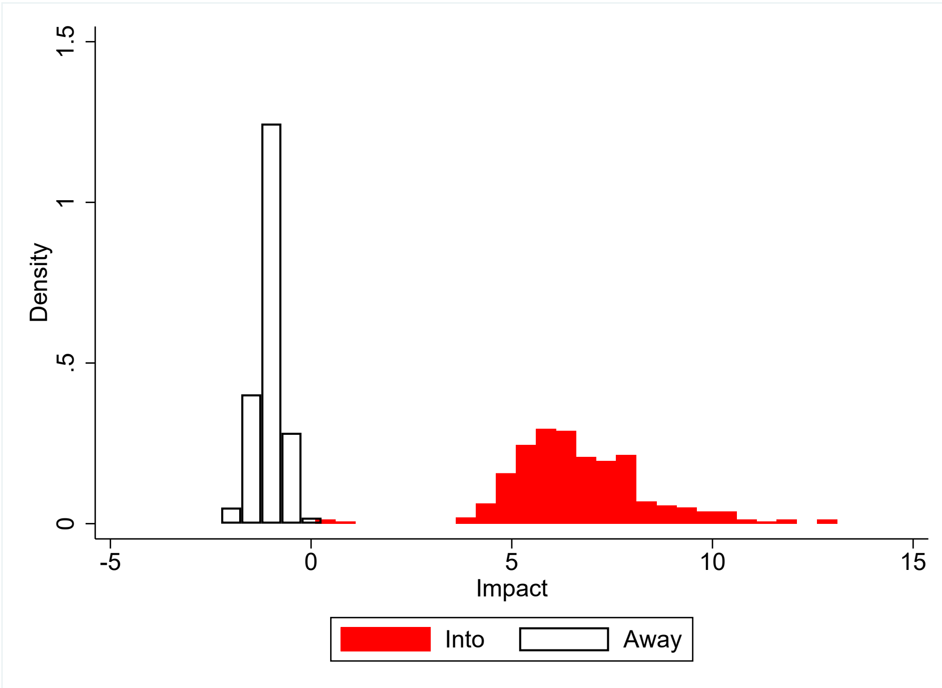
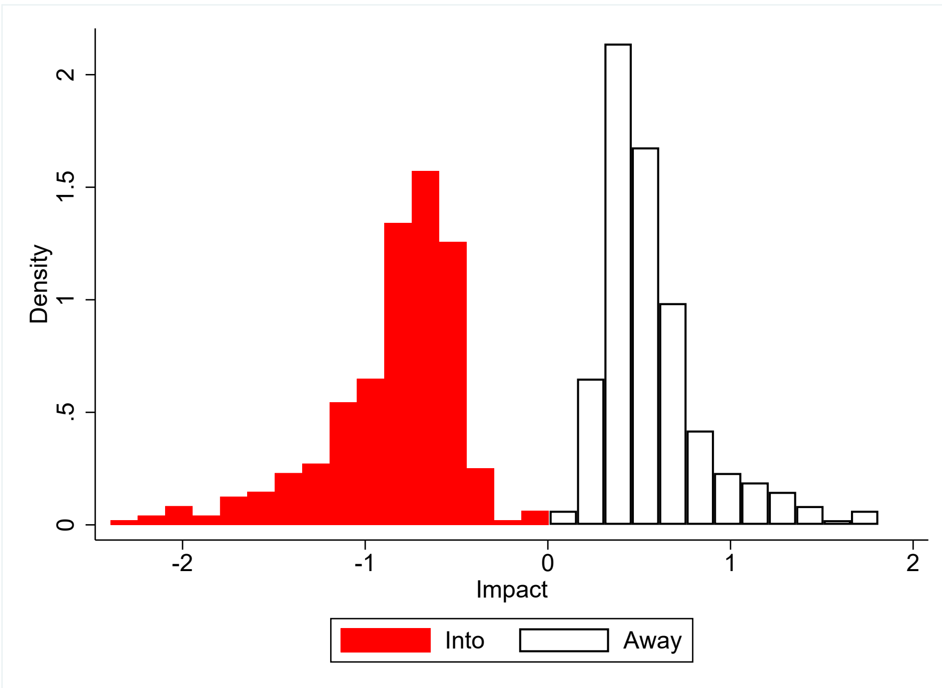


Figure E6: ϕ_3 and ψ_3 using Coefficients from Table 6 (with censored selection) and a 5% rebate



Appendix F: *Into* and *Away* events During with Periods of Excess Renewable Electricity in Denmark

Table F1: Effects of 5% *Into* rebate during oversupply periods

Date	Hour	Period length	Demand change during *Into* period	Demand change *Before* and *After Into* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	16:00	2h	26.11	-22.98	-36.07	462.91	498.99
2016-11-26	13:00	3h	33.94	-20.36	-439.20	2,705.90	3,145.10
2016-12-26	10:00	3h	33.35	-16.73	-331.84	3,632.54	3,964.38
2017-02-22	14:00	3h	41.51	-25.49	-475.76	3,210.50	3,686.26
2017-03-18	14:00	2h	20.22	-20.43	295.83	-143.98	-439.81
2017-04-08	16:00	2h	21.19	-17.80	52.11	688.65	636.53
2017-04-24	15:00	2h	25.32	-24.98	-135.82	-497.15	-361.33
2017-12-24	14:00	2h	25.82	-20.30	106.41	1,161.44	1,055.03
2018-04-24	14:00	3h	37.67	-23.53	-272.00	2,971.27	3,243.27
2018-09-27	15:00	2h	26.33	-24.21	17.00	123.16	106.16
2018-12-04	15:00	2h	30.70	-26.99	-24.42	439.76	464.19
2019-09-17	14:00	2h	27.81	-27.17	388.63	43.61	-345.01
2020-01-02	15:00	2h	27.09	-22.54	-28.52	720.92	749.44
2020-02-22	15:00	2h	23.65	-19.92	-43.17	530.58	573.74
2020-05-07	18:00	2h	17.19	-16.47	-567.86	-605.70	-37.84
Sum			417.90	-329.90	-1,494.68	15,444.41	16,939.10

Table F2: Effects of 20% *Into* rebate during oversupply periods

Date	Hour	Period length	Demand change during *Into* period	Demand change *Before* and *After* oversupply period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	16:00	2h	25.94	-28.95	91.61	-2,151.22	-2,242.82
2016-11-26	13:00	3h	33.72	-25.68	-249.58	-34.05	215.54
2016-12-26	10:00	3h	33.13	-21.12	-394.69	913.75	1,308.44
2017-02-22	14:00	3h	41.23	-32.12	-268.83	-197.43	71.40
2017-03-18	14:00	2h	20.08	-25.75	438.56	-2,345.38	-2,783.94
2017-04-08	16:00	2h	21.05	-22.44	153.64	-1,377.70	-1,531.34
2017-04-24	15:00	2h	25.15	-31.44	8.75	-3,229.11	-3,237.86
2017-12-24	14:00	2h	25.65	-25.60	137.85	-1,384.65	-1,522.50
2018-04-24	14:00	3h	37.42	-29.64	-62.24	-120.99	-58.75
2018-09-27	15:00	2h	26.16	-30.51	276.16	-2,494.47	-2,770.63
2018-12-04	15:00	2h	30.50	-34.02	178.45	-2,623.65	-2,802.10
2019-09-17	14:00	2h	27.63	-34.23	632.35	-2,869.01	-3,501.36
2020-01-02	15:00	2h	26.91	-28.41	50.33	-1,992.48	-2,042.81
2020-02-22	15:00	2h	23.49	-25.15	-62.17	-1,960.44	-1,898.27
2020-05-07	18:00	2h	17.08	-20.69	-716.33	-2,637.55	-1,921.22
Sum			415.14	-415.75	213.86	-24,504.38	-24,718.22

Table F3: Effects of 50% *Into* rebate during oversupply periods

Date	Hour	Period length	Demand change during *Into* period	Demand change *Before* and *After Into* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	16:00	2h	42.69	-12.72	-582.19	1,775.35	2,357.55
2016-11-26	13:00	3h	55.50	-10.23	-1,530.77	3,417.92	4,948.69
2016-12-26	10:00	3h	54.53	-7.79	-353.42	5,159.50	5,512.92
2017-02-22	14:00	3h	67.86	-14.02	-1,600.18	4,033.37	5,633.54
2017-03-18	14:00	2h	33.05	-11.25	-131.30	1,465.98	1,597.27
2017-04-08	16:00	2h	34.64	-9.48	-370.88	1,774.99	2,145.87
2017-04-24	15:00	2h	41.40	-14.93	-879.62	859.21	1,738.83
2017-12-24	14:00	2h	42.22	-10.43	54.65	3,124.71	3,070.06
2018-04-24	14:00	3h	61.59	-13.57	-1,346.27	3,522.67	4,868.93
2018-09-27	15:00	2h	43.05	-13.13	-1,056.52	1,404.87	2,461.39
2018-12-04	15:00	2h	50.20	-14.54	-1,003.77	2,077.45	3,081.22
2019-09-17	14:00	2h	45.47	-15.06	-392.37	1,913.46	2,305.83
2020-01-02	15:00	2h	44.29	-12.38	-328.36	2,523.15	2,851.51
2020-02-22	15:00	2h	38.66	-9.23	-48.40	2,895.72	2,944.12
2020-05-07	18:00	2h	28.10	-11.40	-533.10	191.06	724.15
Sum			683.25	-180.16	-10,102.50	36,139.41	46,241.88

Table F4: Effects of same length 5% *Away* rebate just before oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	14:00	2h	-8.44	17.98	-240.57	2,522.29	2,762.87
2016-11-26	10:00	3h	-11.65	14.18	-104.99	722.21	827.20
2016-12-26	7:00	3h	-10.02	12.27	57.27	799.44	742.17
2017-02-22	11:00	3h	-14.23	19.38	-136.06	1,385.05	1,521.11
2017-03-18	12:00	2h	-7.77	14.93	-228.73	1,875.52	2,104.24
2017-04-08	14:00	2h	-6.57	14.03	-301.44	1,867.01	2,168.45
2017-04-24	13:00	2h	-9.45	18.77	-288.06	2,399.57	2,687.63
2017-12-24	12:00	2h	-7.90	15.06	-32.72	2,050.76	2,083.48
2018-04-24	11:00	3h	-13.37	17.14	-264.10	849.86	1,113.97
2018-09-27	13:00	2h	-9.11	18.52	-444.96	2,286.52	2,731.48
2018-12-04	13:00	2h	-9.82	21.26	-547.88	2,764.28	3,312.16
2019-09-17	12:00	2h	-10.09	20.14	-448.18	2,480.25	2,928.44
2020-01-02	13:00	2h	-8.64	17.06	-118.13	2,353.58	2,471.70
2020-02-22	13:00	2h	-7.03	15.90	-51.02	2,559.78	2,610.80
2020-05-07	16:00	2h	-6.19	13.20	65.50	1,898.90	1,833.41
Sum			-140.28	249.82	-3,084.07	28,815.02	31,899.11

Table F5: Effects of same length 20% *Away* rebate just before oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	14:00	2h	-7.40	-1.59	188.46	-2,857.78	-3,046.25
2016-11-26	10:00	3h	-10.21	-1.88	434.18	-3,630.82	-4,065.01
2016-12-26	7:00	3h	-8.78	-1.86	-75.63	-3,646.33	-3,570.70
2017-02-22	11:00	3h	-12.47	-1.81	461.28	-4,333.63	-4,794.91
2017-03-18	12:00	2h	-6.81	-1.32	175.18	-2,588.77	-2,763.95
2017-04-08	14:00	2h	-5.76	-1.41	95.84	-2,326.15	-2,422.00
2017-04-24	13:00	2h	-8.29	-1.26	245.58	-3,000.60	-3,246.18
2017-12-24	12:00	2h	-6.93	-2.17	26.96	-2,999.53	-3,026.48
2018-04-24	11:00	3h	-11.73	-1.58	390.00	-4,071.86	-4,461.86
2018-09-27	13:00	2h	-7.99	-1.77	389.77	-2,909.06	-3,298.83
2018-12-04	13:00	2h	-8.61	-2.02	259.78	-3,336.22	-3,596.00
2019-09-17	12:00	2h	-8.85	-1.76	282.71	-3,317.21	-3,599.91
2020-01-02	13:00	2h	-7.58	-1.74	132.23	-3,024.89	-3,157.12
2020-02-22	13:00	2h	-6.16	-2.00	-39.25	-2,797.18	-2,757.92
2020-05-07	16:00	2h	-5.42	-0.58	-162.01	-2,100.41	-1,938.41
Sum			-122.99	-24.75	2,805.08	-46,940.44	-49,745.53

Table F6: Effects of same length 50% *Away* rebate just before oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	14:00	2h	-5.48	7.14	-41.72	-431.68	-389.96
2016-11-26	10:00	3h	-7.56	4.83	117.02	-1,766.90	-1,883.92
2016-12-26	7:00	3h	-6.50	3.88	39.01	-1,661.26	-1,700.27
2017-02-22	11:00	3h	-9.23	7.58	100.81	-1,721.94	-1,822.75
2017-03-18	12:00	2h	-5.04	5.94	-56.13	-588.70	-532.57
2017-04-08	14:00	2h	-4.26	5.36	-95.60	-455.00	-359.40
2017-04-24	13:00	2h	-6.13	7.97	-29.75	-462.43	-432.67
2017-12-24	12:00	2h	-5.13	4.91	-2.04	-847.26	-845.22
2018-04-24	11:00	3h	-8.68	6.72	2.13	-1,814.37	-1,816.50
2018-09-27	13:00	2h	-5.91	7.19	-68.14	-629.82	-561.68
2018-12-04	13:00	2h	-6.37	8.26	-131.77	-601.29	-469.52
2019-09-17	12:00	2h	-6.55	8.03	-134.82	-738.99	-604.18
2020-01-02	13:00	2h	-5.61	6.48	-8.34	-639.24	-630.90
2020-02-22	13:00	2h	-4.56	5.55	-14.59	-465.31	-450.72
2020-05-07	16:00	2h	-4.01	5.99	78.78	71.67	-7.11
Sum			-91.02	95.83	-245.15	-12,752.52	-12,507.37

Table F7: Effects of same length 5% *Away* rebate just after oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	18:00	2h	-8.91	15.60	-125.25	1,581.71	1,706.96
2016-11-26	16:00	3h	-12.96	14.84	-51.15	286.87	338.02
2016-12-26	13:00	3h	-10.72	14.50	-101.14	1,009.05	1,110.20
2017-02-22	17:00	3h	-14.93	16.69	10.77	286.44	275.68
2017-03-18	16:00	2h	-7.39	14.75	-214.11	1,697.01	1,911.12
2017-04-08	18:00	2h	-7.19	12.40	-42.53	1,283.12	1,325.65
2017-04-24	17:00	2h	-8.56	17.31	-144.35	2,132.46	2,276.81
2017-12-24	16:00	2h	-9.28	15.32	40.02	1,563.51	1,523.48
2018-04-24	17:00	3h	-12.65	15.24	29.62	564.18	534.56
2018-09-27	17:00	2h	-9.60	17.36	-280.52	1,710.57	1,991.10
2018-12-04	17:00	2h	-11.03	19.42	-132.51	2,013.06	2,145.57
2019-09-17	16:00	2h	-9.81	19.50	-311.03	2,203.66	2,514.69
2020-01-02	17:00	2h	-8.70	16.91	-11.82	2,114.30	2,126.12
2020-02-22	17:00	2h	-9.44	15.28	90.09	1,559.16	1,469.06
2020-05-07	20:00	2h	-5.34	9.40	254.02	1,292.29	1,038.27
Sum			-146.51	234.52	-989.89	21,297.39	22,287.29

Table F8: Effects of same length 20% *Away* rebate just after oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	18:00	2h	-7.81	-0.71	187.27	-2,570.78	-2,758.05
2016-11-26	16:00	3h	-11.36	-1.35	425.45	-3,671.64	-4,097.09
2016-12-26	13:00	3h	-9.40	-1.79	-49.47	-3,777.39	-3,727.92
2017-02-22	17:00	3h	-13.09	-0.67	377.96	-4,101.38	-4,479.34
2017-03-18	16:00	2h	-6.48	-1.40	187.29	-2,323.57	-2,510.87
2017-04-08	18:00	2h	-6.30	-0.63	203.31	-2,038.99	-2,242.30
2017-04-24	17:00	2h	-7.50	-1.09	275.16	-2,485.64	-2,760.79
2017-12-24	16:00	2h	-8.14	-1.15	59.55	-2,926.51	-2,986.06
2018-04-24	17:00	3h	-11.09	-0.49	467.65	-3,308.25	-3,775.90
2018-09-27	17:00	2h	-8.41	-1.46	382.33	-2,777.54	-3,159.87
2018-12-04	17:00	2h	-9.67	-1.66	438.73	-3,187.78	-3,626.51
2019-09-17	16:00	2h	-8.61	-1.81	320.73	-2,997.55	-3,318.28
2020-01-02	17:00	2h	-7.63	-1.43	102.26	-2,791.68	-2,893.93
2020-02-22	17:00	2h	-8.27	-1.86	54.68	-3,170.65	-3,225.34
2020-05-07	20:00	2h	-4.68	0.74	56.00	-1,278.92	-1,334.92
Sum			-128.44	-16.76	3,488.90	-43,408.27	-46,897.17

Table F9: Effects of same length 50% *Away* rebate just after oversupply periods

Date	Hour	Period length	Demand change during *Away* period	Demand change *Before* and *After Away* period	Wholesale cost savings	Change in retail profit	Change in customer's bill
2016-06-08	18:00	2h	-5.78	7.05	-13.54	-456.51	-442.97
2016-11-26	16:00	3h	-8.41	5.85	86.45	-1,762.62	-1,849.07
2016-12-26	13:00	3h	-6.96	5.10	-21.14	-1,559.25	-1,538.11
2017-02-22	17:00	3h	-9.69	7.67	43.63	-1,834.99	-1,878.62
2017-03-18	16:00	2h	-4.80	5.73	-8.73	-408.90	-400.17
2017-04-08	18:00	2h	-4.66	5.52	45.59	-359.81	-405.41
2017-04-24	17:00	2h	-5.55	7.44	37.50	-205.77	-243.26
2017-12-24	16:00	2h	-6.02	6.34	14.94	-720.99	-735.94
2018-04-24	17:00	3h	-8.21	7.15	132.77	-1,280.67	-1,413.44
2018-09-27	17:00	2h	-6.23	6.99	-22.12	-663.97	-641.85
2018-12-04	17:00	2h	-7.15	7.79	103.99	-700.48	-804.46
2019-09-17	16:00	2h	-6.37	7.64	-4.91	-528.00	-523.08
2020-01-02	17:00	2h	-5.65	6.80	-19.63	-474.93	-455.30
2020-02-22	17:00	2h	-6.12	5.41	70.30	-961.51	-1,031.81
2020-05-07	20:00	2h	-3.47	5.75	194.15	343.81	149.66
Sum			-95.07	98.23	639.25	-11,574.59	-12,213.83

Appendix G: Effects of *Into* versus *Away* events in Connection with Morning and Evening Demand Peaks

Table G1: Effects of 5% *Into* rebate at 14:00

Date	Demand change during target hour	Demand change before and after target hour	Wholesale cost savings	Change in retail profit	Change in customer's bill
2018-07-07	19.67	-18.57	495.49	415.75	-79.74
2017-05-04	24.36	-22.80	369.79	347.78	-22.02
2018-10-10	25.05	-23.61	381.85	312.37	-69.48
2019-12-06	27.52	-25.83	332.11	306.46	-25.66
2017-04-08	19.81	-18.49	279.44	267.09	-12.35
2018-03-16	32.26	-30.11	250.42	246.39	-4.03
2016-10-26	27.17	-25.42	248.11	236.17	-11.94
2018-10-26	26.41	-24.81	273.38	232.83	-40.55
2018-03-31	22.97	-21.40	231.54	230.44	-1.09
2017-06-16	22.45	-21.58	374.94	205.12	-169.82
2018-10-19	24.17	-23.03	324.11	198.29	-125.82
2017-10-13	25.49	-23.88	216.22	193.79	-22.42
2017-04-23	19.52	-18.87	362.64	167.76	-194.88
2016-06-22	23.77	-22.26	190.42	167.21	-23.21
2020-04-24	19.83	-18.65	205.76	164.30	-41.46
Sum	360.45	-339.31	4,536.22	3,691.75	-844.47

Table G2: Effects of 5% *Into* rebate at 14:00

Date	Demand change during target hour	Demand change before and after target hour	Wholesale cost savings	Change in retail profit	Change in customer's bill
2019-09-17	27.81	-27.17	388.63	43.61	-345.01
2019-06-28	26.04	-25.08	277.05	50.60	-226.45
2019-10-18	26.90	-25.88	332.83	124.57	-208.26
2017-04-23	19.52	-18.87	362.64	167.76	-194.88
2017-06-16	22.45	-21.58	374.94	205.12	-169.82
2020-03-20	19.52	-18.85	281.57	114.19	-167.38
2017-02-10	30.84	-29.35	161.82	14.96	-146.87
2017-09-22	23.75	-22.71	166.17	22.44	-143.72
2018-06-05	22.56	-21.44	186.55	59.43	-127.12
2018-10-19	24.17	-23.03	324.11	198.29	-125.82
2019-05-29	26.57	-25.21	127.81	9.28	-118.53
2019-04-14	22.63	-21.46	159.06	43.24	-115.82
2019-05-31	23.01	-21.84	153.74	45.00	-108.74
2019-03-22	28.63	-27.13	138.20	32.47	-105.73
2018-09-04	23.95	-22.71	130.71	29.27	-101.44
Sum	368.35	-352.31	3,565.83	1,160.23	-2,405.59

Table G3: Effects of 50% *Away* rebate at 18:00

Date	Demand change during target hour	Demand change before and after target hour	Wholesale cost savings	Change in retail profit	Change in customer's bill
2020-06-04	-3.79	5.67	121.22	119.21	-2.01
2020-04-27	-4.12	6.17	56.81	53.51	-3.30
2020-03-18	-4.70	6.89	89.31	47.03	-42.27
2020-05-08	-2.82	4.20	46.68	40.00	-6.68
2019-10-08	-6.68	8.91	340.50	39.18	-301.32
2020-04-13	-3.57	4.71	214.41	37.73	-176.67
2020-04-16	-4.24	6.07	113.68	34.05	-79.64
2020-04-30	-3.98	5.83	59.62	20.97	-38.65
2020-05-27	-3.85	5.70	29.48	10.04	-19.44
2019-12-05	-6.76	8.93	338.45	8.40	-330.05
2020-06-08	-3.70	5.46	28.23	1.47	-26.76
2020-03-25	-4.46	6.53	44.95	1.46	-43.49
2020-03-26	-4.49	6.60	38.50	1.13	-37.37
Sum	-57.16	81.67	1,521.84	414.18	-1,107.65