Summertime Sadness: Time Sensitivity of Electricity Savings from a Behavior Nudge

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Abstract

The paper provides the results of evaluating the hourly impact of an energy behavior intervention tested in a randomized controlled trial. Under the program, a randomly selected group of households in Alberta was provided visual information on their home heat loss. I find that the households conserve the same amount of electricity during peak and off-peak electricity demand hours, which lowers the economic value of their electricity savings.

Keywords: Timing of Electricity Savings, Energy Efficiency, Randomized Controlled Trial

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1 Introduction

The presence of an energy efficiency gap, a difference between the cost-minimizing level of energy efficiency and the level actually realized (Allcott and Greenstone, 2012), has encouraged the implementation of programs focused on household energy conservation. Recent years have witnessed a large number of residential energy-saving programs aimed at mitigating greenhouse gas (GHG) emissions (Bulkeley, 2010; Broto and Bulkeley, 2013). These programs are expected to bring private savings – household energy savings that lead to lower energy bills – as well as social savings due to reduced external costs of pollution. However, evaluations of these programs typically do not consider the full set of benefits from these energy savings. In particular, since the wholesale price of electricity varies at high frequency over time, electricity conservation during peak demand times, when the marginal cost of an additional unit of electricity is relatively high, is more valuable than conservation during off-peak periods. Put differently, two programs that save the same total amount of electricity may result in different savings values if they have a different distribution of savings across hours. This heterogeneity is not generally considered in evaluations of energy-efficiency programs, which typically estimate total energy savings but ignore specific points in time when these savings occur (Boomhower and Davis, 2020).

According to recent findings (Mertens et al., 2021; Maier et al., 2022; Szaszi et al., 2022), one should not expect large and consistent impacts of nudges as tools for behavior change and the effect of behavior nudges is subject to substantial heterogeneity across published studies. In other words, under specific conditions, nudge interventions could work, yet their effectiveness can vary a lot (Szaszi et al., 2022). In the paper, I somewhat follow this nudge heterogeneity approach focusing on the hourly heterogeneity of a behavior intervention's impact: even if shifting energy consumer behavior does not induce any energy conservation or only brings small energy savings on aggregate, it may still have a relatively large impact in some specific hours.

I estimate the within-day distribution of household electricity savings from a novel randomized controlled trial in Medicine Hat, Alberta. Under the program, households were provided either visual information on their home heat loss or a comparison of their energy consumption to that of similar homes (Papineau and Rivers, 2022). Considering the former group of households, I evaluate the experiment's impact across peak and off-peak demand hours. During peak periods, any decrease in electricity demand is highly beneficial since it reduces electricity generation costs that are significantly higher in peak hours compared to the off-peak ones. Moreover, if energy sources that are more GHG-intensive and cause higher regional pollution, such as coal, are the marginal fuel at peak times, electricity conservation during peak hours could deliver environmental benefits.

I then go on to estimate the economic value of electricity savings arising from the experiment. In Alberta's energy-only market[1], a wholesale price of electricity is a complete measure of the value of electricity. The price represents an economic value of a decrease in electricity demand by one unit (Boomhower and Davis, 2020). Wholesale electricity prices vary across hours, so the economic value of electricity savings (put simply, quantity saved times the wholesale price of electricity) depends on when these savings take place. For example, a reduction in electricity consumption at night is less valuable than a decrease in electricity use during peak load periods.

My paper builds on a small number of studies that use hourly electricity data for program evaluation.

[1]There is no capacity market for electricity in Alberta (Government of Alberta, 2022a).

Boomhower and Davis (2020) evaluate a rebate program for energy-efficient air conditioners in Southern California and find that the air conditioner investments deliver savings during periods when electricity is the most valuable (i.e. wholesale prices are at their highest). When they account for the fact that electricity savings are strongly positively correlated with the wholesale price of electricity, the economic value of the investments in energy-efficient air conditioners increases by 40%.

Murphy et al. (2021) demonstrate the results similar to those in Boomhower and Davis (2020), but the authors use data for more energy efficiency measure categories.

Novan and Smith (2017) use hourly data from a rebate program for energy efficient air conditioners in Sacramento, California and find that the average household is faced with an incentive to over-invest in energy efficiency due to the design of retail rates in California.

Martin and Rivers (2018) show that real-time, high frequency information on electricity consumption among Ontario customers on time-of-use pricing is associated with a decrease in household electricity use, and this response is relatively invariable throughout the day, counter to some existing literature (for example, Houde et al. (2013)[2]) showing that electricity savings vary across hours of the day. The authors also find that the effect of real-time information on household responsiveness to electricity prices is ambiguous.

Using hourly electricity consumption data for residential customers in Arizona who replaced their air conditioners with the energy-efficient ones, Liang et al. (2021) concludes that both consumers on time-of-use and increasing block pricing have an incentive to over-invest in energy efficiency with the over-investment being less for non-time-of-use consumers. The authors demonstrate that non-time-of-use consumers are more likely to under-invest in energy efficiency than the time-of-use ones, which implies that consumers on non-time-of-use pricing should be the primary focus of energy efficiency interventions rather than time-of-use consumers. In addition, the paper's results provide evidence that energy efficiency makes time-of-use consumers' price elasticity of electricity demand increase.

My paper differs from the extant literature in that it estimates the intraday impact heterogeneity of a program that does not explicitly aim at yielding this type of heterogeneity, in contrast to rebates for installing an energy-efficient air conditioner with its time-sensitive electricity consumption or providing real-time feedback on electricity prices and usage that are usually expected to bring electricity conservation varying across hours of a day. In addition, I use Canadian data (the academic literature that I have just described, except Martin and Rivers (2018), use U.S. data).

The treatment was built around visualizing residential home heat loss. Medicine Hat is called 'The Gas City' on its utility bills (Papineau and Rivers, 2022), so the intervention was focused on increasing natural gas during the heating season. Although Papineau and Rivers (2022) show that the program does induce electricity savings, the decrease in electricity use was considerably lower than the natural gas savings. I argue that the intervention could continue to motivate electricity conservation of households during summer months as well when the treatment was not being sent to the households.

The thermal images show the amount of heat leaving the building. In general, if a building has good thermal insulation, it is likely to be more 'cooling-efficient' too (i.e. it might use less electricity for air conditioning during summer months)[3].

[2] Houde et al. (2013) use hourly electricity consumption data for residential customers in California; most of households in the sample are not on time-of-use electricity pricing scheme.

[3] This holds true if the behavioral aspect is taken into account, i.e. the two buildings with the same heat loss rating may consume quite different amounts of electricity for air conditioning in the summertime depending on their owner's preferences on the inside temperature of the house and the type of an air conditioner itself.

In addition, the households reduce their electricity use in response to the treatment employing the two mechanisms: behavior changes (habit formation such as turning off the lights when leaving the room, etc.) and structural changes to their home's building envelope. The former channel is of the most importance for the given intervention since the program's focus is on communicating to a residential consumer the building envelope characteristics of their house. Papineau and Rivers (2022) show that the intervention is associated with a higher rate of energy efficiency durables investment such as improving insulation or installing more energy-efficient windows. These energy efficiency programs improve a home's thermal envelope, so the households that do these home improvements will benefit from them in summer too.

I find that households in Medicine Hat conserve electricity due to the program overall, but, when considering the hourly distribution of the program's impact, I observe that households do not save more electricity in peak demand hours. As a result, accounting for the hourly distribution of the savings does not make the program more economically valuable than ignoring timing.

The fact that the hourly electricity savings profile is flat contradicts to what I would normally expect: since air conditioner usage can vary substantially within a day depending on outdoor temperatures (Boomhower and Davis, 2020), I would assume that there should be some sort of hourly variation in the electricity savings induced by the program during summer months. There could be several possible explanations for that, with the absence of time-varying retail electricity prices as the most plausible one.

The rest of the paper proceeds as follows. Section 2 presents background information relevant to the study, including generation and consumption of electricity in Alberta. In Section 3, I describe the experiment and the data obtained from it. Section 4 shows the results of the study, and Section 5 concludes.

2 Background

2.1 Electricity Generation in Alberta

Fossil fuels are the primary source for electricity production in Alberta: as shown in Figure 1, in 2018, most of electricity in the province was produced from coal (51%) and natural gas (37%).

At the same time, fossil fuels, especially coal, are main contributors to pollution and climate change. Figure 3 shows the four provinces that generated the largest amount of electricity in 2018: Alberta was not the top producer of electricity in Canada. However, if we look at greenhouse gas emissions from generating electricity, Alberta took the leading role (see Figure 4). Indeed, because of its reliance on coal-fired generation, Alberta's electricity generation produced 52% of total Canada's greenhouse gas emissions (Government of Canada, 2022) in 2018, and 71% of those emissions came from coal (Figure 2).

Coal generation was the most common price-setting technology in the Alberta wholesale electricity market in 2018. That was due to the baseload operation of coal generation technology. Baseload generation technologies offer energy to the market at a low price and produce energy in the majority of hours. In other words, coal assets tend to operate in both on-peak and off-peak hours of the day. Thus, in 2018, the year overlapping most of our sample period, coal generation set the wholesale electricity price in 81% of the on-peak hours and in 75% of the off-peak hours (Alberta Electric System Operator, 2018)[4].

[4]The Alberta Electric System Operator (AESO) defines the on-peak period as starting at 8 a.m. and ending at 11 p.m.

In Alberta, baseload technologies also include cogeneration and combined-cycle, both of which use natural gas as an energy source. In addition, there exist peaking generation technologies that operate using natural gas, such as combustion turbines used in simple-cycle gas generation (Alberta Electric System Operator, 2018). Although peaking generation technologies only produce energy when strong demand drives the wholesale price of electricity higher (and they offer energy at a higher price), they still combust fossil fuels in addition to the coal baseload technology during on-peak hours.

With respect to reducing pollution, electricity savings incurred in peak electricity demand hours are more valuable to society than those delivered during off-peak hours. In Alberta, that difference in the social value of the savings, i.e. the on-peak versus off-peak difference in greenhouse gas emissions, was not substantial in 2018 (specifically, in summer 2018, the part of the study period) since coal was used to generate electricity in the majority of off-peak and on-peak hours (see Figures 5 and 6).

However, coal-fired generation is scheduled to be gradually phased out by the end of 2023 (Government of Alberta, 2022b): Figure 7 shows that coal-fired power plants currently provide only about 20% of the province's electricity.

After coal generation is no longer used in Alberta, for the foreseeable future the electric grid will still require a technology with the ability to produce electricity in peak demand times. Such a technology will be natural gas, a fossil fuel generation technology (Figure 7). Any other generation technologies cannot increase electricity supply in a short period of time as required during peak periods (Bushnell and Novan, 2021). So, in the limit, when Alberta has only renewable energy generation for off-peak times and natural gas for on-peak times, the difference between the off-peak and on-peak energy savings in terms of reducing pollution should become more prominent.

2.2 Electricity Consumption in Alberta

In Alberta, electricity comprised 7% of end-use energy demand in 2018, whereas natural gas with its 57% share was the largest fuel consumed in the province (Canada Energy Regulator, 2021). Most of the end-use energy demand was taken by the industrial sector, and the share of the residential sector was 6% (Canada Energy Regulator, 2021). Figure 8 shows that the residential sector primarily consumed natural gas, electricity was in the second place with its 16% share.

In Medicine Hat, and Alberta more generally, there is no hourly time variation in retail electricity prices. The retail prices are fixed within months, and over the treatment evaluation period they changed from 6.1 cents/kWh in February 2018, when the treatment was first deployed, to 7.5 cents/kWh in February 2019, the end of the data sample.

Such a pricing policy does not reflect the hour-by-hour variation in the underlying cost of electricity (i.e. in the wholesale price of electricity). Households do not see or pay these time-varying wholesale prices – they face constant retail prices instead. Moreover, currently, due to the rising market price of electricity, even more Albertans are interested in paying monthly electricity rates that are fixed within several years (CityNews Calgary, 2022; Medicine Hat News, 2021).

The remaining hours of the day make up the off-peak period.

3 Experiment Design and Data

Papineau and Rivers (2022) deploy a randomized controlled trial to test the electricity and natural gas consumption impact of providing visual information on residential home heat loss in on-bill treatments[5]. The authors find that the program did reduce households' electricity and gas consumption. The results in that study were obtained using daily energy consumption data, so that the hourly distribution of savings was not evaluated. I re-estimate the program's results with hourly electricity consumption data[6].

The experiment took place in Medicine Hat, Alberta, a city of about 60,000. Households in Medicine Hat receive utility bills each month, and the intervention began by including the treatments on the February 2018 bills. The intervention was repeated in March, April and November 2018. These months were chosen because they cover the heating season when building heat loss is most important for determining energy consumption. Single-detached households were randomly divided into a treatment group and a control group of equal sizes (the groups were balanced on pre-intervention gas and electricity consumption, year of construction, assessed value, building size, and a heat loss score).

Households in the treatment group were shown infrared images of their roof. Thermal images were acquired using the technology platform developed by a company called MyHEAT; they were taken at night in the heating season immediately before the experiment. Using the thermal images, each dwelling was assigned a heat loss score, or so-called HEAT Rating, ranging from 1 to 10, which indicates the amount of heat loss from the roof and walls. The higher your home's heat loss score is, the more energy (natural gas and electricity) you tend to consume. Households were also shown how their heat loss score compares to that of their neighbors and an estimate of potential annual bill dollar savings from improving their heat loss score to that of 1 (the best possible score). Finally, the bill included a list of potential options for reducing energy consumption. Appendix Section A shows an example of the bill.

I use hourly electricity consumption data for the period from June 1, 2017 until September 30, 2017 and from June 1, 2018 until September 30, 2018[7]; I have chosen this time range to capture the warmest part of the summer season in Medicine Hat[8].

[5] The authors also estimate the effect of sending a 'traditional' home energy report to households on their electricity and natural gas consumption. Traditional home energy reports provide energy consumers with feedback that compares their own usage to that of similar households. Since the authors find that a home energy report has no impact on household electricity use, I do not test this type of the treatment in my paper.

[6] I do not use gas data because gas can be stored, so wholesale gas prices are not as volatile as wholesale electricity prices.

[7] I drop observations in which bill dollar savings, building size, building assessment value, year built, or HEAT Rating are missing. I also drop observations with no electricity consumption (electricity use that is less than 100 kWh) during the whole period of analysis, observations with zero daily electricity consumption (I allow electricity use to be zero in some hours), observations in which there are less than 24 hours of consumption data within in a day, as well as observations with less than the full set of days in the panel. I drop around 6.6% of the total number of observations. Dropping the observations has not affected the balance statistics for the two groups.

[8] According to AESO, the summer season starts on May 1 and ends on October 31 (Alberta Electric System Operator, 2018).

4 Analysis

4.1 Intraday Electricity Conservation

Before estimating the hourly distribution of electricity savings, I estimate total electricity savings for the whole period of study using a standard difference-in-difference approach[9]:

$$Y_{ith} = \beta_0 + \beta_1 T_i \times P_{it} + \beta_2 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \tag{1}$$

where i indexes the household, t indexes each day of the experiment (each day of the sample), h indexes each hour of the day.

The dependent variable, Y_{ith}, represents the electricity consumption for household i on day t in hour h; the electricity consumption is normalized by average post-treatment consumption in the control group to avoid dropping zero consumption observations (Papineau and Rivers (2022) use the normalization too). T_i is a dummy variable indicating a household's treatment status (i.e., whether a household belongs to the treatment group), P_{it} is a post-treatment dummy variable[10]. The term μ_{ih} represents a household by hour-of-day fixed effect to account for any hour-specific differences between households, and the term λ_t indicates a day-of-sample fixed effect, which absorbs factors that shift over time and affect electricity demand (weather, seasonal changes, etc.). The error term is ϵ_{it}. Specification (1) is estimated in ordinary least squares using standard errors that are clustered by household and day of the sample.

β_0 is the constant term showing the average electricity consumption of the control group prior to the intervention; β_2 represents how much the average electricity consumption of the control group has changed in the post-treatment period compared to the pre-treatment period[11]. Finally, β_1 indicates how much the average electricity consumption of the treatment group has changed in the post-treatment period relative to the pre-treatment period, compared to the post- versus pre-intervention difference in the average electricity consumption of the control group. In other words, β_1 is the average effect of the treatment on electricity consumption in the post-treatment period; β_1 is estimated from within-household-by-hour and within-day differences between treated and untreated households. The coefficient multiplied by 100 can be interpreted as percentage change because electricity usage is normalized.

Households that are informed that there are large potential savings from improvements in energy efficiency are likely to respond differently to the treatment than households who are told that there are small savings. In Specification (2), the treatment and post-treatment period dummies are interacted with the dollar savings shown to customers (D):

$$Y_{ith} = \gamma_0 + \gamma_1 D_{im} \times T_i \times P_{it} + \gamma_2 T_i \times P_{it} + \gamma_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \tag{2}$$

where D_{im} represents the dollar savings estimate (in units of hundreds of dollars) for household i in the treatment group; the estimate is shown on household i's utility bill in billing month m.

The coefficient γ_1 multiplied by 100 shows the percent reduction in consumption in the treatment group per hundred dollars of non-zero estimated savings. The interpretation of the coefficient γ_2 is the percent reduction in consumption in the treatment group when dollar

[9] In Appendix Section C, I also provide calculations using the data for the winter season.

[10] Despite the fact that a day-of-sample fixed effect is included in the specification, the post-treatment dummy is not omitted because the treatment start dates vary from household to household.

[11] The solo term T_i is omitted from the specification because there are household-level fixed effects; the coefficient on that term would show the difference between the treatment group and the control group in the pre-treatment period.

savings are zero. The meaning of the coefficients γ_0 and γ_3 stays the same as in Specification (1).

The main coefficient of interest is γ_1. Papineau and Rivers (2022) show that reductions in gas and electricity consumption are the largest when the authors account for the heterogeneity in potential dollar savings shown to the treated households; however, this only applies to the households that were shown non-zero potential dollar savings since the customers with zero potential dollar savings (the most efficient households) experience a boomerang effect by increasing their energy consumption.

Table 1 reports the results of estimating Specifications (1) – (2). According to Column (2), on average a household in the treatment group did decrease its hourly electricity consumption by 4.1% per hundred dollars of estimated savings relative to the control group after the treatment versus before the treatment.

Next, I estimate Specification (2) separately for peak and off-peak hours because it is preferred that households save more at peak electricity load times, as discussed above. According to Alberta Electric System Operator (2018), on-peak hours are from 7 a.m. till 11 p.m. However, by looking at Figure 10 showing average hourly electricity load for Alberta, I assume that on-peak hours actually differ from those. So, based on the hourly dynamics of the electricity load, I define the on-peak period to be from 11 a.m. till 5 p.m.

Specification (3) is the same as Specification (2), except that the treatment and post-treatment period dummies are now interacted with the variable indicating peak or off-peak time:

$$\begin{aligned} Y_{ith} =& \theta_0 + \sum_{d=1}^{2} \theta_{1d} D_{im} \times T_i \times P_{it} \times TimeOfDay_{hd} + \sum_{d=1}^{2} \theta_{2d} T_i \times P_{it} \times TimeOfDay_{hd} \\ &+ \theta_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \end{aligned} \tag{3}$$

where $TimeOfDay_{hd}$ is a variable showing whether hour h belongs to off-peak time ($d = 1$) or peak time ($d = 2$).

In Specification (3), I treat $D_{im} \times T_i \times P_{it}$ as a continuous variable due to the presence of the dollar savings D_{im}. So, when I interact the continuous variable with $TimeOfDay_{hd}$, I estimate the separate slope coefficients of $D_{im} \times T_i \times P_{it}$ for peak and off-peak times, i.e. I estimate the decrease in electricity consumption per hundred dollars of non-zero estimated savings among the treated households during off-peak (θ_{11}) and peak hours (θ_{12}). I do this in order to present the results for the peak and off-peak hours separately and then see if the difference between the peak and off-peak coefficients is statically significantly different from zero. The same logic applies to the term $T_i \times P_{it}$ even though $T_i \times P_{it}$ is not a continuous variable. The interpretation of θ_{2d} is the percent reduction in electricity consumption in the treatment group when dollar savings are zero for off-peak (θ_{21}) and peak times (θ_{22}). The meaning of the coefficients θ_0 and θ_3 is the same as in Specification (1).

Appendix Section B contain the results of the following robustness checks: in Table B1, I re-estimate Specification (3) using various combinations of fixed effects; in Table B2, Specification (3) is estimated for different definitions of peak hours. It is concluded that the coefficient of interest, θ_{1d}, is robust to changes in fixed effects or peak hours.

In addition, I check how similar the peak electricity savings are in weekends as opposed to

weekdays[12]:

$$
\begin{aligned}
Y_{ith} =& \kappa_0 + \sum_{w=1}^{2}\sum_{d=1}^{2} \kappa_{1dw} D_{im} \times T_{ik} \times P_{it} \times TimeOfDay_{hd} \times TimeOfWeek_{tw} \\
&+ \sum_{w=1}^{2}\sum_{d=1}^{2} \kappa_{2dw} T_i \times P_{it} TimeOfDay_{hd} \times TimeOfWeek_{tw} + \kappa_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it},
\end{aligned} \tag{4}
$$

where $TimeOfWeek_{tw}$ indicates if day t belongs to a weekday ($w = 1$) or a weekend ($w = 2$).

The idea regarding the interactions between the terms $D_{im} \times T_i \times P_{it}$ or $T_i \times P_{it}$ and the variables $TimeOfDay_{hd}$ and $TimeOfWeek_{tw}$ is the same as in Specification (3). The only difference is that now I have an additional interaction term $TimeOfWeek_{tw}$, so, say, the four-dimensional vector of coefficients κ_1 includes four slope coefficients of $D_{im} \times T_i \times P_{it}$ for peak and off-peak times during weekends and weekdays.

Figure 11 shows the estimates of the coefficients θ_{1d} in Specification (3), and Figure 12 reports the estimation results for κ_{1dw} in Specification (4).

Then, the Wald test is performed to see if the estimates shown in the two figures are statistically significantly different from each other. The difference between the on-peak and off-peak savings shown in Figure 11 is not statistically significant; the same goes for the estimates in Figure 12: there is no statistically significant difference between the on-peak and off-peak savings during weekends or weekdays. In other words, households save approximately the same amount of electricity during on-peak and off-peak hours, and they do not save more during weekends as opposed to weekdays, or vice versa.

The treatment does not produce more electricity savings in on-peak hours than in off-peak times. I then evaluate if consumers tend to use less electricity in some specific hours. Specification (5) is the same as Specification (3), except that the time-of-day variable is replaced with the indicator for each hour of the day:

$$
Y_{ith} = \alpha_0 + \sum_{h=1}^{24} \alpha_{1h} D_{im} \times T_i \times P_{it} \times Hour_h + \sum_{h=1}^{24} \alpha_{2h} T_i \times P_{it} \times Hour_h + \alpha_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \tag{5}
$$

where $Hour_h$ represents an hour of the day, $h = \{1, 24\}$. The main coefficient of interest, α_1, is a 24-dimensional vector capturing the hourly effect of the treatment.

Again, I estimate Specification (5) separately for weekends and weekdays:

$$
\begin{aligned}
Y_{ith} =& \delta_0 + \sum_{w=1}^{2}\sum_{h=1}^{24} \delta_{1hw} D_{im} \times T_i \times P_{it} \times Hour_h \times TimeOfWeek_{tw} \\
&+ \sum_{w=1}^{2}\sum_{h=1}^{24} \delta_{2hw} T_i \times P_{it} \times Hour_h \times TimeOfWeek_{tw} + \delta_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it},
\end{aligned} \tag{6}
$$

The estimates of the coefficients α_{1h} in Specification (5) are presented in Figure 13, and the δ_{1hw} from Specification (6) are shown in Figure 14. The results of the multiple hypothesis testing of the pairwise difference between the hourly estimates with Holm-adjusted p-values shows that the α_{1h} estimates are not statistically significantly different across 24 hours and most

[12] Figure 10 shows that there is no substantial difference in the electricity load dynamics during weekends compared to weekdays. As a result, the definition of the peak hours stays the same.

of the δ_{1hw} estimates are not statistically significantly different across 24 hours during weekdays and weekends[13].

I cannot identify the exact factors contributing to the flat hourly savings profile, so I am only left to speculate about the potential reasons for such a "sad" (in the context of this paper) situation with the intraday variation of summertime electricity savings.

The most variable part of residential electricity demand in summer is expected to be air conditioning since air conditioner usage normally varies to a great degree within a day depending on outdoor temperatures (Boomhower and Davis, 2020). According to Figure 9, in 2018, space cooling took less than 1% of residential end-use demand, whereas space heating had 70%[14]. Such a small share of space cooling is explained by the fact that only around 30% of households in Alberta had an air conditioner in their homes in 2017, with the national average of 60% (Statistics Canada, 2021), meaning that there is no substantial need for air conditioning in the province (at least, that could be the case in 2018). The situation is changing though: for example, recent heatwaves occurring due to climate change have made those living in Calgary reconsider air conditioning - the demand for air conditioners has started to grow fast (Calgary Herald, 2022; CTV News, 2021).

If Medicine Hat demonstrated the low rate of air conditioning penetration too, I could conclude that the sample just did not have enough homes with air conditioners installed to provide evidence on the substantial intraday variation in the electricity savings. However, I have neither the air conditioning statistics for the city nor the data on which homes in my sample have air conditioning. Yet, I examine if the electricity savings in the summertime vary with ambient temperature.

First, I estimate the relationship between electricity consumption and outdoor air temperature: I divide hourly outdoor temperature into 10 temperature bins defined in roughly 5°C increments from the lowest (-3.6°C)[15] to the highest (40°C) temperature observed in the sample, and then I regress non-normalized hourly electricity use on the hourly outdoor temperature:

$$Y_{ith} = \sum_{b=1}^{10} \phi_b TempBin_{thb} + \mu_{ih} + \lambda_t + \epsilon_{it}, \tag{7}$$

where $TempBin_{thb}$ is a dummy variable for each temperature bin. The temperature bin $(17.5, 22.5]$ is the reference category, and I estimate the change in hourly electricity consumption relative to that category. The fixed effects and standard errors are the same as before.

Interestingly, the summer consumption pattern is quite standard: the consumption does vary with outdoor temperature, with higher consumption during the hottest hours (Figure 15).

Then, I check how outdoor temperature changes within a day. I regress average hourly outdoor temperature on a dummy that corresponds to each of the 24 hours of the day using day-of-sample fixed effects and clustering standard errors at the day-of-sample level:

$$T_{th} = \sum_{h=1}^{24} \omega_h Hour_h + \lambda_t + \epsilon_t, \tag{8}$$

[13] During weekends, the estimates for hour 14 and hour 15 are statistically significantly different from each other, as well as the estimate for hour 9 is statistically significantly different from the estimates for hours 21, 22, 23, 24. The difference between hour 14 and hour 15, as well as hour 9 and hour 24 is statistically significant only at 10%.

[14] The residential sector in Alberta mostly used natural gas for space heating: around 90% of the energy use for space heating was taken by natural gas and only 5.5% went to electricity (Natural Resources Canada, 2022).

[15] Yes, I do have temperatures below zero in my "summer" data; however, re-running the temperature-related specifications only with temperatures above zero has not changed the results.

where $Hour_h$ is an hour-of-the-day dummy variable with $Hour = 16$, which corresponds to the hottest temperature of the day on average, taken as the reference category.

Figure 16 shows how hourly temperature changes relative to the temperature at 4 pm. One can see that the highest temperatures concentrate around the peak hours.

So far, it looks like households consume more during hours with the highest outdoor temperature which are simultaneously the peak hours. As a result, I would expect the treated households to save more electricity compared to the control group during times when their electricity consumption is high, i.e. in the peak hours. However, previously, we saw that households do not save more during the peak hours. Let's see if this pattern changes depending on the heat loss score. I run Specification (2) separately for households with high (8-10), medium (4-7), and low (1-3) HEAT Ratings. The results of estimating coefficient γ_1 are presented in Figure 17. Only the most efficient households with the lowest HEAT Ratings do save more during the peak hours, whereas the high and medium groups have relatively flat savings profiles[16].

Finally, I re-estimate Specification (5) with the dummy for each hour of the day replaced by the dummy showing one of the 10 temperature bins generated above:

$$\begin{aligned} Y_{ith} =& \chi_0 + \sum_{b=1}^{10} \chi_{1b} D_{im} \times T_i \times P_{it} \times TempBin_{thb} \\ &+ \sum_{b=1}^{10} \chi_{2b} T_i \times P_{it} TempBin_{thb} + \chi_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \end{aligned} \tag{9}$$

Figure 18 shows the estimated coefficients χ_{1b}. I observe that treated households save more electricity relative to the control group during hours with cool or mild outdoor temperature, but they consume more electricity than the control group when the outdoor temperature is quite high, which is exactly the opposite of what I would expect to see.

Figure 19 shows the results of re-estimating Specification (9) for households in each of the three HEAT Rating groups separately. One can observe that the pattern presented in Figure 18 is especially bright for the most energy-efficient households.

As for the structural aspect, there is academic literature examining whether increased building envelope insulation (in our case, the buildings in the lowest HEAT Rating group) may be associated with larger electricity consumption in summer due to overheating of the building (Fosas et al., 2018; Chvatal and Corvacho, 2009). The relationship between building insulation and overheating is complicated. Fosas et al. (2018) conclude that improving insulation can increase overheating in buildings with purge ventilation. At the same time, this applies to the buildings that are already overheated meaning that insulation is likely not the cause of overhearing - it might be just the lack of proper ventilation and some flaws in the building design (for example, many large unshaded windows in the house). Unfortunately, I lack the data required to test that in my sample.

On the behavior side, the only explanation I could think of, and I find the explanation quite odd, is as follows: the on-bill treatment stated "The lower the rating, the less heat is leaving your home"; households, especially the ones with the lowest HEAT Ratings, must have misunderstood that phrase thinking that heat hardly leaves their homes when it is hot outside, so they have to consume more electricity to cool down their homes. However, the treatment was not being sent in the summer months, so households' efforts to conserve electricity could start to decline

[16]The pattern of higher usage relative to higher outdoor temperatures shown in Figure 15 stays the same if I run the specification separately for the three HEAT Rating groups of households.

after they stopped receiving the on-bill treatment messaging as discussed in Allcott and Rogers (2014), and that's probably why I observe such a strange relationship between hourly electricity savings and outdoor temperature.

In order to check this, I again re-estimate Specification (5) with the hour dummy replaced by the dummy showing the week number in the pre and post-treatment periods:

$$\begin{aligned} Y_{ith} =& \eta_0 + \sum_{s=1}^{18} \eta_{1s} D_{im} \times T_i \times P_{it} \times Week_s \\ &+ \sum_{s=1}^{18} \eta_{2s} T_i \times P_{it} \times Week_s + \eta_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{it}, \end{aligned} \tag{10}$$

where $Week_s$ is a week-of-the year dummy. There are 18 weeks of the year in the pre-treatment period (week 22 to week 39; the weeks refer to June - September of the 2017 year) and 18 weeks of the year in the post-treatment period (also, week 22 to week 39), so $s = \{1, 18\}$. For example, the coefficient η_{11} shows the change in electricity consumption per hundred dollars of non-zero estimated savings among the treated households in the first week of the post-treatment period relative to the first week of the pre-treatment period, compared to the corresponding post- versus pre-treatment change in the electricity consumption of the control group.

According to Figure 20, the highest savings are concentrated around the first and the last weeks of the sample that correspond to the months of June and September, respectively. After I run Specification (10) for the three HEAT Rating groups of households separately, I observe that the pattern of increased electricity savings at the beginning and end of summer is the same across the three groups (Figure 21) with larger effects for the most efficient households. This is also something I would not expect to see. However, the pattern observed in Figure 20 matches the one shown in Figure 18: the higher the outdoor temperature, the lower the electricity savings (June and September have on average lower outdoor temperature than July and August). Thus, I could guess that temperature still influences households' electricity conservation more than the time since when they received the treatment.

As discussed in Papineau and Rivers (2022), the share of environmentally conscious population is relatively low in Medicine Hat, which could also negatively affect the way the treated households respond to the intervention.

Some may argue that the intervention was not 'built' to induce hourly electricity savings. The on-bill treatment contained a list of options for reducing energy consumption which mostly included energy efficiency rebates aimed at improving insulation and installing energy-efficient windows. Papineau and Rivers (2022) provide evidence that the treatment is associated with increased uptake of such energy efficiency programs. These home-improvement rebates focus on changing the structural characteristics of the home, and one could assume such building envelope measures tend to deliver less time-sensitive savings than the measures related to behavior change. At the same time, recent literature provides evidence against that. Novan et al. (2022) study the adoption of energy building codes that contain building-envelope requirements aimed at decreasing the amount of energy used for indoor temperature control in California. The authors conclude that adopting the codes is associated with electricity savings driven by reduction in cooling that do vary within a day (the savings are the largest in the afternoon and evening, when demand for cooling is highest). The authors study Sacramento, California, where high summer temperatures make space cooling account for a large share in residential electricity consumption. Murphy et al. (2021) show that building-envelope energy efficiency measures, including but not limited to installing new windows, doors, or upgrading insulation, motivate

hourly electricity savings that also vary within a day in both summer and non-summer seasons. However, the two papers use the data from California where households apparently use more electricity for cooling compared to their counterparts in Alberta. That being said, I must admit that I cannot do a credible assessment if the hourly electricity savings profile is different for the households that installed efficient windows and/or upgraded their home's insulation in the post-treatment period in comparison to those who did not: after the intervention began, only around 45 households (1%) in each of the two groups installed envelope-related measures during the summer months (and roughly 80 households in each of the groups installed any energy-efficient measures).

Finally, another possible reason (and it could be a very likely one) why households in Medicine Hat are not motivated to reduce their electricity consumption during on-peak hours is zero hourly variation in the retail electricity prices they face.

Jessoe and Rapson (2014) set up a randomized control trial to test whether exposing residential customers on a flat retail electricity rate to exogenous price changes during peak hours and real-time feedback on their electricity consumption (via in-home displays) increases the price elasticity of demand. Using 15-minute interval meter data during the summer months of 2011 for residential electricity customers in Connecticut, the authors find that households introduced to retail price variation decrease their usage by 0% to 7% on average during peak pricing events, in comparison to the control group. At the same time, the households exposed to the retail price changes and real-time feedback on their electricity usage demonstrate much larger electricity conservation of 8% to 22%.

Utilizing high-frequency residential electricity consumption data in a South-Central U.S. state for the summer of 2011, Harding and Lamarche (2016) show that time-of-use pricing combined with the technology automating household responses to the intraday changes in retail electricity rates ("smart" thermostats) brings even higher electricity savings during on-peak periods than providing residential customers on the time-of-use pricing scheme with in-home displays. Interestingly, the authors find that the households with "smart" thermostats also shift their consumption to off-peak hours, while the customers with in-home displays do not shift their load to off-peak. The latter is consistent with the findings of Martin and Rivers (2018) who suggest that households underestimating electricity prices could be a reason why information makes residential customers less responsive to time-of-use electricity rates. The authors also find that households tend to under-estimate retail electricity prices during colder months, while they over-estimate the prices during warmer (summer) months.

It is worth mentioning that most of Californian households in the sample Houde et al. (2013) use for their analysis do not face time-varying retail electricity prices, yet their electricity savings induced by real-time information feedback technology vary within a day. Additionally, while Boomhower and Davis (2020) do not specify the electricity rate plan of the households during the time of the analysis (2012 – 2015), the households did not face time-varying prices since Southern California Edison began transitioning their customers to time-of-use rate plans only in the fall of 2021 (CBS News Los Angeles, 2021). In contrast, Martin and Rivers (2018) show that the effect of real-time information on hourly electricity consumption of customers in Ontario is relatively constant on days without time-of-use pricing (weekends, holidays). The papers mentioned above are not fully comparable to mine though: the studies test the effect of providing households with a real-time feedback technology (Houde et al., 2013; Martin and Rivers, 2018) or an energy-efficient air conditioner (Boomhower and Davis, 2020), while the experiment conducted by Papineau and Rivers (2022) did not involve supplying any appliance to the treatment group.

4.2 Timing Premium

Finally, following Boomhower and Davis (2020), I calculate the 'timing premium', which is the percentage difference between the total average dollar value of the electricity savings from the program, and the dollar value of the program's impact adjusted for the hourly distribution of the savings. The timing premium reflects how accounting for timing affects the estimated economic value of electricity savings. For example, Boomhower and Davis (2020) obtain the positive value of the timing premium for a rebate program for energy-efficient air conditioners. In their case, accounting for timing increases the value of the estimated savings. The positive timing premium is due to the fact that the electricity savings are positively correlated with the wholesale price of electricity: households save more during periods when wholesale prices are at their highest. In my case, the hourly savings profile of the households is essentially flat meaning that the timing premium might be close to zero or even negative. The timing premium is calculated as follows:

$$\begin{aligned} TimingPremium &= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecAve \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}} \times 100\% - 100\% \\ &= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{PriceElecAve} \times 100\% - 100\% \\ &= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecHour_h \times LoadElecHour_h}{\sum_{h=1}^{24} LoadElecHour_h}} \times 100\% - 100\%, \end{aligned} \tag{11}$$

where α_{1h} represents electricity savings in kWh in hour h; α_{1h} comes from re-estimating Specification (5) using non-normalized electricity consumption on the left-hand side[17]. $PriceElecHour_h$ and $LoadElecHour_h$ show the the pool price for wholesale electricity and Alberta Internal Load for hour h, respectively. $PriceElecAve$ is the load-weighted average hourly wholesale electricity price.

The numerator and denominator both measure the economic value of the program's impact in dollars per MWh. The numerator shows the dollar value of the electricity savings when timing of the savings is taken care of. In the denominator, the electricity consumption changes are valued at the same load-weighted average electricity price meaning the denominator gives the value of the program's impact when the impact's hourly distribution is not taken into account.

The value of the numerator is \$41.17 per MWh; this is the value of the program's impact when one accounts for timing. The denominator, the value of the program's impact not adjusted for its hourly distribution, is \$40.69 per MWh. As a result, the timing premium is 1.17%. The value is positive but very small meaning timing hardly matters when calculating the economic value of the program.

However, again, the α_{1h} estimates are not statistically significantly different across 24 hours. Therefore, I could replace all of the α_{1h} estimates with the same value and re-calculate the timing premium. Replacing the values with -0.0432 kWh, which is the average across the 24 estimates, gives me the timing premium of -2.35%[18]. Adjusting the program's impact for the hourly distribution of the savings makes the program less economically valuable than ignoring

[17] The estimates of the coefficient α_{1h} are all negative and statically significant.

[18] Replacing the 24 estimates with any other number yields the same value of the timing premium.

timing in the calculations. The result is consistent with Boomhower and Davis (2020) who showed that the energy efficiency investments with flat hourly electricity savings profiles, such as residential refrigerators and freezers, have a negative timing premium.

The concept of a timing premium can also be applied to the social value of the program, i.e. the amount of GHG emissions reduced due to the treatment. The carbon intensity of electricity consumption varies across hours being the highest during times with more GHG-intensive marginal fuels, so accounting for timing of the electricity savings can affect their social value.

Neither AESO nor the Government of Alberta collect hourly-level data on GHG emissions from electricity generation or electricity consumption. Yet, considering the program produced relatively the same level of electricity savings across hours, I can expect the timing premium of the program's social impact to be around zero meaning that the GHG intensity of the electricity savings when timing of the savings is taken care of would be the same as the average GHG intensity of electricity consumption. The latter is quite large in Alberta (see Figure 22). This already makes any programs aiming at energy conservation in the province highly socially valuable, and saving more during peak hours would potentially make it even more beneficial.

5 Conclusion

The paper measures the hourly distribution of household electricity savings from a behavior change intervention in Medicine Hat, Alberta. I find that the treatment delivers electricity savings in general, but households have relatively flat hourly savings profile, i.e. they do not save more electricity during peak electricity demand hours. Consequently, the timing premium is around or even below zero which means that timing hardly matters when calculating the economic and social value of the program.

In the long term, Rivers and Shaffer (2020) examine the effect of higher temperatures due to climate change on electricity consumption through mid- and end-century in Canada. The authors find that Alberta might see the shift in peak hourly electricity demand from winter to summer followed by a substantial increase in peak demand arising from larger air conditioner adoption and higher hourly temperatures in the peak of summer[19]. Moreover, Alberta could face a significant increase in within-day range of demand in summer months meaning the province might experience increased intraday ramping requirements (the 'ramp' is the difference between the minimum and maximum hourly electricity demand during a day), which will require more flexibility of electricity supply.

As a policy recommendation, switching residential customers in Medicine Hat to retail electricity prices varying within a day coupled with some form of real-time feedback on their electricity usage could help alleviate the challenges related to the mismatch between wholesale and retail hourly prices of electricity, particularly during summer months. More specifically, incorporating time variation in the retail rates could help mitigate the volatility of wholesale electricity prices (Griffin and Puller, eds, 2005) that Albertans have been so concerned about recently, as discussed in Section 2. In addition, time-varying retail prices could motivate households to shift their electricity consumption to off-peak, which might become especially important in the future.

[19] For example, the heatwave in 2021 led to a record high electricity demand with AESO asking Albertans to reduce their electricity use within peak times (CBC News, 2021).

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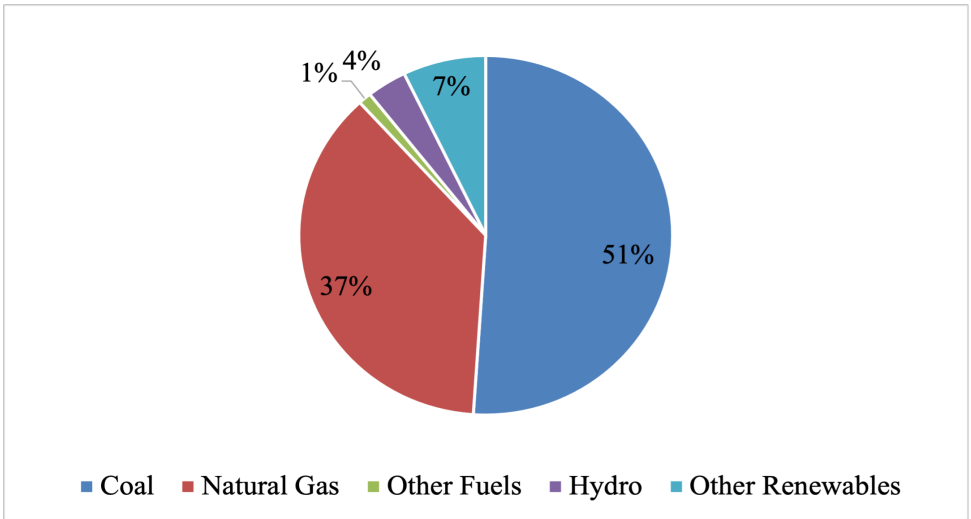
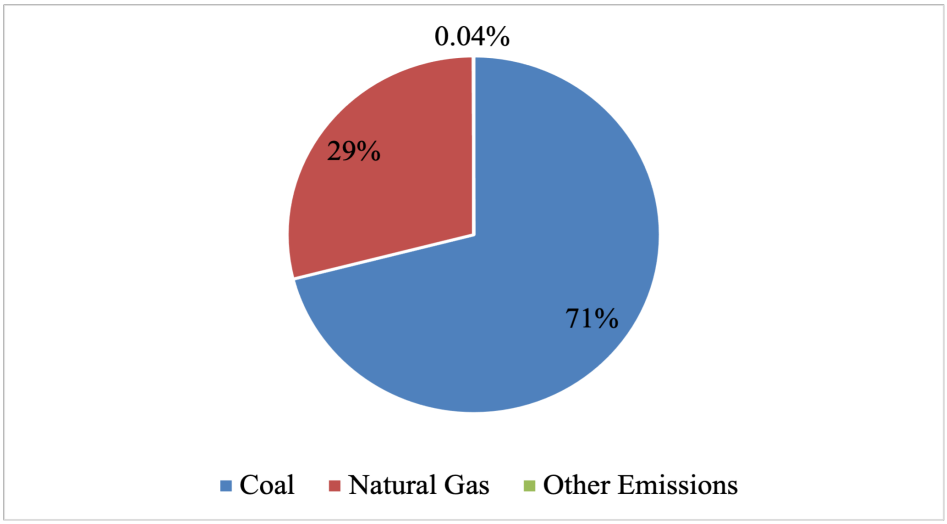
Tables and Figures

Figure 1: Electricity Generation by Source in Alberta in 2018



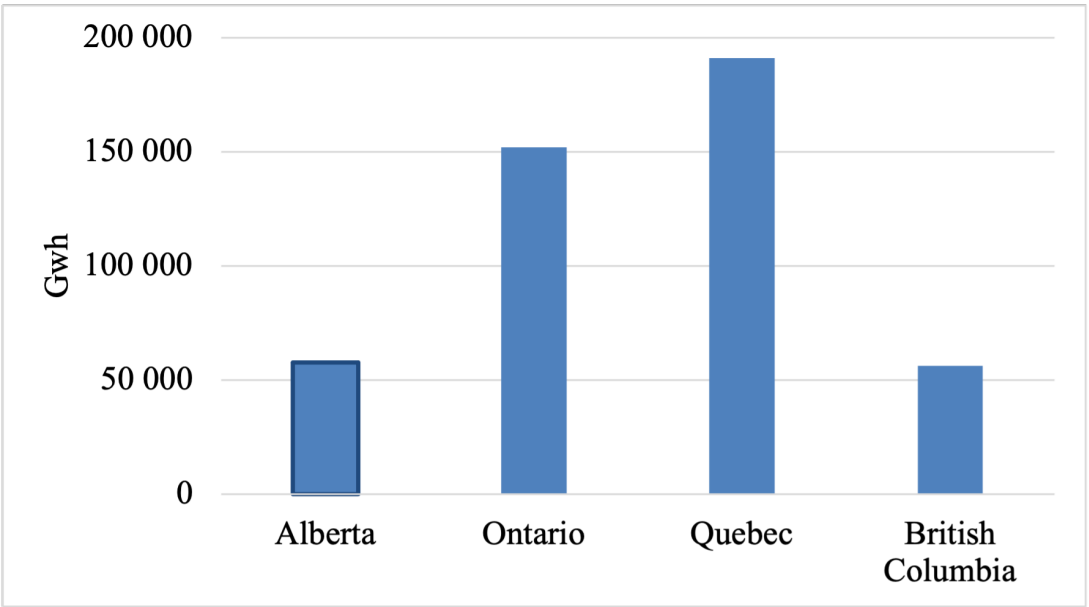
Source: Government of Canada (2022).

Figure 2: Greenhouse Gas Emissions from Electricity Generation by Source in Alberta in 2018



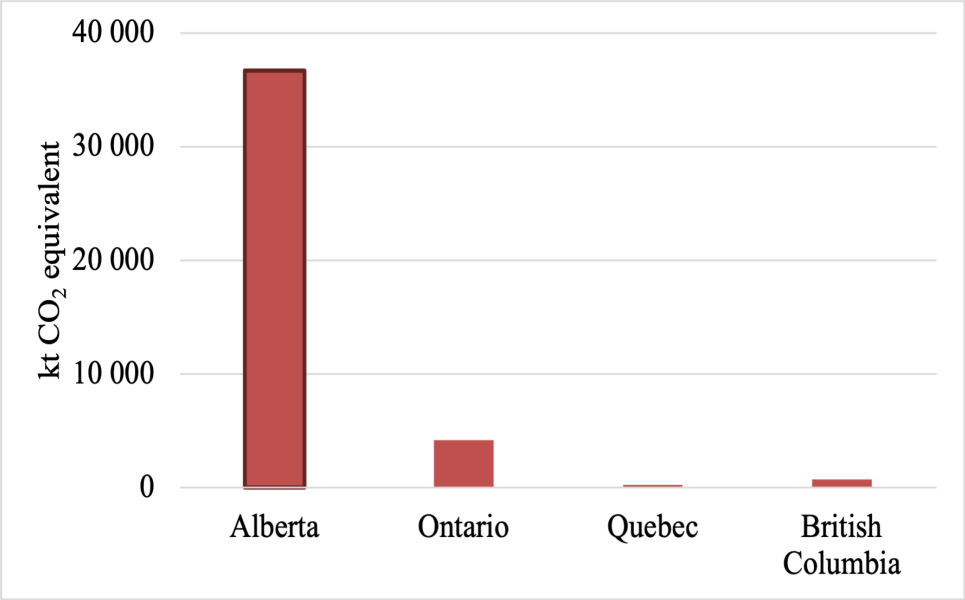
Source: Government of Canada (2022).

Figure 3: Electricity Generation by Province in 2018



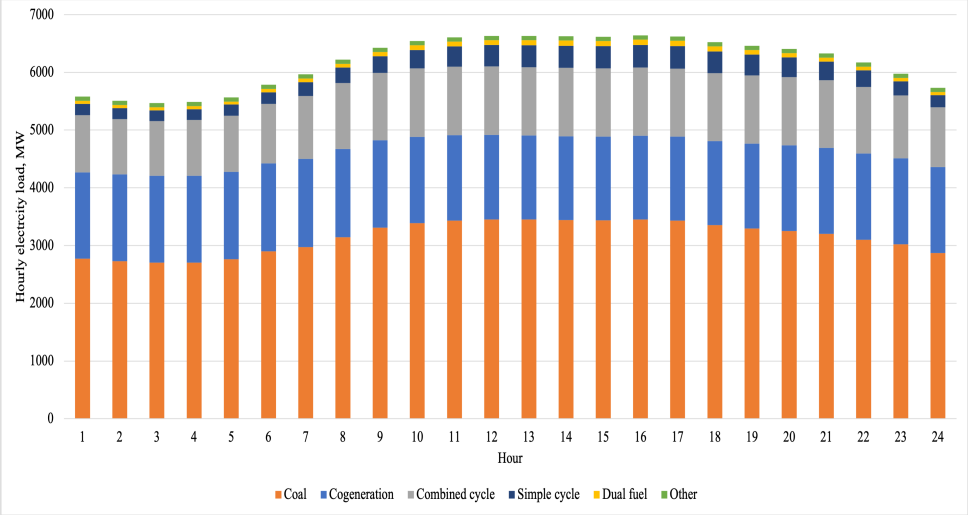
Source: Government of Canada (2022).

Figure 4: Greenhouse Gas Emissions from Electricity Generation by Province in 2018



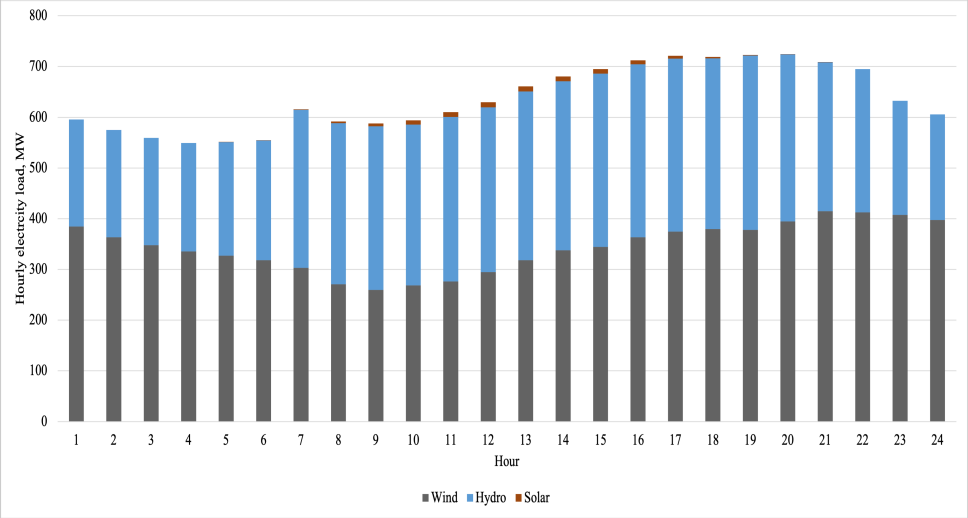
Source: Government of Canada (2022).

Figure 5: Hourly Electricity Generation by Non-Renewable Source in Alberta in June - September 2018



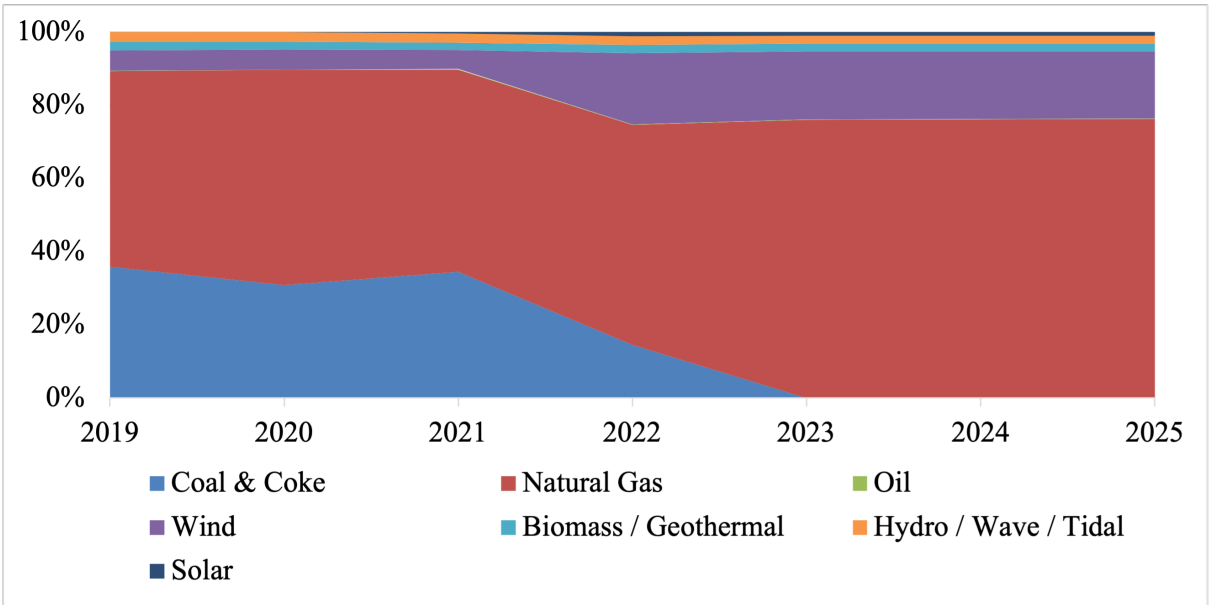
Source: Alberta Electric System Operator (2022).

Figure 6: Hourly Electricity Generation by Renewable Source in Alberta in June - September 2018



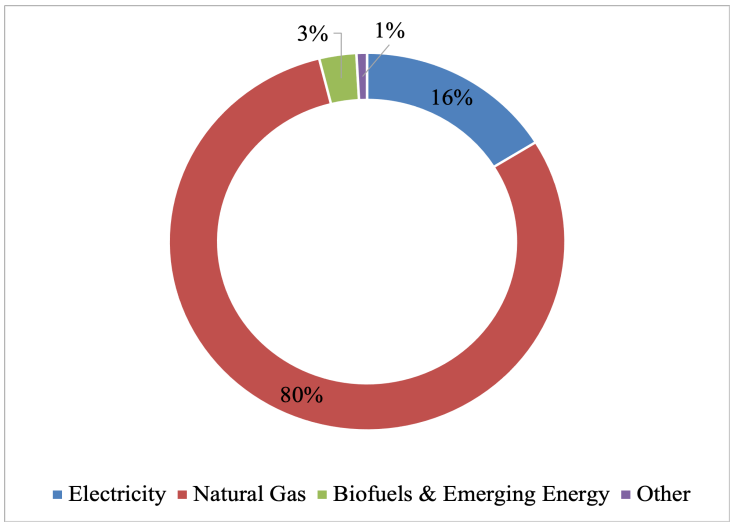
Source: Alberta Electric System Operator (2022).

Figure 7: Changing Electricity Generation by Source in Alberta, Share of Total Electricity Generation



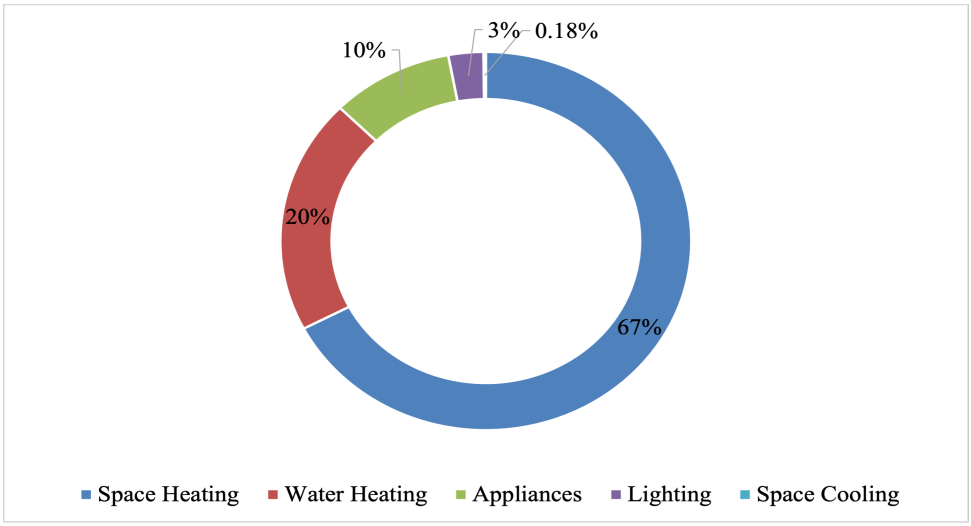
Source: Canada Energy Regulator (2021).

Figure 8: End-Use Energy Demand by Source in Residential Sector in Alberta in 2018



Source: Canada Energy Regulator (2021).

Figure 9: End-Use Energy Demand by Type in Residential Sector in Alberta in 2018



Source: Natural Resources Canada (2022).

Table 1: General Regression Results

Dependent variable:	Hourly Electricity Use	
	(1)	(2)
Treatment, $T \times P$	-0.00672	0.05634***
	(0.00650)	(0.02118)
Treatment × Dollar Savings, $D \times T \times P$		-0.04128***
		(0.01390)
Observations	43,587,912	43,587,912
R-squared	0.49755	0.49765

Notes: Standard errors are two-way clustered by household and day-of-sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 10: Hourly Alberta Internal Load in June - September 2018

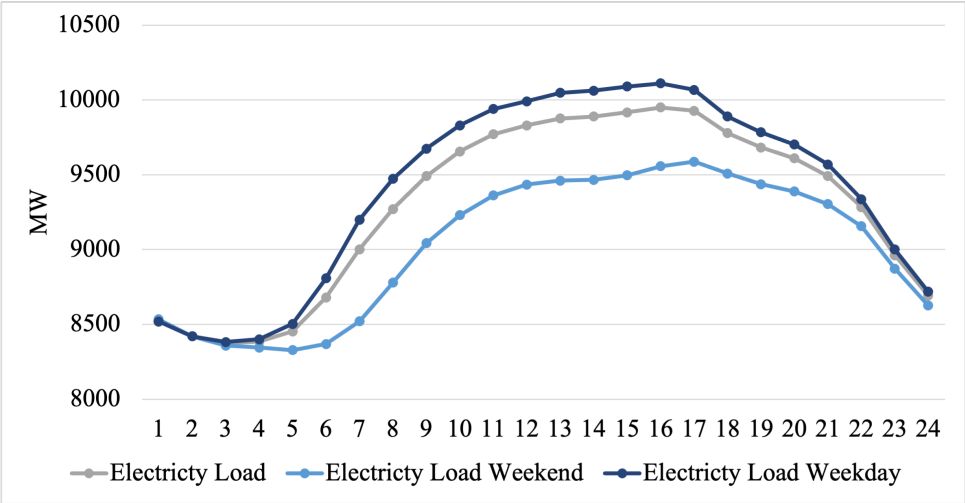


Figure 11: Peak Regression Results

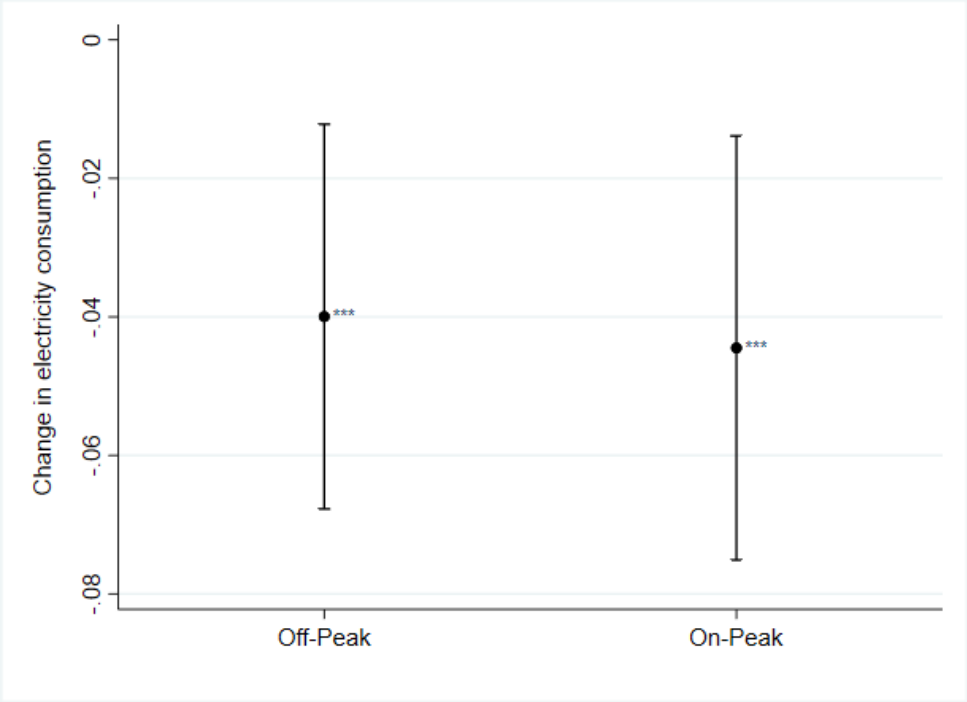
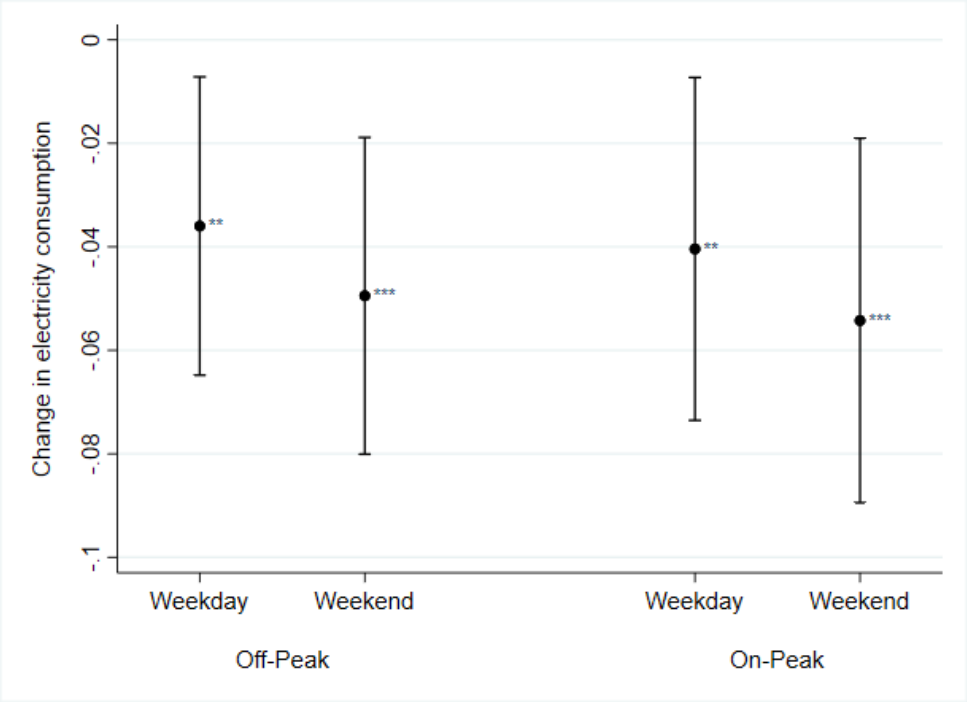


Figure 12: Peak Regression Results: Weekends Vs. Weekdays



Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 13: Hourly Regression Results

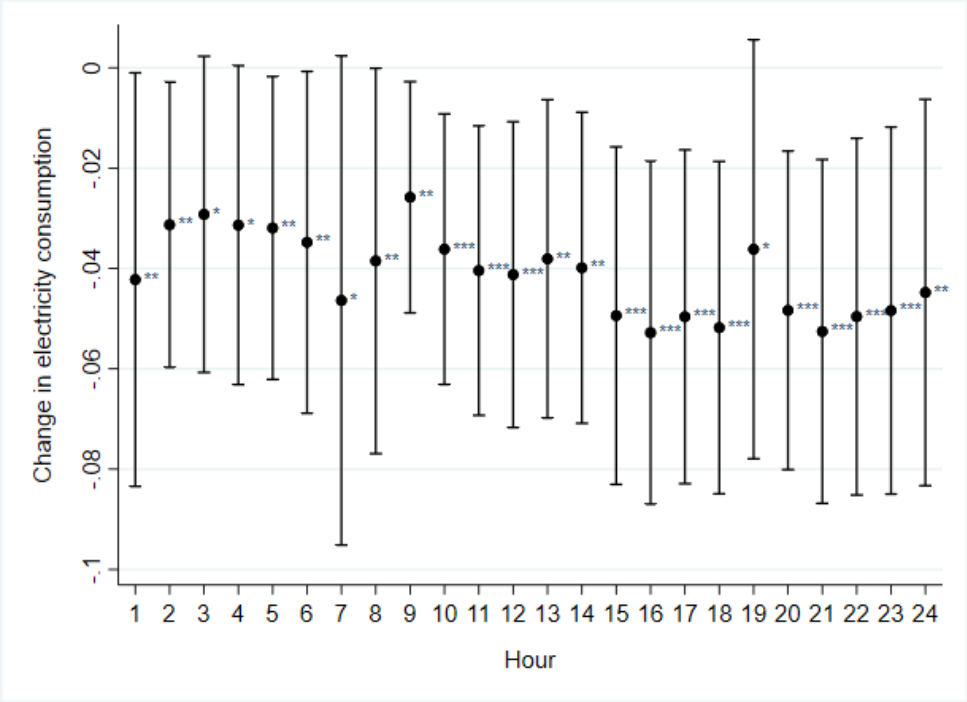
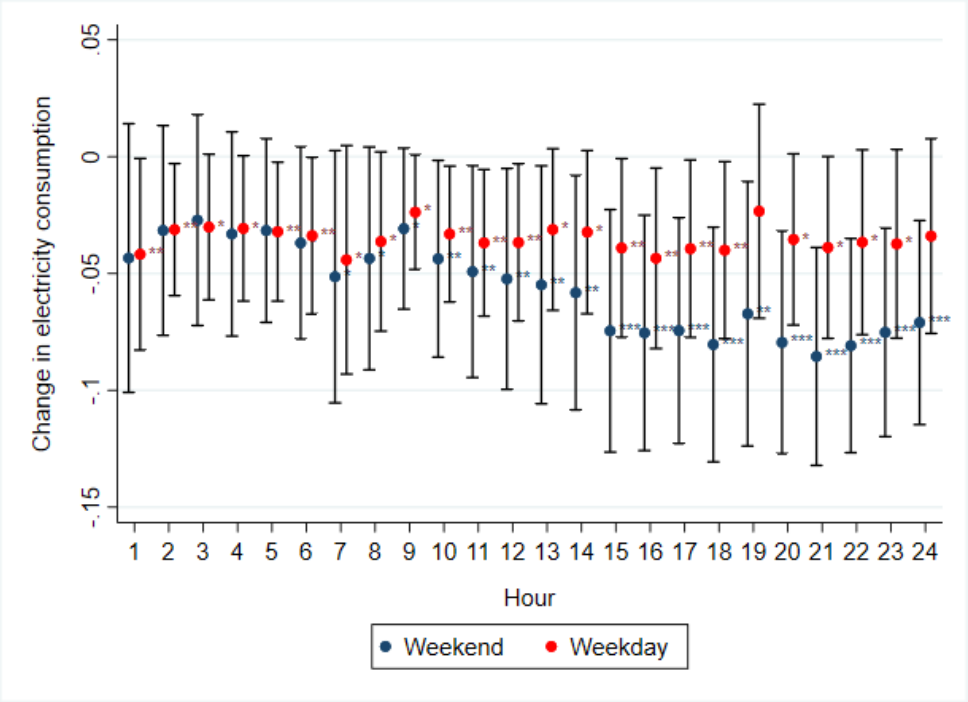


Figure 14: Hourly Regression Results: Weekends Vs. Weekdays



Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 15: Electricity Consumption and Outdoor Air Temperature

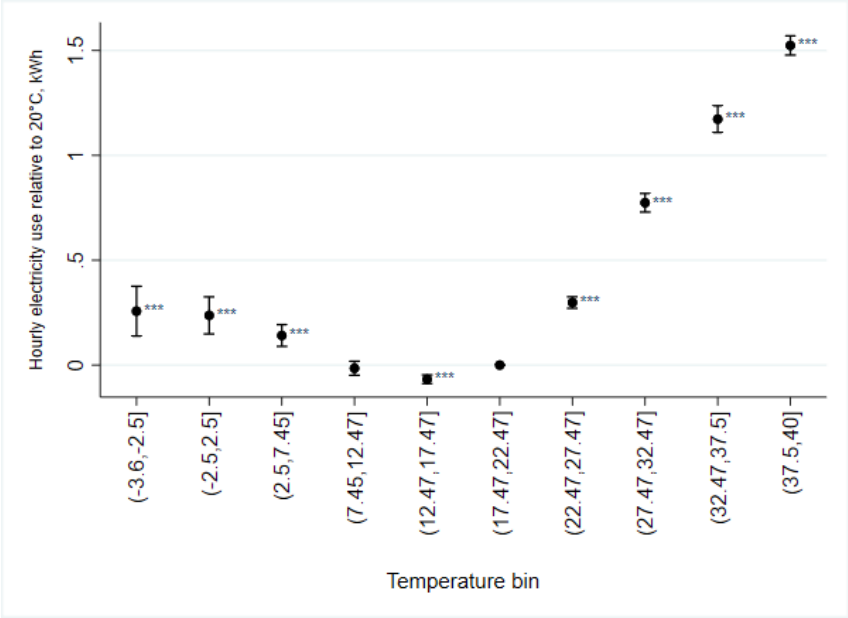
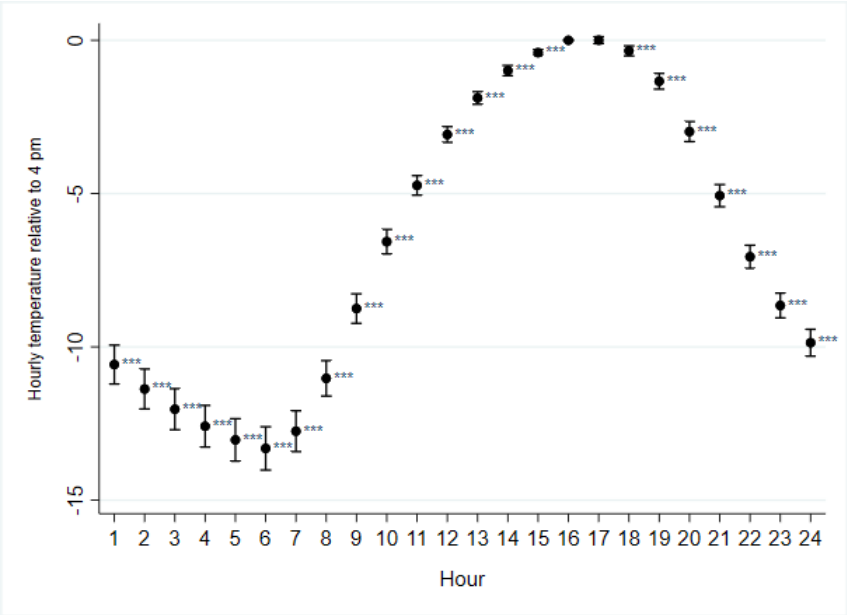
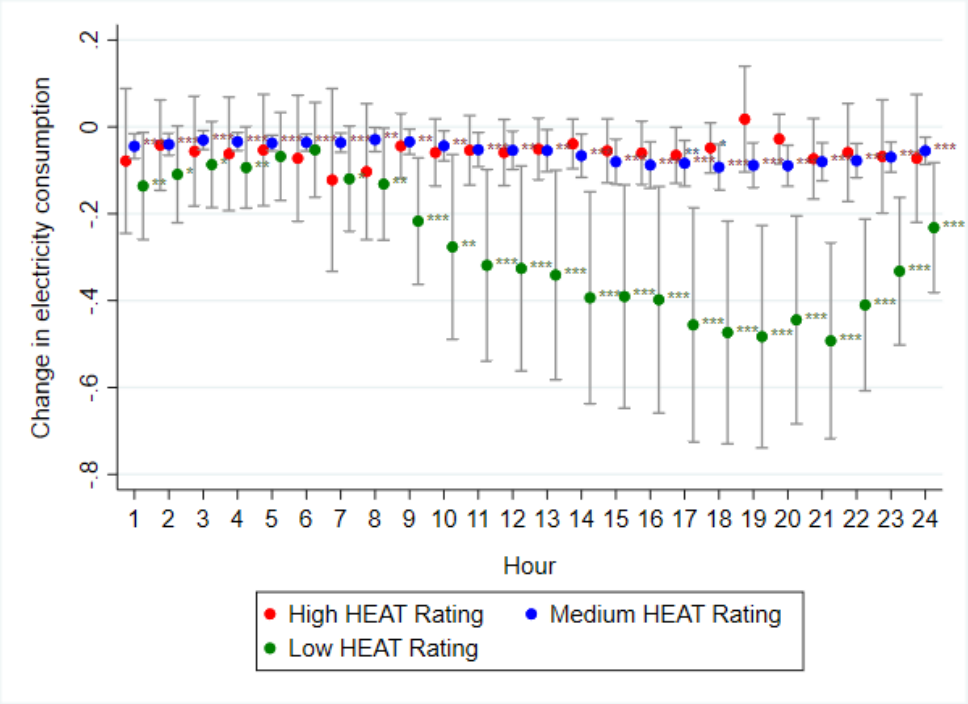


Figure 16: Hourly Outdoor Air Temperature



Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are clustered by day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 17: Hourly Regression Results by HEAT Rating Group



Notes: The figure displays point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 18: Hourly Electricity Conservation and Outdoor Air Temperature

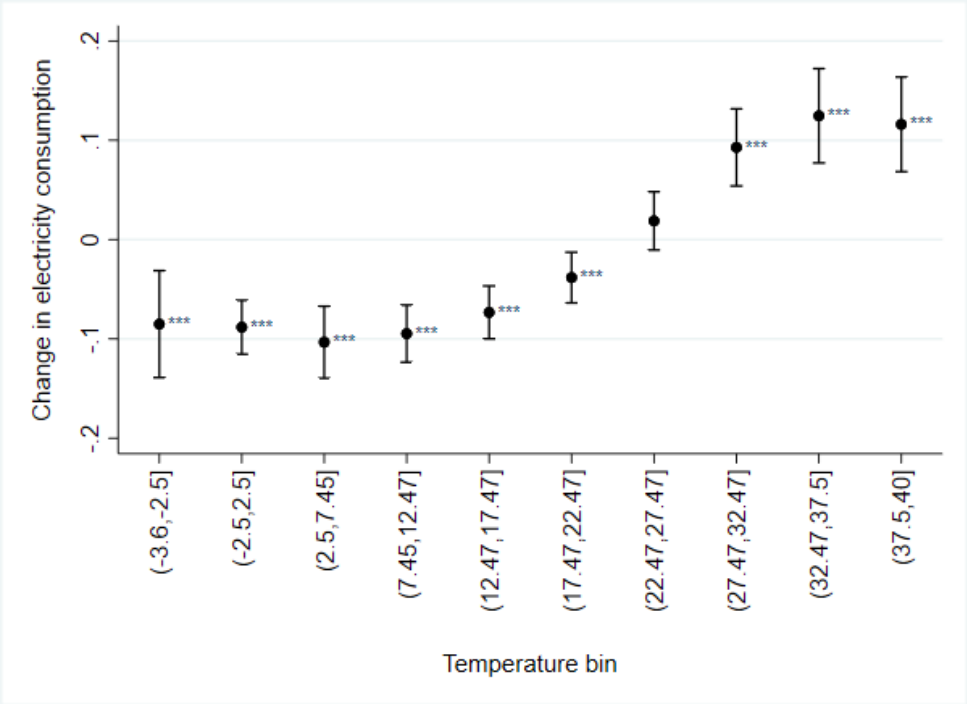
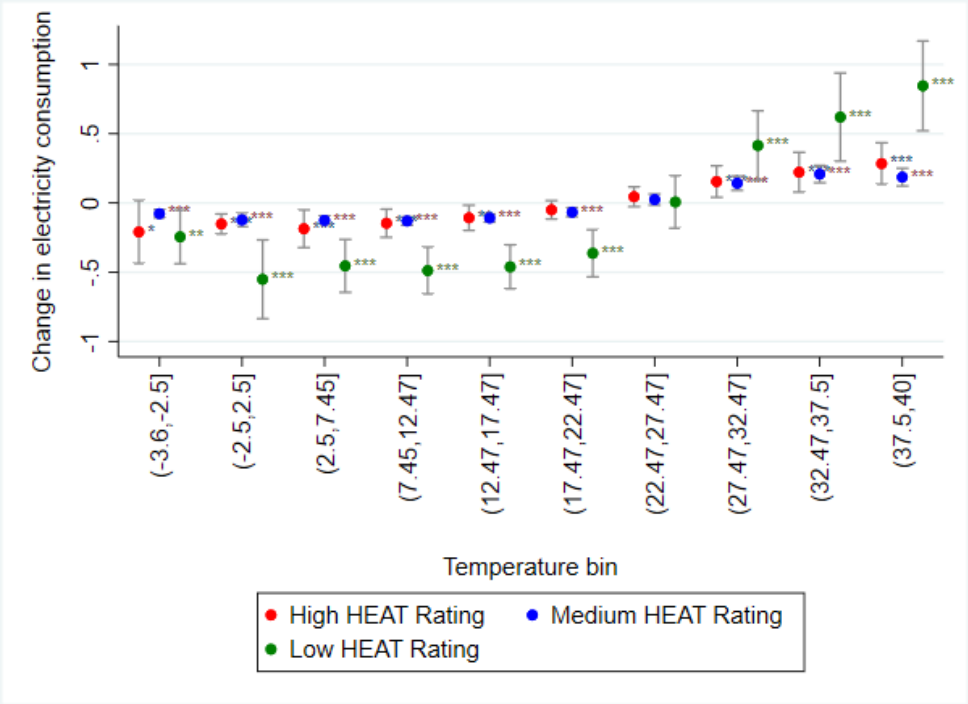


Figure 19: Hourly Electricity Conservation and Outdoor Air Temperature: HEAT Rating Groups



Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 20: Hourly Electricity Conservation Changing During the Experiment

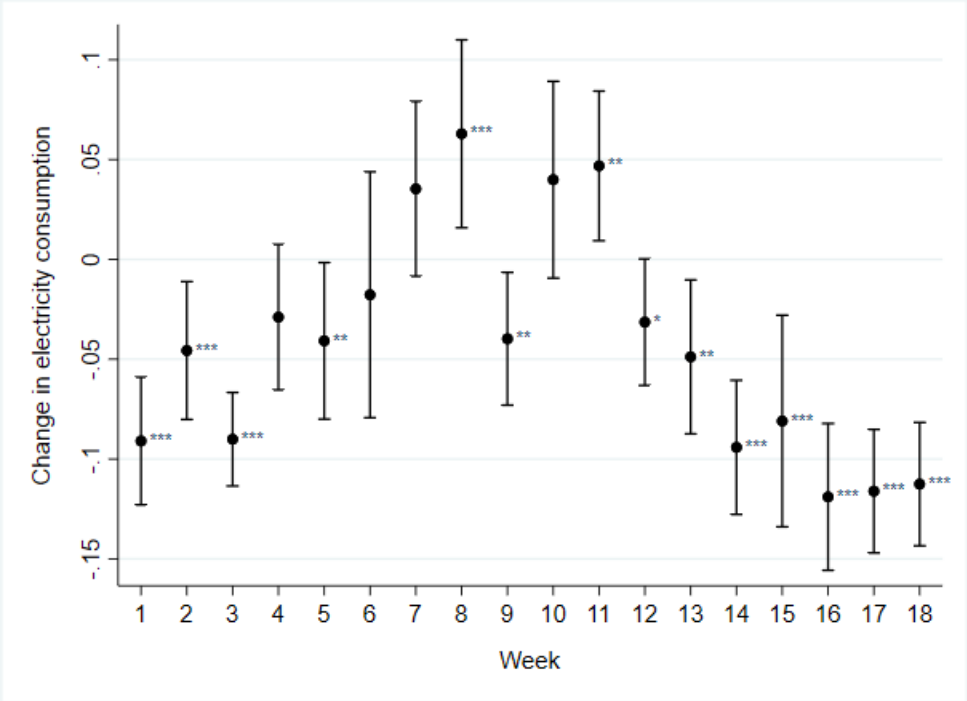
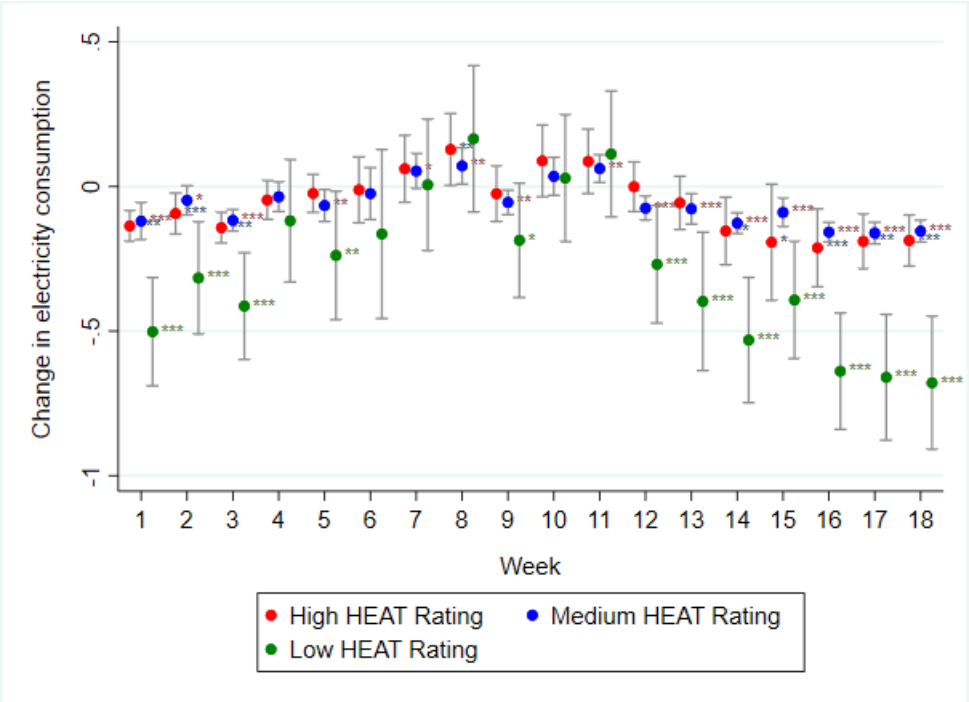
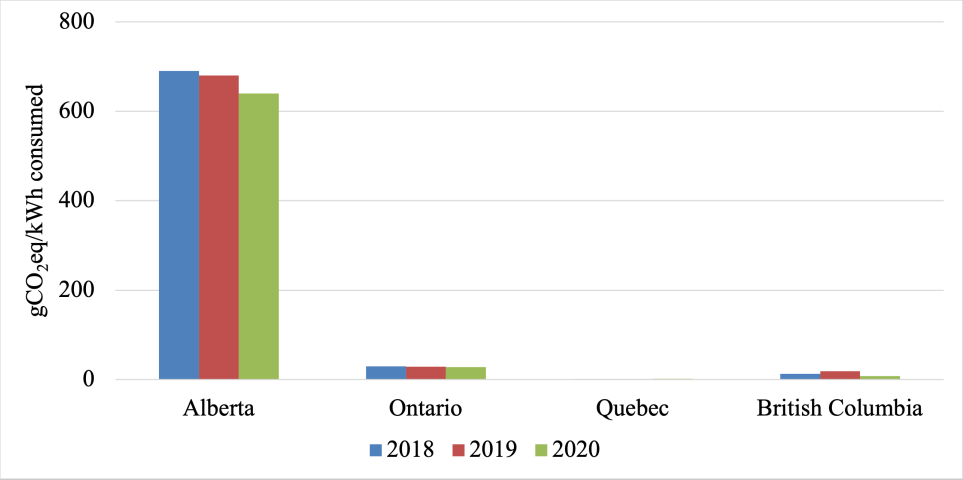


Figure 21: Hourly Electricity Conservation Changing During the Experiment: HEAT Rating Groups



Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 22: Electricity Consumption GHG Intensity by Province in 2018 - 2020



A Treatment Sample Bill

A.1 Page 1

Medicine Hat
The Gas City

Utility Statement February 14 2018
580 1 St SE, Medicine Hat, AB T1A 8E6
customer_accounts@medicinehat.ca
403 529 8111

C-10

Utility bill for:

[redacted]

[redacted] [redacted]

Bill Period **Jan 06 to Feb 06**

Your billed amounts history:

Knowledge Saves Power

Your home's heat loss rate is **average.** You could **save $125** per year on your bills by improving this score.

See page 4 for your personalized comparison and options to save energy.

You currently owe 288.38
Please pay by March 13 2018

Your account activity

Amount on your last bill	260.20
Payment (Feb 1, 2018)	-260.20
Your balance forward	0.00

Current Charges

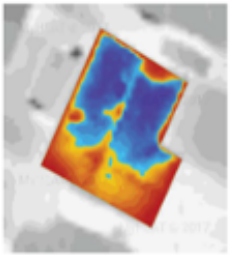
*Electric (518 kwh)	64.46
*Gas (18.40 GJ)	112.85
Water (9.00 CM)	37.12
Sewer	42.18
Solid Waste	22.91
*GST(Registration 121408967 RT0001)	8.86
Total new charges	**288.38**

Total you now owe **288.38**

After March 13 pay 294.15

A.2 Page 2

Your home has a medium heat loss rate with a score of 5/10



Low High Low High

The lower the rating, the less heat is leaving your home. You could save **$125** per year on your bills by lowering this score.

The thermal image was taken of your home's roof using an infrared camera in fall 2017. This image can help you identify air leaks that may be wasting energy in your home and resulting in higher bills.

Red areas on your heat map show potential heat loss and can be improved with simple weatherization techniques.

For more information on your home's MyHeat score, visit **www.myheat.ca/thehat/EJMDXA.**

KNOWLEDGE SAVES POWER

What can you do to save?

Seal Air Leaks	You may be eligible for a rebate of up to $700 from HAT Smart for reducing air leakage in your home.
Turn Down the Heat	Avoid heat loss by simply turning down the heat to 16°C when you leave home.

Learn more at **www.hatsmart.ca**

Upgrade Your Insulation	You may be eligible for a rebate of up to $3,500 from Energy Efficiency Alberta for upgrading insulation in your home.
Install New Windows	You may be eligible for a rebate of up to $1,500 from Energy Efficiency Alberta for switching to efficient windows.

Learn more at **www.efficiencyalberta.ca**

For more information on the Knowledge Saves Power project, visit **www.hatsmart.ca** or call **403.502.8799**.

B Robustness Checks

Table B1: Peak Regression Specifications Test

Dependent variable:	Hourly Electricity Use			
	(1)	(2)	(3)	(4)
Treatment, $T \times P$				
Off-Peak	0.055***	0.074***	0.074***	0.074***
	(0.021)	(0.026)	(0.025)	(0.028)
On-Peak	0.059**	0.012	0.012	0.012
	(0.025)	(0.020)	(0.020)	(0.019)
Treatment × Dollar Savings, $D \times T \times P$				
Off-Peak	-0.040***	-0.040***	-0.040***	-0.040***
	(0.014)	(0.014)	(0.014)	(0.014)
On-Peak	-0.045***	-0.044***	-0.044***	-0.044***
	(0.016)	(0.014)	(0.014)	(0.016)
Fixed effects	household by hour, day-of-sample by hour	household by month by hour, month of sample	household by month by hour, week of sample	household by weekend by hour, day of sample
Observations	43,587,912	43,587,912	43,587,912	43,587,912
R-squared	0.540	0.509	0.523	0.505

Notes: Standard errors are two-way clustered by household and day-of-sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Peak Hours Test

Dependent variable:	Hourly Electricity Use	
	(1)	(2)
Treatment, $T \times P$		
Off-Peak	0.063**	0.054**
	(0.025)	(0.023)
On-Peak	0.045**	0.059***
	(0.019)	(0.022)
Treatment × Dollar Savings, $D \times T \times P$		
Off-Peak	-0.042***	-0.042***
	(0.014)	(0.014)
On-Peak	-0.040***	-0.040***
	(0.014)	(0.014)
Peak Hours	8 a.m. - 4 p.m.	6 a.m. - 4 p.m.
Observations	43,587,912	43,587,912
R-squared	0.498	0.498

Notes: Standard errors are two-way clustered by household and day-of-sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

C Winter Data

C.1 Analysis: Standard Approach

I re-estimate some of the specifications for the period from November 1, 2017 until April 30, 2018 and from November 1, 2018 until February 28, 2019; the period captures the winter season (and, at the same time, the heating season) in Medicine Hat: the winter season starts on November 1 and ends on April 30 of the following year (Alberta Electric System Operator, 2018).

In Section 4, it is stated that only one-third of households in Alberta use air conditioning in summer months (based on the 2017 data) and most of Albertans heat their homes with natural gas in winter. As a result, I expect that residential electricity consumption patterns do not differ substantially between the two seasons.

Table C1 contains the results of estimating Specifications (1) and (2). According to Column (2), on average a household in the treatment group decreased its hourly electricity consumption by 4.1% per hundred dollars of estimated savings as a result of the treatment, relative to the control group[20]. The value of the electricity savings is very similar to the one reported for the summer data.

Figure C1 shows the estimates of the coefficients θ_{1d} in Specification (3), and Figure C2 reports the estimation results for κ_{1dw} in Specification (4). The on-peak hours are selected to be from 6 a.m. until 9 a.m. and from 4 p.m. until 6 p.m. The difference between the on-peak and off-peak savings shown in Figure C1 is not statistically significant; the same goes for the estimates in Figure C2 except for the difference between the on-peak and off-peak savings during weekdays; however, the difference is statistically significant only at the 10% level of significance.

Table C2 reports the results of a robustness check. In particular, I re-estimate Specification (3) using different fixed effects. The coefficients of interest, θ_{1d}, are robust to changes in fixed effects.

Finally, Figure C3 contains the estimates of the coefficients δ_{1hw} from Specification (6). In comparison to the results obtained using the summer data, there are some δ_{1hw} estimates that are statistically significantly different across 24 hours during weekdays and weekends. Mostly, those are the estimates for some peak hours that are statistically significantly different from some of the off-peak estimates. One possible reason as to why I observe higher heterogeneity in hourly electricity savings in the winter season as compared to the summer months is that the households could spend more time at home during winter (due to cooler outside temperatures), so they could have more 'opportunities' to adjust their electricity consumption behavior.

C.2 Analysis: Heterogeneous Treatment Effects

The treatment messaging was first included on the February 2018 billing cycle. Due to differences in billing cycle schedules, different groups of treated households received their treatment on different dates.

In such a case, i.e. in case of heterogeneous treatment effects, recent academic literature (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020, 2022) has shown that using a two-way-fixed-effects regression with time and group

[20] Papineau and Rivers (2022) obtain a 3% reduction in electricity use per hundred dollars of estimated savings; the fact that I get a larger value of the estimate is likely due to the specification that I use and not because of the data: my hourly data should match the daily consumption in Papineau and Rivers (2022) (I have only 30-40 building less in each of the two groups compared to the authors' data sample).

fixed effects to estimate a treatment effect might result in the estimate showing what it is not supposed to show. Currently, there are a number of estimators that are being proposed to solve the problem. These estimators are robust to heterogeneous treatment effects unlike a two-way fixed effects regression.

The research on new estimators for heterogeneous treatment effects is in progress. Nevertheless, I have made an attempt to use one of the estimators developed by de Chaisemartin and D'Haultfoeuille (2022). The estimator is computed using the Stata *did_multiplegt* command. The use of the estimator is limited in my experimental setting, so I cannot re-estimate the exact copy of Specification (1). As a result, the command I use to re-estimate the treatment effect for the winter season[21] is as follows:

$$\begin{aligned}&\text{did\_multiplegt } \mathrm{Y}_{ith}\ i\ t\ T_i \times P_{it},\\ &\qquad\qquad \text{robust\_dynamic controls}(\mathrm{CDH}_{th}\ HDH_{th})\ \text{cluster}(i),\end{aligned} \tag{C1}$$

where the group variable is i which indexes the household, and the time period variable is t representing each day of the experiment (each day of the sample). The treatment variable is $T_i \times P_{it}$ with T_i indicating a household's treatment status and P_{it} which is a post-treatment dummy variable. The outcome variable is Y_{ith} representing the electricity consumption for household i on day t in hour h. The controls are CDH_{th} and HDH_{th} that show cooling degree hours and heating degree hours, respectively (I calculated heating and cooling degree hours using 18 °C as the reference point). The standard errors are clustered at the household level[22].

Despite the fact that the command does not allow you to estimate directly how the treatment effect varies with respect to a certain variable, I also try interacting the treatment and post-treatment period dummies with the dollar savings shown to customers:

$$\begin{aligned}&\text{did\_multiplegt } \mathrm{Y}_{ith}\ i\ t\ T_i \times P_{it} \times D_{im},\\ &\qquad\qquad \text{robust\_dynamic controls}(\mathrm{CDH}_{th}\ HDH_{th})\ \text{cluster}(i),\end{aligned} \tag{C2}$$

where D_{im} represents the dollar savings estimate (in units of hundreds of dollars) for household i in the treatment group; the estimate is shown on household i's utility bill in billing month m.

In order to compare the results obtained using the *did_multiplegt* command with the results I got in the paper, I change Specifications (1) and (2) so that they fit the setup of *did_multiplegt* command, (C1) and (C2), respectively.

$$Y_{ith} = \omega_0 + \omega_1 T_i \times P_{it} + \omega_2 P_{it} + \omega_3 CDH_{th} + \omega_4 HDH_{th} + \mu_i + \lambda_t + \epsilon_i \tag{C3}$$

and

$$Y_{ith} = \nu_0 + \nu_1 D_{im} \times T_i \times P_{it} + \nu_2 P_{it} + \nu_3 CDH_{th} + \nu_4 HDH_{th} + \mu_i + \lambda_t + \epsilon_i, \tag{C4}$$

where the term μ_i represents a household fixed effect, and ϵ_i is the error term (standard errors that are clustered by household). The two models are estimated in ordinary least squares using the *reghdfe* command in Stata.

Table C3 contains the results. The first row and the second row of Column *reghdfe* contains the estimates of ω_1 and ν_1 from Specifications (C3) and (C4), respectively. The second column, *did_multiplegt*, shows the estimated treatment effect obtained after running the (C1) and (C2)

[21] I do not use the estimator for the summer data since the households in the treatment group are technically all treated in the post-treatment period without any heterogeneity in the treatment dates.

[22] The command does not allow two-way clustered standard errors.

commands in Stata.

According to the coefficients' estimates shown in the first row, the two-way-fixed-effects regression shows that the treatment has no effect on electricity consumption, whereas the heterogeneous-treatment-effects regression shows a 0.8% decrease in electricity usage due to the treatment.

The second row shows the opposite. The two-way-fixed-effects model reports that a household in the treatment group decreased its hourly electricity consumption by 1.6% per hundred dollars of estimated savings as a result of the treatment, relative to the control group. The heterogeneous-treatment-effects regression shows no treatment effect.

As research in the area of heterogeneous treatment effects develops, I will be updating the results reported in this section of Appendix.

Table C1: General Regression Results (Winter)

Dependent variable:	Hourly Electricity Use	
	(1)	(2)
Treatment, $T \times P$	-0.00204	0.05727***
	(0.00552)	(0.01253)
Treatment × Dollar Savings, $D \times T \times P$		-0.04144***
		(0.00856)
Observations	50,515,800	50,515,800
R-squared	0.46426	0.46440

Notes: Standard errors are two-way clustered by household and day-of-sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure C1: Peak Regression Results (Winter)

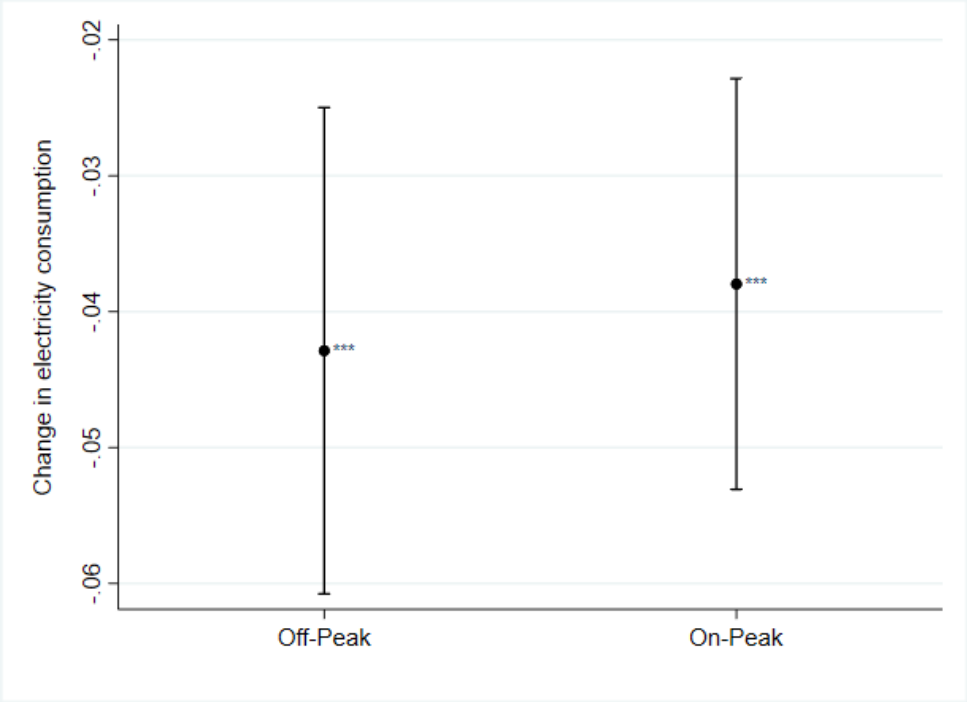
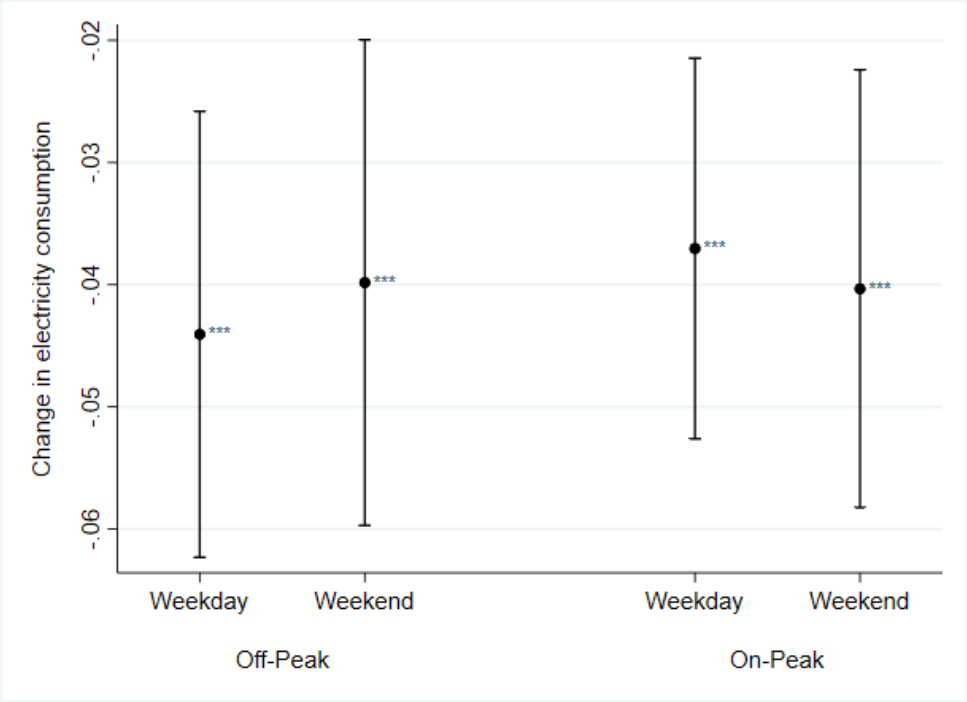


Figure C2: Peak Regression Results: Weekends Vs. Weekdays (Winter)



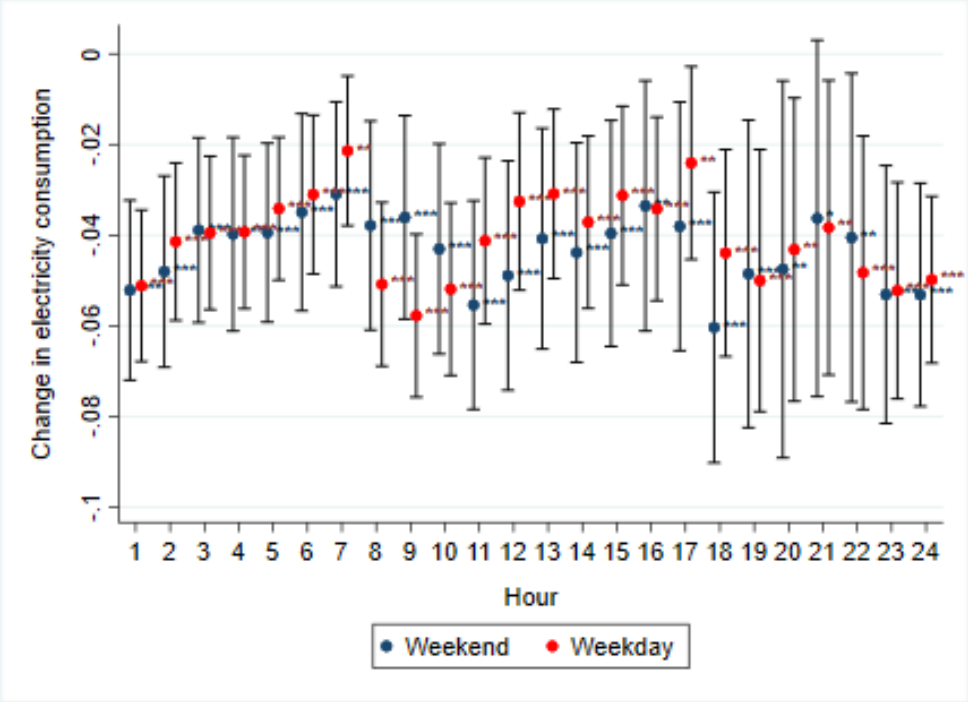
Notes: The figures display point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Peak Regression Specifications Test (Winter)

Dependent variable:	Hourly Electricity Use			
	(1)	(2)	(3)	(4)
Treatment, $T \times P$				
Off-Peak	0.058***	0.040**	0.047***	0.052***
	(0.013)	(0.016)	(0.016)	(0.013)
On-Peak	0.056***	0.031	0.038*	0.069***
	(0.012)	(0.020)	(0.019)	(0.012)
Treatment × Dollar Savings, $D \times T \times P$				
Off-Peak	-0.042***	-0.034***	-0.036***	-0.043***
	(0.009)	(0.011)	(0.011)	(0.009)
On-Peak	-0.039***	-0.025*	-0.027**	-0.038***
	(0.008)	(0.013)	(0.013)	(0.008)
Fixed effects	household by hour, day-of-sample by hour	household by month by hour, month of sample	household by month by hour, week of sample	household by weekend by hour, day of sample
Observations	50,515,800	50,514,816	50,514,816	50,515,800
R-squared	0.475	0.512	0.519	0.476

Notes: Standard errors are two-way clustered by household and day-of-sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure C3: Hourly Regression Results: Weekends Vs. Weekdays (Winter)



Notes: The figure displays point estimates and the corresponding 95% confidence intervals. Standard errors are two-way clustered by household and day-of-sample; *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Two-Way-Fixed-Effects Model Vs. Heterogeneous-Treatment-Effects Model (Winter)

Dependent variable:	Stata command	
	reghdfe	did_multiplegt
Treatment, $T \times P$	-0.00342	-0.00750*
	(0.00571)	(0.00446)
Treatment × Dollar Savings, $D \times T \times P$	-0.01648***	-0.00601
	(0.00398)	(0.00481)

Notes: Standard errors are clustered by household, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.