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

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Abstract

The paper reports the results of evaluating the hourly impact of a behavioral 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, i.e. the intervention has failed to target peak times, so accounting for the intraday distribution of the electricity savings is not important when measuring the social benefits of the program. The most plausible reason for the flat savings profile could be the absence of hourly variation in retail electricity rates. As a policy recommendation, the study suggests implementing retail electricity prices fluctuating within a day.

Keywords: Peak Electricity Demand, Behavior Nudge, Energy Efficiency, Randomized Controlled Trial

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1 Introduction

Residential buildings are responsible for around one-fifth of global energy consumption and greenhouse gas (GHG) emissions in the energy sector (IEA, 2022). Therefore, decarbonizing the housing stock matters for achieving net-zero emissions across the world by 2050, with energy efficiency improvements being an essential part of these efforts (IEA, 2021). 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 GHG emissions (Bulkeley, 2010; Broto and Bulkeley, 2013), including programs targeting electricity conservation. These programs are expected to bring private benefits – household electricity savings that lead to lower utility bills – as well as social benefits due to avoided electricity production and external pollution costs (Borenstein and Bushnell, 2022).

However, evaluations of the programs typically demonstrate some inaccuracy when it comes to measuring the social benefits of electricity savings. In particular, 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. Moreover, if energy sources that are more GHG-intensive and cause higher regional pollution, such as fossil fuels, are the marginal fuel at peak times, electricity conservation during peak hours could deliver environmental benefits. Put differently, given that the wholesale price of electricity varies at high frequency over time, 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 usually estimate total electricity savings but ignore specific points in time when these savings occur (Boomhower and Davis, 2020).

I focus on evaluating a novel randomized controlled trial in Medicine Hat, Alberta, deployed in 2018. Under the program, households were provided recurrent behavioral nudges towards their energy conservation, namely either visual information on their home heat loss or a comparison of their energy usage to that of similar homes (Papineau and Rivers, 2022). Considering the former group of households, I examine whether the intervention is effective at targeting peak electricity demand times by looking at the within-day distribution of the experiment's impact on electricity consumption in summer.

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 behavioral 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 behavioral 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 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

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

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 usage during peak load periods.

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

The paper closest to mine is that of Boomhower and Davis (2020). The authors examine 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 results similar to those in Boomhower and Davis (2020), but the authors use data for more energy efficiency measures.

Another strand of literature studies the effects of energy efficiency programs under different retail electricity pricing regimes.

Novan and Smith (2017) use hourly data from a rebate program for energy-efficient air conditioners in Sacramento, California, and find that the electricity savings are concentrated around hours when space cooling demand is at its peak. 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 and price 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]) demonstrating that electricity savings induced by a real-time feedback technology 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) conclude that the electricity savings from air conditioners replacements have more intraday variation for consumers who pay time-of-use prices than for those with increasing block pricing. 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.

The interventions studied in the aforementioned papers are expected to bring electricity conservation that varies from hour to hour. For example, air conditioners tend to have quite time-sensitive electricity use, and providing households with real-time feedback on electricity consumption and price is supposed to induce the hourly variation in the households' electricity savings.

In contrast, my paper estimates the intraday impact heterogeneity of the program that does not explicitly aim at yielding this type of heterogeneity, although maximizing energy savings

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

at peak times is still a desirable outcome of any energy efficiency interventions. Moreover, the academic literature that I have just described, except Martin and Rivers (2018), uses U.S. data, primarily from California. The share of residential energy demand from space cooling is six times higher in the U.S. than in Canada (Natural Resources Canada, 2019; U.S. Energy Information Administration, 2019), so conducting research on energy efficiency for Canadian climatic conditions is worthy of note.

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 natural gas consumption during the heating season. Papineau and Rivers (2022) show that the program also induces electricity savings, and I argue that the intervention could continue to motivate electricity conservation of households during summer months as well.

The thermal images show the amount of heat leaving the building. The corresponding HEAT Rating of the building is associated with its energy consumption: the lower the rating, the lower the residential natural gas and electricity usage (Papineau and Rivers, 2022). 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).

In addition, the households reduce their electricity use in response to the treatment employing 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 latter 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 have done these home improvements will benefit from them in summer too. Of course, modified behavioral patterns may also aid in electricity conservation during summer.

I find that households in Medicine Hat decrease their electricity usage due to the program overall, but, when considering the hourly distribution of the program's impact, I observe that households save the same amount of electricity in peak and off-peak demand hours. As a result, accounting for the hourly distribution of the savings does not amplify the program's social benefits.

The fact that the hourly electricity savings profile is flat contradicts 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 the finding, 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 the 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 of electricity production in Alberta: as shown in Figure 1, in 2018, the year overlapping the sample period, most of the electricity in the province was produced from coal (51%) and natural gas (37%).

[Figure 1 goes here.]

At the same time, fossil fuels, especially coal, are the main contributors to pollution and climate change. Because of its reliance on coal-fired generation, Alberta's electricity generation produced 52% of total Canada's GHG emissions in 2018 (Government of Canada, 2022a), which was more than in any other province, and 71% of those emissions came from coal (Figure 2).

[Figure 2 goes here.]

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 electricity to the market at a low price and produce electricity 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, coal generation set the wholesale electricity price in 81% of on-peak hours and in 75% of off-peak hours (Alberta Electric System Operator, 2018)[3].

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 electricity 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 environmental value of the savings[4], i.e. the on-peak versus off-peak difference in GHG emissions, was not substantial in 2018 (specifically, in the summer of 2018, the post-treatment period in the study) since coal was used to generate electricity in the majority of off-peak and on-peak hours (see Figure 3).

[Figure 3 goes here.]

However, coal-fired generation is scheduled to be gradually phased out by the end of 2023 (Government of Alberta, 2022b): Figure 4 shows that coal-fired power plants currently provide less than 20% of the province's electricity.

[Figure 4 goes here.]

After coal generation is no longer used in Alberta, the electric grid will still require technology with the ability to produce electricity in peak demand times. In the nearest future, such technology will be natural gas, a fossil fuel generation technology (Figure 4). Any other generation technologies cannot increase electricity supply in a short period of time as required during peak periods (Bushnell and Novan, 2021). Moreover, currently, the province has no plans to significantly reduce its natural gas use after achieving the coal phase-out; Alberta's electricity generation will likely continue to be heavily reliant on fossil fuels, and the province will not demonstrate any substantive GHG emissions reductions from electrification until 2030 (Bataille et al., 2021). 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.

[3]The Alberta Electric System Operator (AESO) defines the on-peak period as starting at 8 a.m. and ending at 11 p.m. The remaining hours of the day make up the off-peak period.

[4]The economic value of the program quantified using wholesale electricity prices and the environmental value of the savings in the form of reduced GHG emissions represent the social benefits of the program.

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 5 shows that the residential sector primarily consumed natural gas, electricity was in the second place with its 16% share.

[Figure 5 goes here.]

Overall, residential electricity consumption made up around 13% of the total electricity end-use in the province in 2018 (Figure 6), and the share is predicted to increase to 15% by 2025 and 18% by 2050 (Canada Energy Regulator, 2021).

[Figure 6 goes here.]

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 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 used in Papineau and Rivers (2022).

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 (Figure 7). Households do not see or pay these time-varying wholesale prices – they face constant retail prices instead. 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).

[Figure 7 goes here.]

3 Experiment Design and Data

Papineau and Rivers (2022) deployed 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 experiment took place in Medicine Hat, Alberta, a medium-sized city with a population of about 60,000 people (Statistics Canada, 2021b) located in the southeast of the province (Figure 8).

[Figure 8 goes here.]

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

[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 treatment in my paper.

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.

The authors find that the program reduces households' electricity and gas consumption. The results in that study were obtained using daily energy consumption data, so the hourly distribution of the savings was not evaluated.

I re-estimate the program's results with hourly electricity consumption data[6] focusing on electricity usage during summer months since it is likely to have a greater degree of intraday variation compared to its winter counterpart (the energy consumption in winter is heavy on gas as the main source of residential space hating). I use hourly electricity consumption data for the period from June 1, 2017 until September 30, 2017 (pre-treatment) and from June 1, 2018 until September 30, 2018 (post-treatment)[7]; this time range is chosen to capture the warmest part of the summer season in Medicine Hat[8].

4 Analysis

4.1 Intraday Electricity Conservation

Before estimating the hourly distribution of electricity savings, I estimate the model that captures total electricity savings for the whole period of study[9]:

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

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 in order to be in line with Papineau and Rivers (2022) who use the normalization too. In this case, the interpretation of the coefficients is identical to that in the models with a logged dependent variable. 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 an hour of the day fixed

[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 - such observations make up less than 1% of the total number), 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).

[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. Dropping the variable from

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_{ith}; standard errors 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 should be interpreted as a percentage change.

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):

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

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

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

[Table 1 goes here.]

Next, I estimate Specification (2) separately for peak and off-peak hours because I aim to test if 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. until 11 p.m. However, by looking at Figure 9 showing the 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

Specifications (1) - (6) does not change the results.

[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 in the electricity use between the treatment group and the control group in the pre-treatment period.

load[12], I define the on-peak period to be from 11 a.m. to 5 p.m.

[Figure 9 goes here.]

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:

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

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 change 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 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 change 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 contains 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 and peak hours[13].

In addition, I check how similar the peak electricity savings are in weekends as opposed to weekdays[14]:

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

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

[12] More specifically, I select the hours with the highest load, making sure that its change between the two subsequent hours (e.g., 11 a.m. relative to 10 a.m., 12 p.m. relative to 11 a.m., etc.) is positive, i.e. the electricity demand is increasing. Although the load change in $Hour = 17$ relative to $Hour = 16$ is negative, it is relatively small (-0.23%), so $Hour = 17$ is still considered a peak hour.

[13] In addition, estimating Specifications (1) - (6) with different standard errors, namely standard errors clustered by household and week of the sample, has not led to drastically different results, except it has brought fewer statistically significant coefficient estimates.

[14] Figure 9 shows that there is no substantial difference in the electricity load dynamics during weekends compared to weekdays. As a result, the definition of peak hours stays the same.

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 10 shows the estimates of the coefficients θ_{1d} in Specification (3), and Figure 11 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 10 is not statistically significant; the same goes for the estimates in Figure 11: 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.

[Figure 10 goes here.]

[Figure 11 goes here.]

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:

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

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[15]:

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

The estimates of the coefficients α_{1h} in Specification (5) are presented in Figure 12, and the δ_{1hw} from Specification (6) are shown in Figure 13.

I perform the multiple hypothesis testing of the pairwise difference between the hourly estimates with Holm-adjusted p-values. I have chosen the Holm-adjusted p-values over other standard p-value adjustment methods, such as Bonferroni and Sidak, because the Holm procedure is less conservative and uniformly more powerful than the Bonferroni correction and it does not assume that all the individual tests within the set are independent of each other, as is the case with the Sidak adjustment method (VanderWeele and Mathur, 2019; Blakesley et al., 2009). In addition, the three approaches have yielded the same results in terms of multiple hypothesis testing, namely the α_{1h} estimates are not statistically significantly different across 24 hours and most of the δ_{1hw} estimates are not statistically significantly different across 24 hours during weekdays and weekends[16]. So, in addition to the fact that the households do not save

[15] Due to insufficient computing power, instead of using the interactions with $TimeOfWeek$ in Specification (6), I have to estimate it separately for the weekend and weekday sub-samples of the data.

[16] During weekends, the estimates for hour 14 and hour 15 are statistically significantly different from each other, the same applies to the estimates for hour 3 and hour 20, the estimate for hour 9 is also statistically significantly

more in peak hours, I do not observe any intraday variation in the electricity savings induced by the treatment.

[Figure 12 goes here.]

[Figure 13 goes here.]

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 diurnal variation of summertime electricity savings.

As discussed in Papineau and Rivers (2022), the proportion of the potentially environmentally conscious population is relatively low in Medicine Hat (in particular, the region has a large share of conservative voters and a low share of green voters), which could make the treated households less responsive to the intervention.

Next, 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). In 2018, space cooling took less than 1% of residential end-use demand in the province, whereas space heating had 70%, and around 90% of the energy use for residential space heating was taken by natural gas (Natural Resources Canada, 2022). Such a small share of space cooling may be 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, 2021a), 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). In addition, the study area is located in the southeast of the province, i.e. its summers are warmer than those in Alberta as a whole, so the share of households using air conditioning could be higher than the provincial average. During the summer months of 2017 and 2018, the maximum hourly temperatures in Medicine Hat went up to 39.7°C, with the average hourly temperature around 18°C (Figure 14).

[Figure 14 goes here.]

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 of 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[17].

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)[18] to the highest (40°C) temperature observed in the sample,

different from the estimates for hours 21, 22, 23, and 24. The difference between hour 14 and hour 15, hour 3 and hour 20, as well as hour 9 and hour 24 is statistically significant only at 10%. However, none of these hours belong to peak period.

[17] The outdoor temperature for each hour of each day of the sample is the simple average of the corresponding temperatures measured by 3 weather stations closest to Medicine Hat (Government of Canada, 2022b).

[18] 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.

and then I regress non-normalized hourly electricity use[19] on the hourly outdoor temperature:

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

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 corresponding to more extreme (mostly, higher) temperatures (Figure 15). For convenience, Figure 16 shows the average electricity consumption across the ten temperature bins.

[Figure 15 goes here.]

[Figure 16 goes here.]

Then, I check how outdoor temperature changes within a day. I regress the 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:

$$T_{th} = \sum_{h=1}^{24} \omega_h Hour_h + \lambda_t + \epsilon_{th}, \quad (8)$$

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 17 shows how hourly temperature changes relative to the temperature at 4 pm. One can see that the highest temperatures concentrate around peak hours. The same pattern is observed in Figure 18 presenting the variation in the average outdoor temperature within a day.

[Figure 17 goes here.]

[Figure 18 goes here.]

Based on the results demonstrated in Figures 15 - 18, I observe that households consume more during hours with the highest outdoor temperature which are simultaneously peak hours. I then test if this is indeed the case by regressing the average household electricity use on the hour-of-the-day dummy directly:

$$Y_{ith} = \sum_{h=1}^{24} {}_h Hour_h + \mu_i + \lambda_t + \epsilon_{ith}, \quad (9)$$

where the reference category is now $Hour = 17$, the hour with the highest average consumption during a day.

Figures 19 and 20[20] confirm that electricity usage reaches its maximum around peak hours.

[Figure 19 goes here.]

[Figure 20 goes here.]

As a result, intuitively, I would expect the treated households to save more electricity compared to the control group during times when their electricity consumption is larger, i.e. in

[19] In Specifications (7) and (9), I use hourly electricity consumption of the two groups in the pre- and post-treatment periods. The results do not change if I use only pre- or post-treatment period consumption or the consumption of the treatment (control) group only.

[20] Figure 20 shows the average electricity consumption for each of the 24 hours of the day.

peak hours. However, previously, I have found that households do not save more during peak hours. Let's see if this pattern changes depending on the heat loss score. I run Specification (5) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings[21]. The results of estimating the coefficient α_1, showing the change in electricity use in the treatment group per hundred dollars of non-zero estimated savings, are presented in Figure 21. Only the most energy-efficient households with the lowest HEAT Ratings save considerably more during peak hours, whereas the households with high HEAT Ratings and the most populous medium HEAT Rating group still have relatively flat savings profiles.

[Figure 21 goes here.]

The energy-efficient households that saw non-zero potential dollar savings on their bills, i.e. the households that were informed they could save even more electricity despite they are already highly energy-efficient, are more responsive to the treatment compared to the households in the medium and high HEAT Rating groups[22]. Although this finding is promising, more inefficient households, such as those with medium and high HEAT Ratings, have more potential to gain from reductions in electricity use.

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:

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

Figure 22 shows the estimated coefficients χ_{1b}. Previously, it was found that higher consumption corresponds to higher temperatures (Figures 15 and 16), and the latter concentrate around peak hours (Figures 17 and 18), so, naturally, households consume more electricity during times with warmer outdoor temperatures, i.e. in peak hours (Figures 19 and 20). So, the largest savings are expected to happen when it is hotter outside, or during peak hours: the larger the electricity consumption, the higher the savings. Figure 22 demonstrates the opposite. I observe that treated households save electricity relative to the control group when it is cooler outside, which is not typical weather for the summertime, but they consume more electricity than the untreated homes when the outdoor temperature is quite high. Put differently, the increase in electricity usage relative to the control group (in other words, no savings in the treatment group) occurs during times when electricity demand and wholesale prices are soaring (Figure 24). Figure 23 shows the results of re-estimating Specification (10) for households in each of the three HEAT Rating groups separately. One can observe that the pattern presented in Figure 22 is especially bright for the most energy-efficient households.

[Figure 22 goes here.]

[Figure 23 goes here.]

[Figure 24 goes here.]

This could be due to some behavioral changes induced by the treatment. The only explanation I could think of so far 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

[21] I am not able to include the HEAT Rating group as an interaction in Specification (5) due to the lack of computing power. This applies to all the specifications that include the HEAT Rating groups.

[22] Remarkably, these households do not exhibit a boomerang effect, as opposed to the most energy-efficient customers who were shown zero dollar savings (Papineau and Rivers, 2022).

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. I find the explanation quite odd, but, at the same time, one should never underestimate the role of actual human behavior. For example, Davis et al. (2020) conduct a field trial in Mexico in which homes standing next to each other are built according to two different standards (at the time of construction, one group of homes is provided insulation and other energy-efficient upgrades, while the other group does not receive such upgrades). The authors find that the upgrades have zero impact on electricity consumption in new homes. Turns out that it is the behavioral responses that explain the result: most of the households in the sample tend to have their windows open on hot days, which nullifies the benefits of the energy-efficient upgrades.

The treatment was not being sent out in the summer months, so households' efforts to conserve electricity could start to decline 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:

$$\begin{aligned} Y_{ith} = \eta_0 + \sum_{s=1}^{18} \eta_{1s} D_{im} \times T_i \times P_{it} \times Week_s \\ + \sum_{s=1}^{18} \eta_{2s} T_i \times P_{it} \times Week_s + \eta_3 P_{it} + \mu_{ih} + \lambda_t + \epsilon_{ith}, \end{aligned} \tag{11}$$

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 25, 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 (11) 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 26) with larger effects for the most efficient households. The pattern observed in Figure 25 (Figure 26) matches the one shown in Figure 22 (Figure 23): the higher the outdoor temperature is, the lower the electricity savings are (June and September have on average lower outdoor temperature than July and August). Thus, the ambient temperature still influences households' electricity conservation more than the time since when they received the treatment.

[Figure 25 goes here.]

[Figure 26 goes here.]

Overall, the temperature variation in the electricity conservation differs from the savings heterogeneity across hours, but not in a good way. Although, as shown earlier, the households save the same amount of electricity within a day, they demonstrate consistent electricity conservation. As for the outdoor temperature, I do observe the variation in the savings across the temperature bins, but this heterogeneity includes positive savings (i.e. the increase in electricity usage in the treatment group) concentrated around periods of hot weather, which are associated with larger electricity demand and wholesale prices. The findings on temperature-based heterogeneity in the savings confirm that the intervention fails to target the times that could potentially deliver the most economically and socially efficient consumption reductions.

In general, since hourly electricity consumption does vary depending on outdoor temperature, most of the households in the sample use air conditioning, so air conditioning penetration may have nothing to do with the flat hourly savings profile of the households in the sample.

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 Sacramento, California. The authors conclude that adopting the codes is associated with electricity savings driven by reductions in cooling that do vary within a day (the savings are the largest in the afternoon and evening when demand for cooling is highest). 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 data from California where high summer temperatures make households 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), which could indicate that the households in the sample likely needed more time to do home upgrades (additionally, the treatment continued in November 2018).

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) 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 underestimate retail electricity prices during colder months, while they overestimate the prices during warmer (summer) months.

It is worth mentioning that most of the 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 a 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 the 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: as noted in Section 1, 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 “appliances” 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:

$$
\begin{aligned}
Timing\ Premium &= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecAve \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}} \times 100\% - 100\% \\
&= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{PriceElecAve} \times 100\% - 100\% \qquad (12) \\
&= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecHour_h \times LoadElecHour_h}{\sum_{h=1}^{24} LoadElecHour_h}} \times 100\% - 100\%,
\end{aligned}
$$

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[23]. $PriceElecHour_h$ and $LoadElecHour_h$ show the electricity pool price and Alberta Internal Load in 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 the 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, so 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%[24]. Adjusting the program's impact for the hourly distribution of the savings makes the program less economically valuable than ignoring 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 environmental 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 the timing of the electricity savings can affect their environmental value[25].

Neither AESO nor the Government of Alberta collects 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 environmental impact to be around zero meaning that the GHG intensity of the electricity savings when the timing of the savings is taken care of would be the same as the average GHG intensity of electricity consumption. The latter was around 700 grams of CO_2 equivalent per kilowatt-hour of electricity consumed in Alberta in 2018, multiple times larger than in other Canadian provinces (Government of Canada, 2022a). This already makes any programs aiming at energy conservation in the province highly environmentally valuable, and saving more during peak hours would potentially make them even more beneficial.

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

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

[25]At the same time, according to Boomhower and Davis (2020), most of the benefits of energy efficiency investments come from the benefits quantified using wholesale electricity prices, not the benefits associated with externality reductions (avoided air pollutant emissions); in addition, wholesale electricity prices demonstrate much larger hourly variation compared to externality reductions.

5 Conclusion

Alberta is committed to achieving a net-zero electricity system by 2035. Continued decarbonization and electrification of the provincial economy may be associated with an increased supply adequacy risk: compared to the 2021 peak, extensive electrification of end-use consumption, including high adoption of electric vehicles and electric heating, and growth in solar distributed energy resources are expected to increase peak electricity demand by 19% by 2035 and 34% by 2041 (Alberta Electric System Operator, 2022a). As a result, identifying effective ways to lower electricity load during peak times is vital for Alberta's commitment to reaching net-zero emissions. In the short term, a reduction in electricity consumption in peak hours can mitigate GHG emissions in a grid that still uses fossil fuels; in the long term, with non-emitting electricity generation in place, shifting electricity use from peak to off-peak hours can reduce supply adequacy risk and decrease the need for expensive investments in generating capacity required to meet growing demand.

The paper studies if a behavioral intervention in Medicine Hat, Alberta, delivers peak electricity demand savings. Having examined the hourly distribution of household electricity savings from the program, I find that the treatment produces electricity savings in general, but households have a relatively flat hourly savings profile, i.e. they do not conserve more electricity during peak electricity demand hours. Consequently, the intraday timing of the savings hardly matters when calculating the social benefits of the program.

While the failure to adopt retail prices varying hour-to-hour constitutes only one-quarter of the total deadweight loss from retail electricity mispricing and the other three-quarters come from setting a fixed retail price at an inefficient level, these proportions might change in the future as consumer technologies allow electricity demand to be moved away from peak hours (Borenstein and Bushnell, 2022). The flexibility of electricity consumption will become quite important for the province in the long term, as Alberta is expected to exhibit a substantial increase in the peak hourly electricity demand arising from larger air conditioner adoption and higher hourly temperatures in the peak of summer due to climate change[26] (Rivers and Shaffer, 2020).

One implication of these results is that social welfare is likely to increase from shifting to time-varying pricing. Switching residential customers in the regions like Medicine Hat (primarily, in the jurisdictions with more conservative political leanings) to retail electricity prices varying within a day possibly coupled with some form of real-time feedback on their electricity usage may help alleviate the challenges related to the mismatch between wholesale and retail hourly prices of electricity, particularly during summer months. Incorporating time variation in the retail rates could motivate households to shift their electricity consumption to off-peak thereby becoming an important tool for efficiently accommodating transitioning to net zero (Karimu et al., 2022), as well as aid in mitigating the volatility of wholesale electricity prices (Griffin and Puller, eds, 2005).

The findings developed in the paper are not focused on Alberta only. First, the expanded diurnal range of hourly consumption in summer and more air conditioner penetration are projected across all Canadian provinces (Rivers and Shaffer, 2020). Second, currently, time-varying pricing for residential customers is in effect in Ontario and has been recently proposed in British Columbia (BC Hydro, 2023); the rest of the provinces do not have hourly time variation in their retail electricity rates. Third, in most provinces, average electricity generation costs

[26] 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).

will likely rise due to transitioning to net zero, and the potential cost increases will be the largest among 'thermal provinces', such as Alberta, Saskatchewan, or Nova Scotia. Since these provinces currently heavily rely on fossil fuels (natural gas, coal, oil) for most of their electricity generation, they will have to undergo a major transformation of their electricity systems to align them with net zero and so require relatively more investment to support increased system load, which will eventually affect the cost of generating electricity (Dolter and Winter, 2022). Of note, not only Alberta but also other thermal provinces will have a relatively high environmental benefit from energy conservation programs. Finally, since, as mentioned earlier, a large share of conservative voters in Medicine Hat could play a role in the final result, the findings are increasingly likely for residential customers in jurisdictions with more conservative political leanings.

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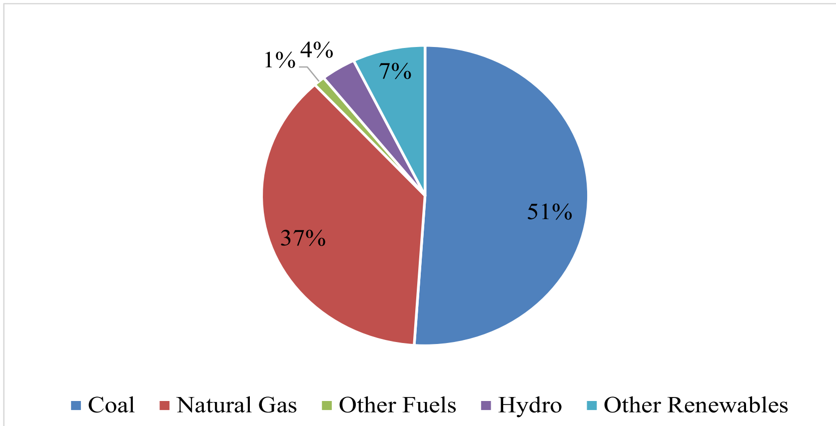
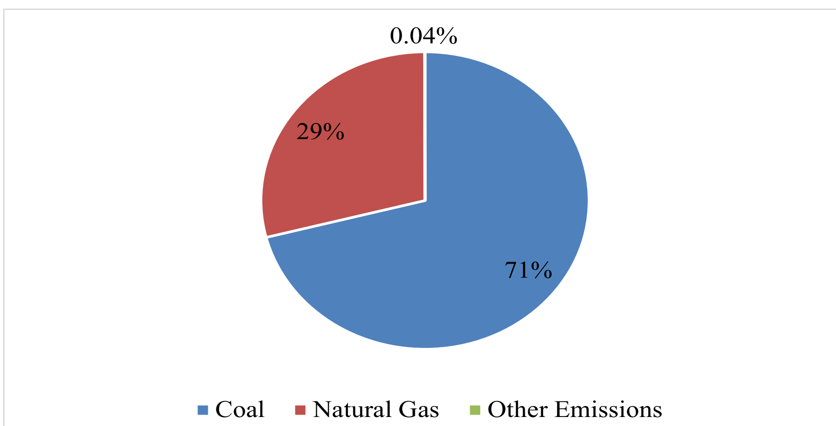
Tables and Figures

Figure 1: Electricity Generation by Source in Alberta in 2018



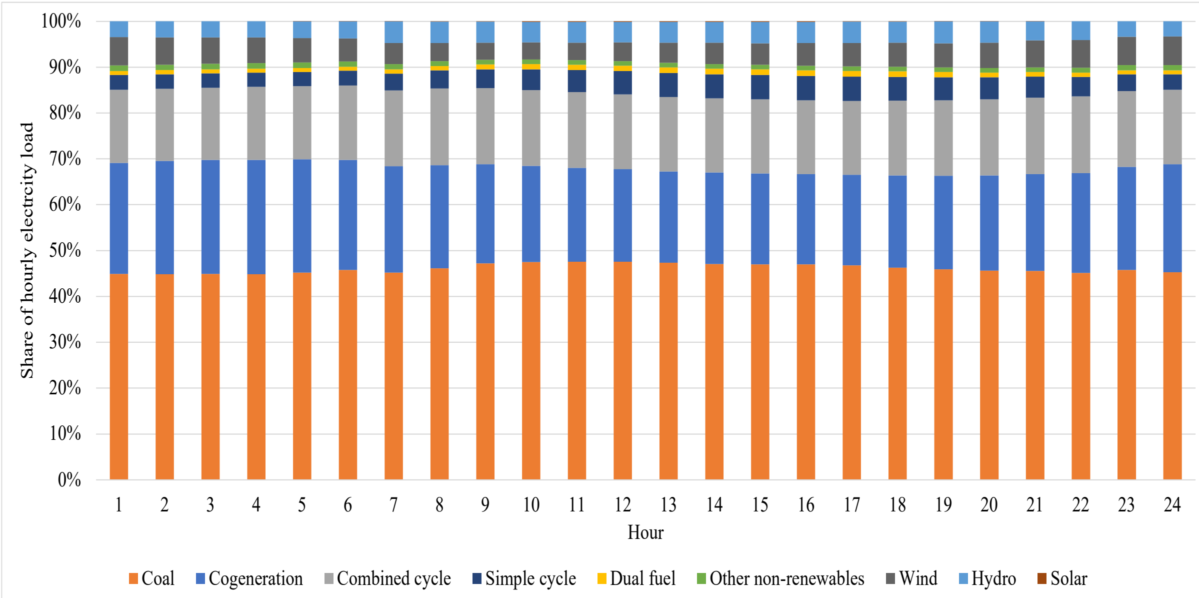
Notes: Fossil fuels, such as coal and natural gas, are the primary source of electricity production in the province. Source: Government of Canada (2022a).

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



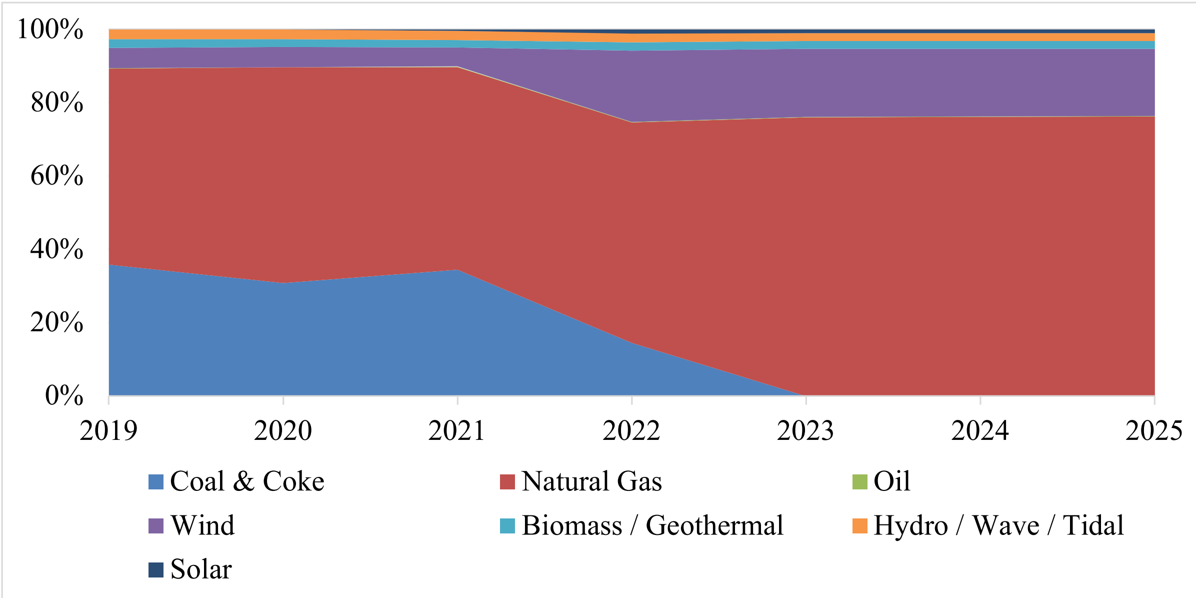
Notes: The majority of GHG emissions come from coal. Source: Government of Canada (2022a).

Figure 3: Hourly Electricity Generation by Source in Alberta in June - September 2018



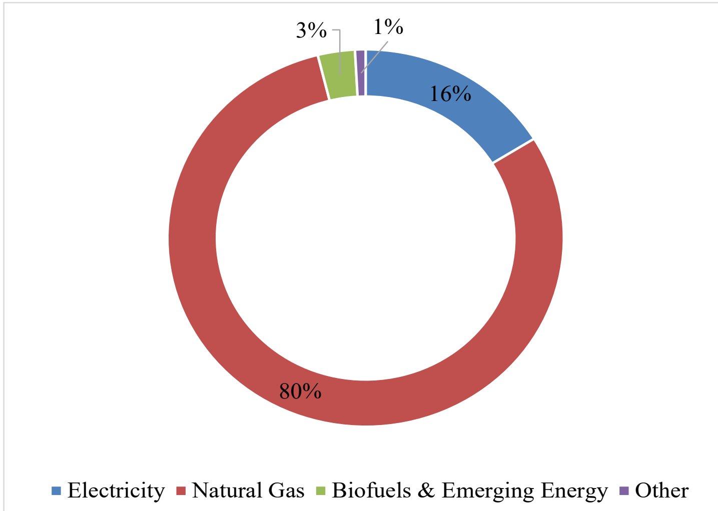
Notes: Coal is used to generate electricity in the majority of off-peak and on-peak hours. Source: Alberta Electric System Operator (2022b).

Figure 4: Changing Electricity Generation by Source in Alberta, Share of Total Electricity Generation



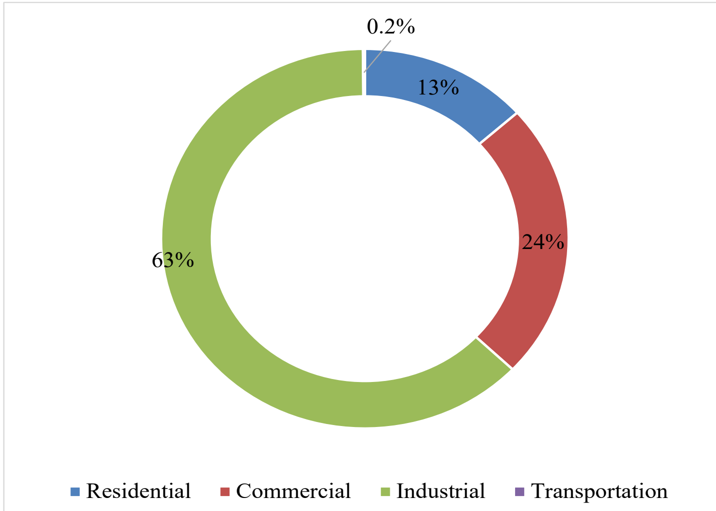
Notes: Coal-fired generation is scheduled to be gradually phased out by the end of 2023. Source: Canada Energy Regulator (2021).

Figure 5: End-Use Energy Demand by Source in Residential Sector in Alberta in 2018



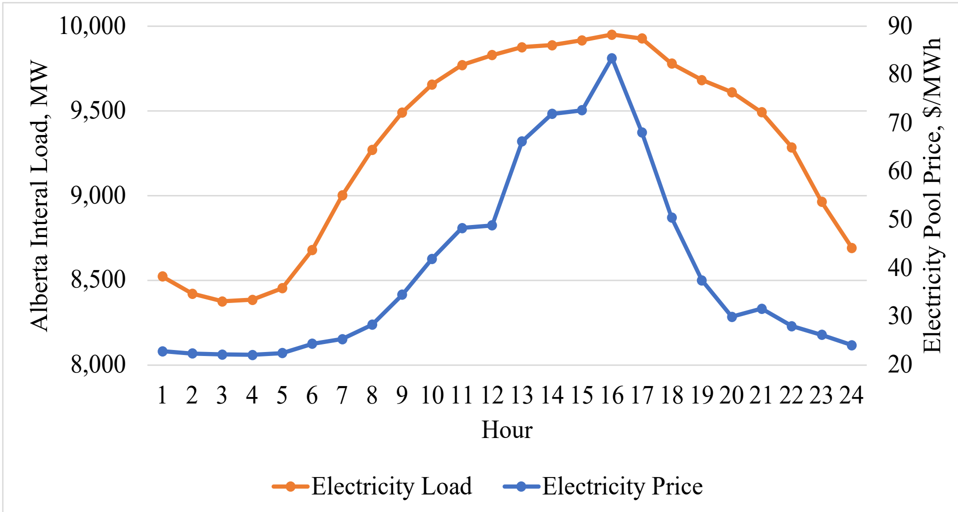
Notes: The residential sector primarily consumes natural gas. Source: Canada Energy Regulator (2021).

Figure 6: End-Use Electricity Demand by Sector in Alberta in 2018



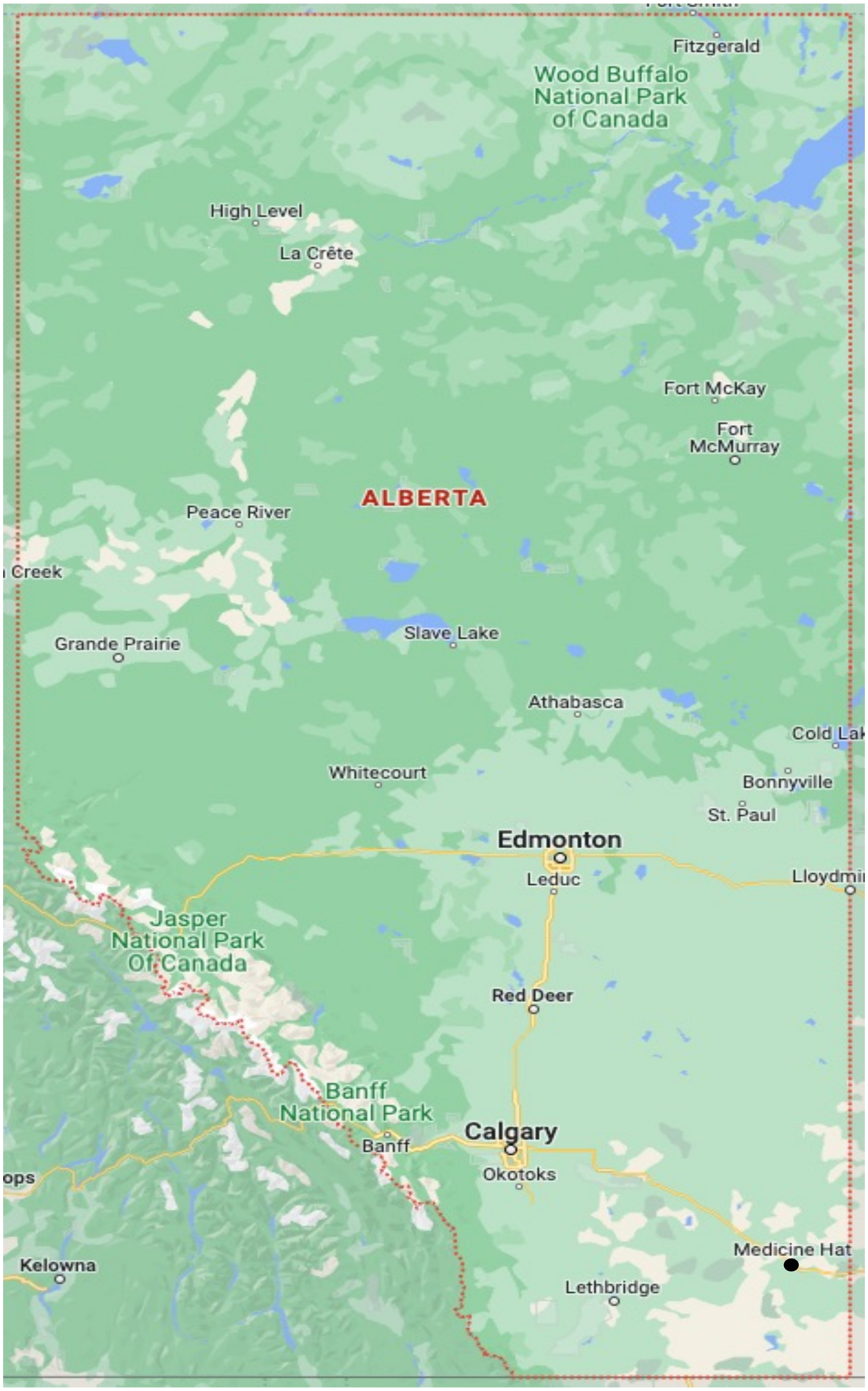
Notes: Residential electricity consumption makes up 13% of the total electricity end-use. Source: Canada Energy Regulator (2021).

Figure 7: Electricity Load and Electricity Wholesale Prices in Alberta



Notes: The figure shows the hourly variation in the electricity demand and wholesale price during the summer months (June - September 2017 and June - September 2018). Source: Alberta Electric System Operator (2020).

Figure 8: The Map of Alberta



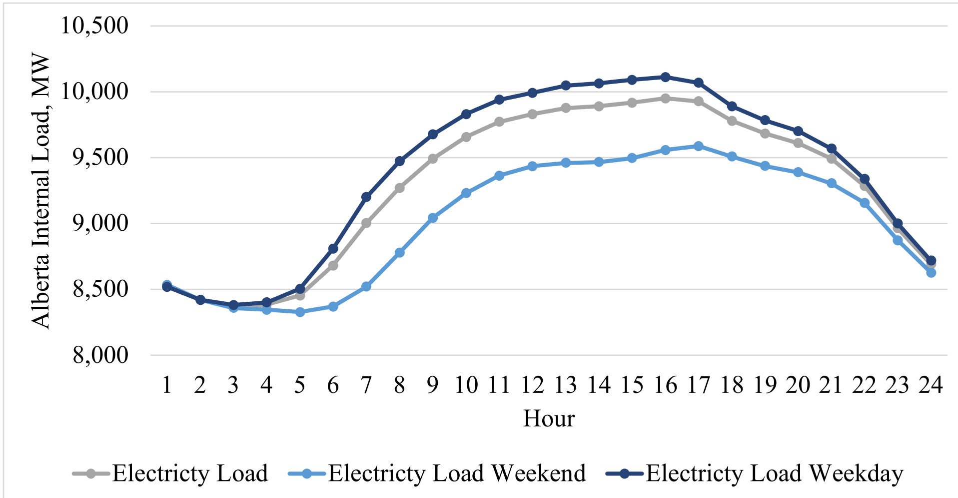
Notes: The map shows the province of Alberta. Medicine Hat is a medium-sized city located in the southeast of the province.

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 $\times$ Dollar Savings, $D \times T \times P$		-0.04128***
		(0.01390)
Observations	43,587,912	43,587,912
R-squared	0.49755	0.49765

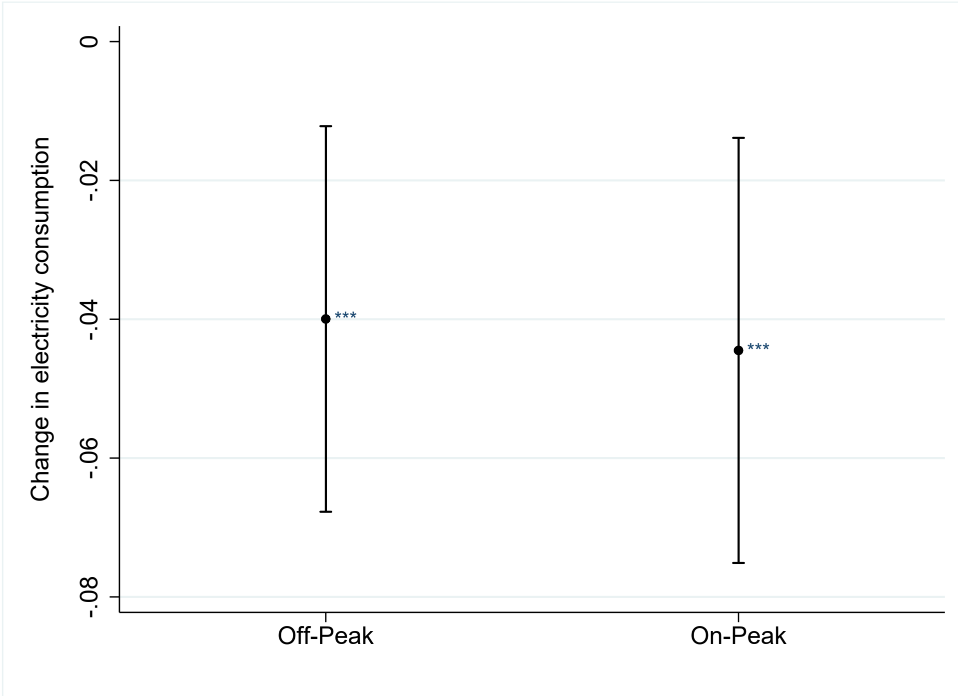
Notes: The table reports the results of estimating Specifications (1) – (2). The dependent variable represents hourly household electricity consumption. T is a dummy variable indicating a household's treatment status (i.e., whether a household belongs to the treatment group), P is a post-treatment dummy variable, D indicates the dollar savings estimate (in units of hundreds of dollars) for a household in the treatment group. The specifications include household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. In Column (2), the coefficient of the $D \times T \times P$ variable, -0.04128, implies that on average a household in the treatment group decreases 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. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 9: Hourly Alberta Internal Load in June - September 2018



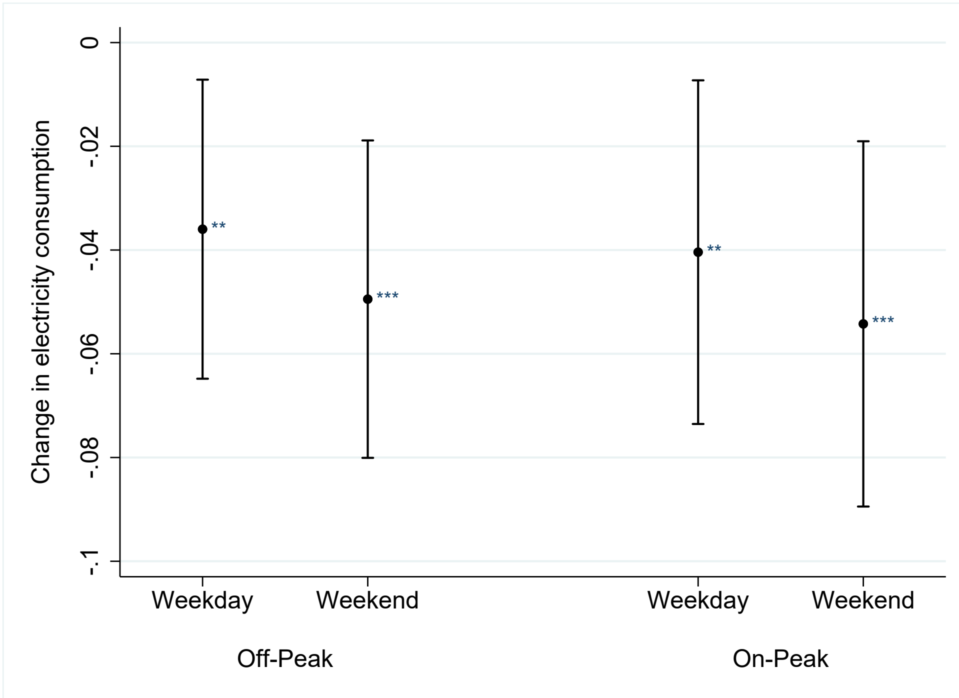
Notes: The figure shows the hourly variation in the electricity demand during the post-treatment period (June - September 2018). Source: Alberta Electric System Operator (2020).

Figure 10: Peak Regression Results



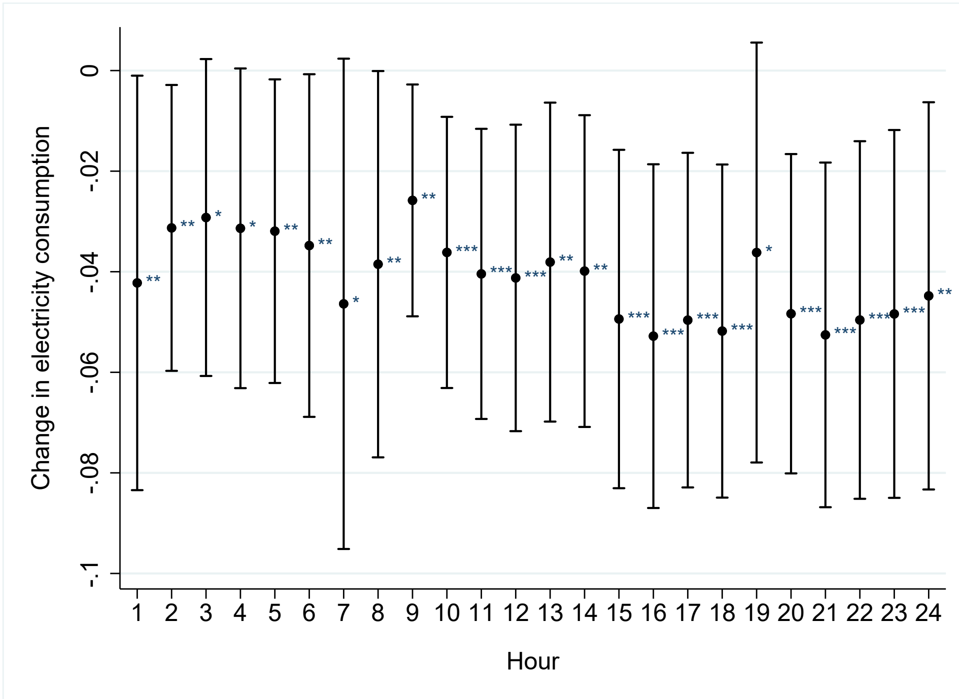
Notes: The figure shows the results of estimating Specification (3). The graph displays point estimates and the corresponding 95% confidence intervals. The specification is the same as Specification (2), except that the treatment and post-treatment period dummies are also interacted with the variable indicating peak or off-peak time. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 11: Peak Regression Results: Weekends Vs. Weekdays



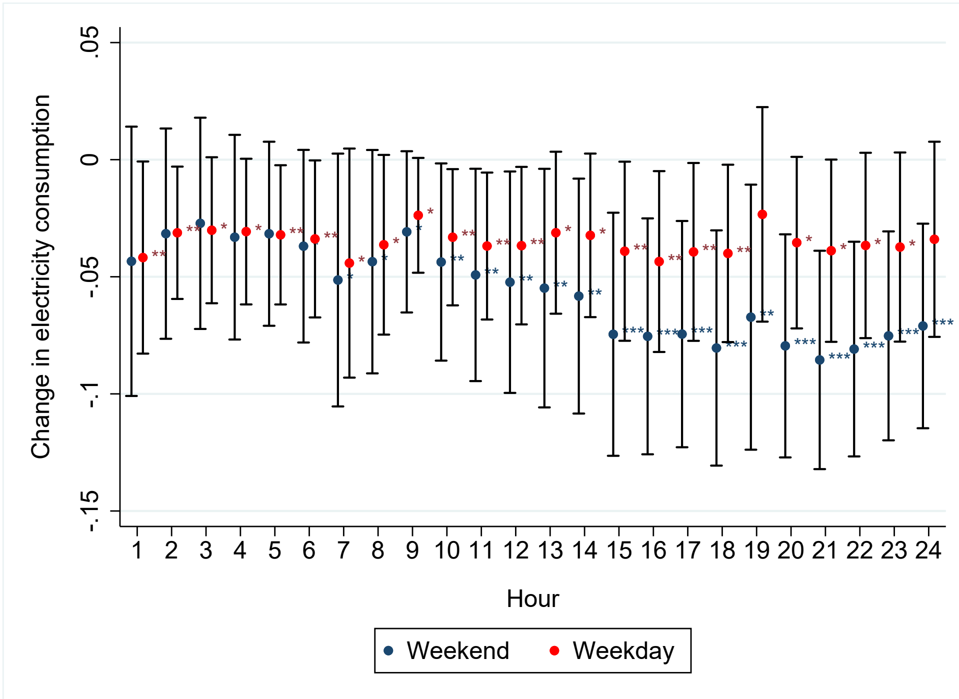
Notes: The figure reports the estimation results for Specification (4). The graph displays point estimates and the corresponding 95% confidence intervals. The specification is the same as Specification (2), except that the treatment and post-treatment period dummies are also interacted with the variable indicating peak or off-peak time and the variable showing if a day belongs to weekdays or a weekend. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 12: Hourly Regression Results



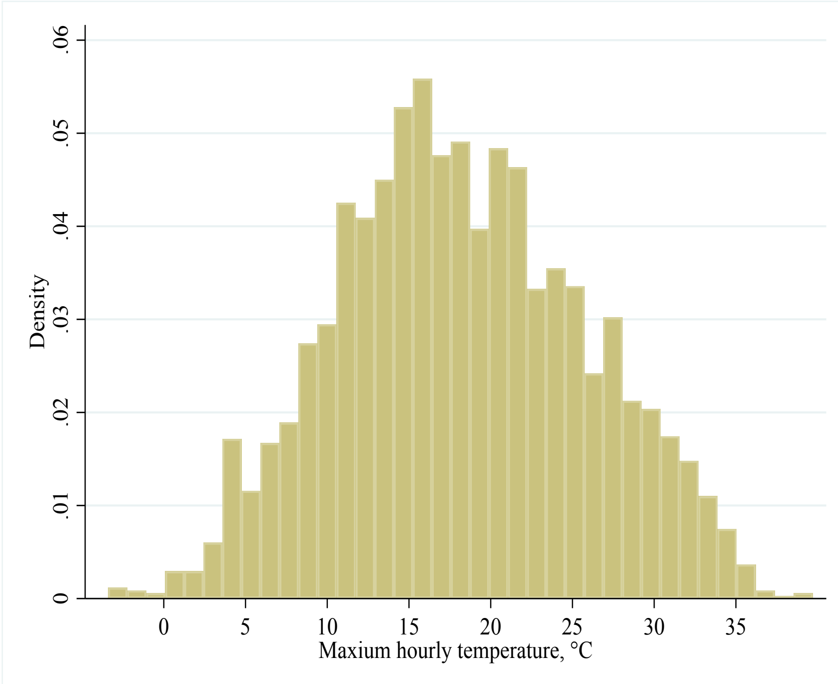
Notes: The figure reports the estimation results for Specification (5). The graph displays point estimates and the corresponding 95% confidence intervals. The specification is the same as Specification (3), except that the time-of-day variable (on-peak or off-peak) is replaced with the indicator for each hour of the day. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 13: Hourly Regression Results: Weekends Vs. Weekdays



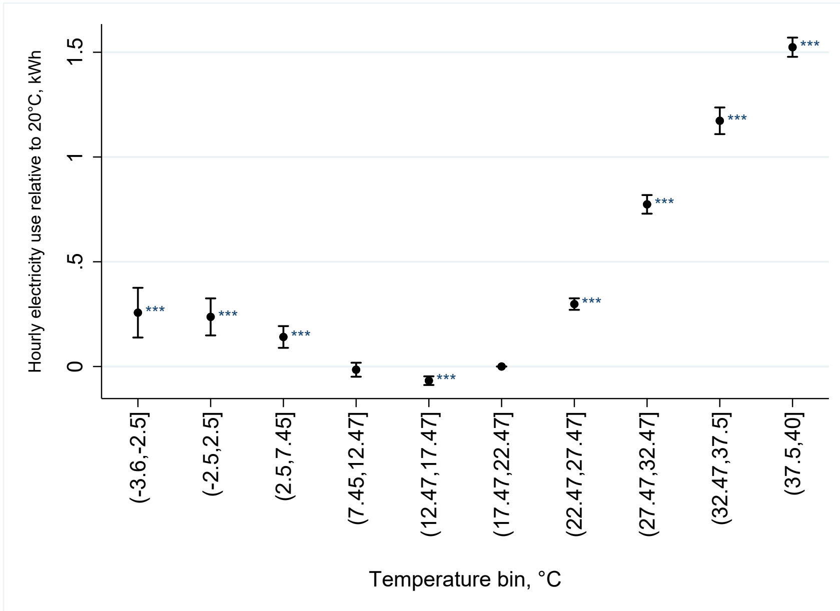
Notes: The figure reports the estimation results for Specification (6), where the hourly electricity savings are estimated separately for weekends and weekdays. The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 14: Maximum Hourly Temperatures During Summer Months in Medicine Hat



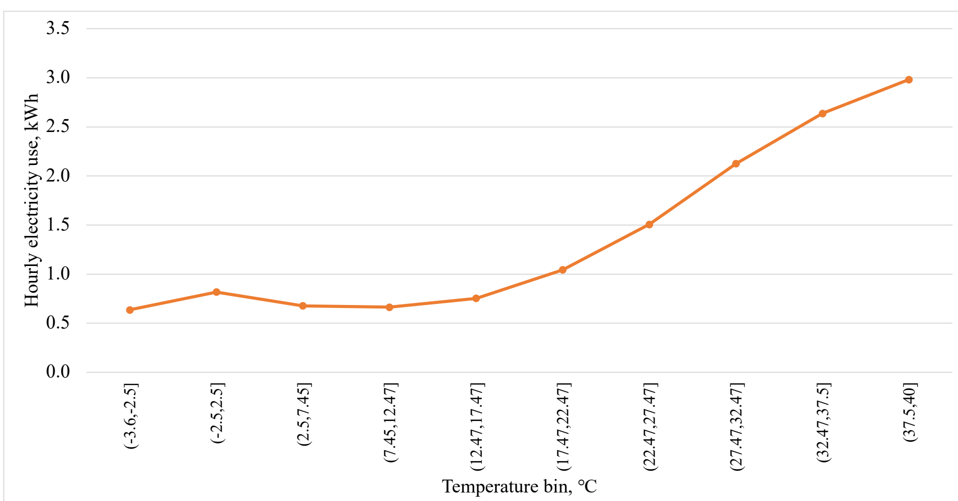
Notes: The histogram shows the distribution of maximum hourly temperatures in Medicine Hat from June until September of 2017 and 2018.

Figure 15: Hourly Electricity Consumption and Outdoor Air Temperature



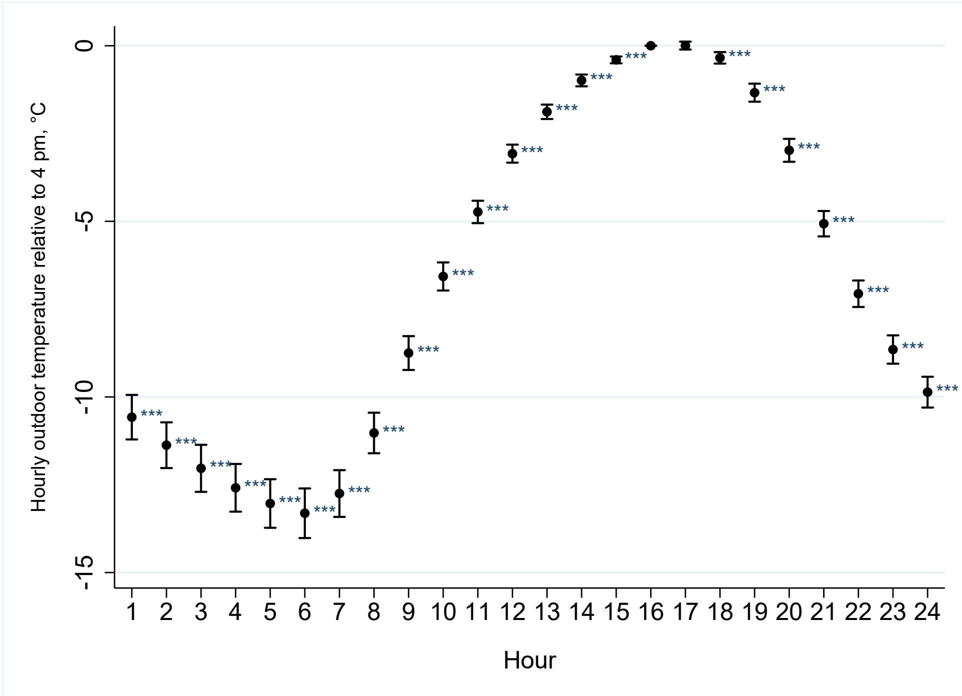
Notes: The figure shows the results of estimating Specification (7). The vertical axis displays hourly household electricity use (non-normalized). The horizontal axis presents the hourly outdoor temperature divided into 10 temperature bins. The temperature bin $(17.47, 22.47]$ is the reference category, so the change in hourly electricity consumption is evaluated relative to this category (the title of the vertical axis refers to this temperature bin as 2020°C). The figure displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 16: Average Hourly Electricity Consumption across Temperature Bins



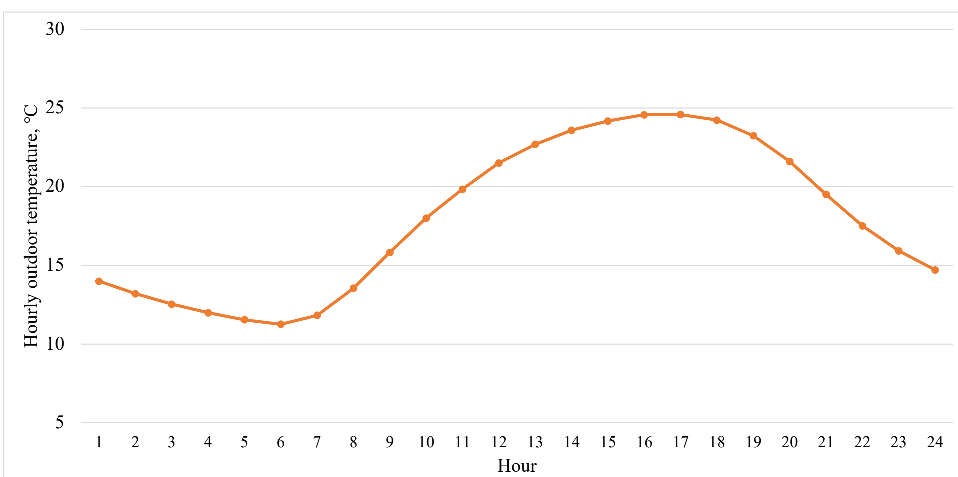
Notes: The figure shows the average electricity consumption across ten temperature bins. The average electricity consumption and the temperature bins are calculated for the period of June - September 2017 and June - September 2018. The pattern presented in the figure does not change if I use pre-treatment electricity consumption or the consumption of the control group only.

Figure 17: Outdoor Air Temperature: Hourly Variation



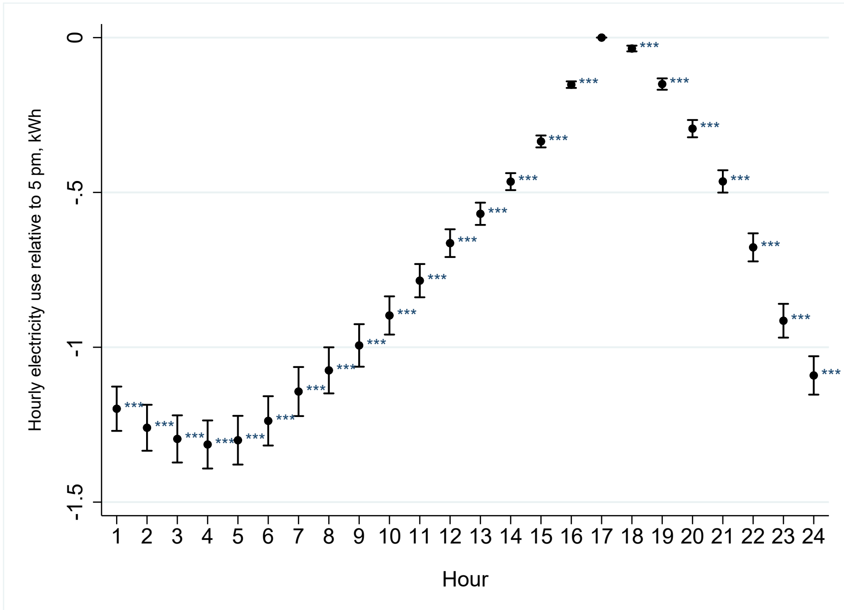
Notes: The figure shows the results of estimating Specification (8). The vertical axis displays the hourly outdoor temperature, and the horizontal axis shows each hour of the day. The 4 pm hour, which corresponds to the hottest temperature of the day on average, is the reference category, so the change in hourly outdoor temperature is evaluated relative to 4 pm. The figure displays point estimates and the corresponding 95% confidence intervals. The specification includes day-of-sample fixed effects. Standard errors are clustered by day of the sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 18: Average Outdoor Air Temperature across Hours



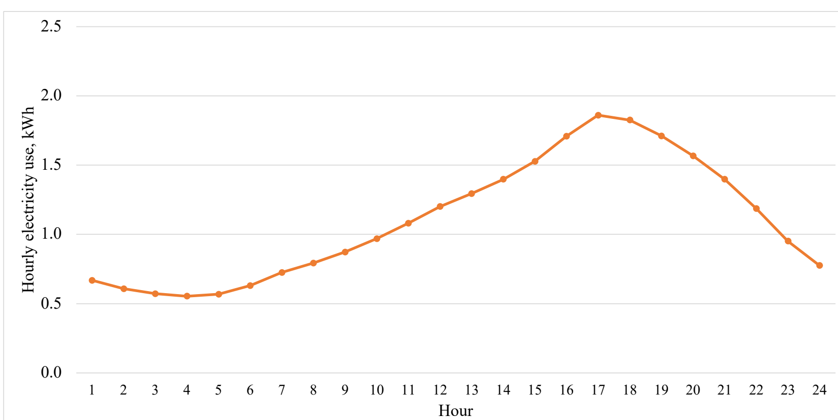
Notes: The figure shows the variation in the average outdoor temperature within a day. The average hourly temperature is calculated for the period of June - September 2017 and June - September 2018.

Figure 19: Electricity Consumption: Hourly Variation



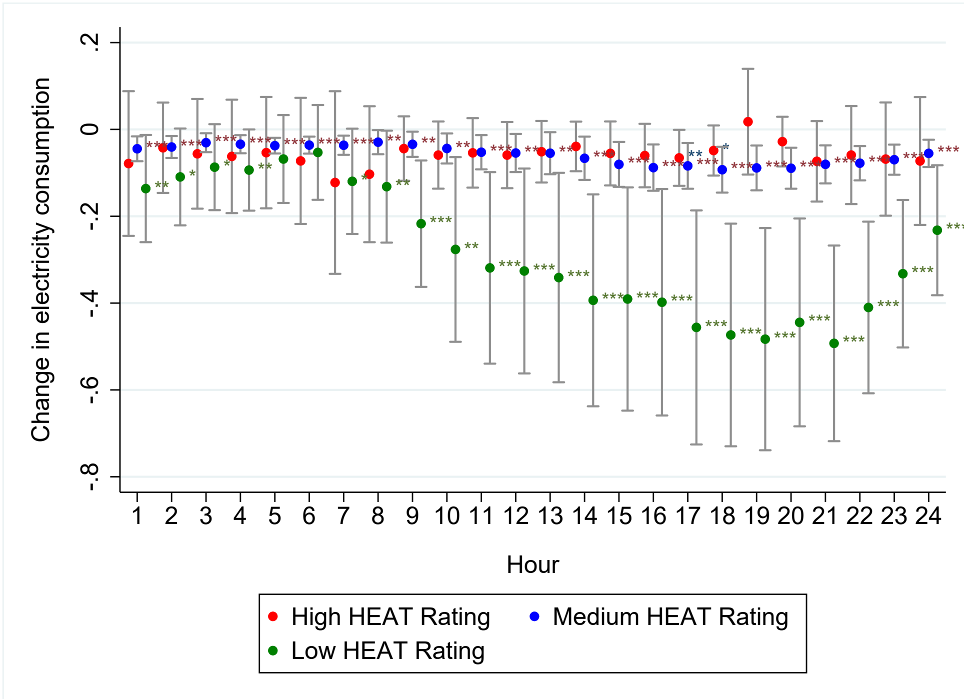
Notes: The figure shows the results of estimating Specification (9). The vertical axis displays hourly household electricity use (non-normalized), and the horizontal axis shows each hour of the day. The 5 pm hour, the hour with the highest average consumption during a day, is the reference category, so the change in hourly electricity consumption is evaluated relative to 5 pm. The figure displays point estimates and the corresponding 95% confidence intervals. The specification includes household and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample; *** p<0.01, ** p<0.05, * p<0.1.

Figure 20: Average Electricity Consumption across Hours



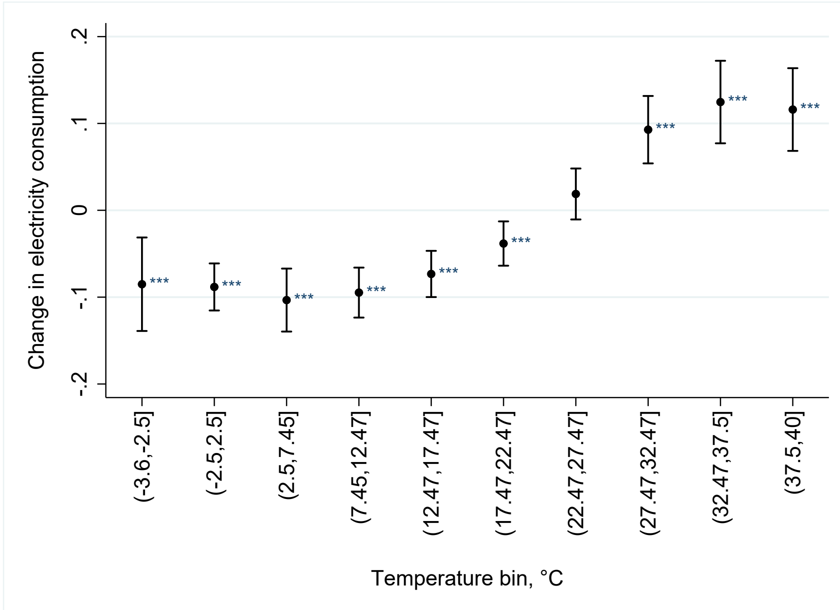
Notes: The figure shows the average electricity consumption for each of the 24 hours of the day. The average electricity consumption is calculated for the period of June - September 2017 and June - September 2018. The pattern presented in the figure does not change if I use pre-treatment electricity consumption or the consumption of the control group only.

Figure 21: Hourly Electricity Conservation by HEAT Rating Group



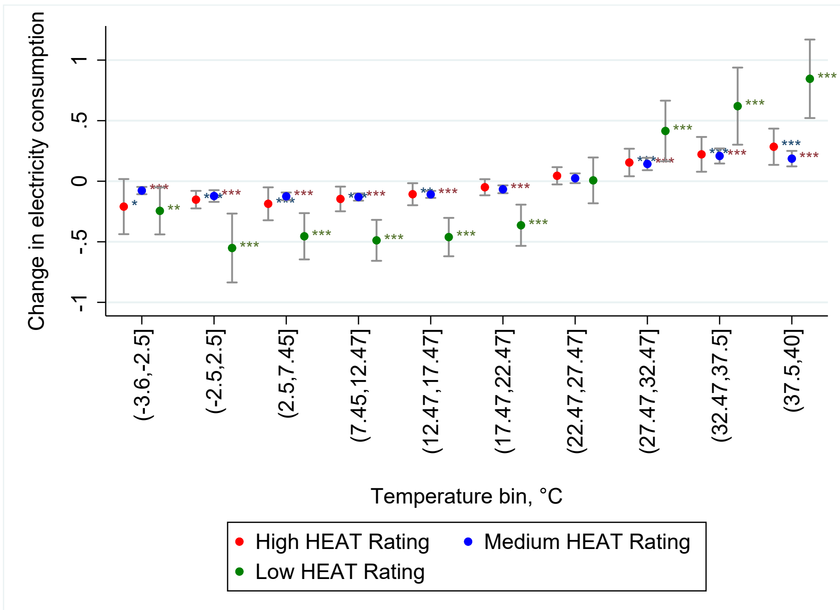
Notes: The figure shows the results of estimating Specification (5) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings. The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 22: Hourly Electricity Conservation and Outdoor Air Temperature



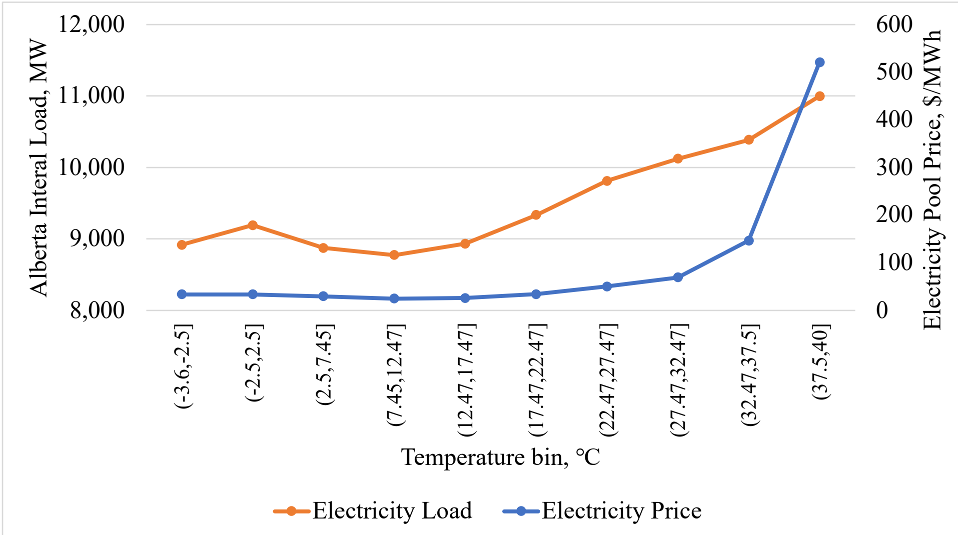
Notes: The figure reports the estimation results for Specification (10). The specification is the same as Specification (5), except that the hour-of-day dummy is replaced with the indicator for each of the 10 temperature bins. The dependent variable (hourly household electricity use, shown on the vertical axis) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 23: Hourly Electricity Conservation and Outdoor Air Temperature: HEAT Rating Groups



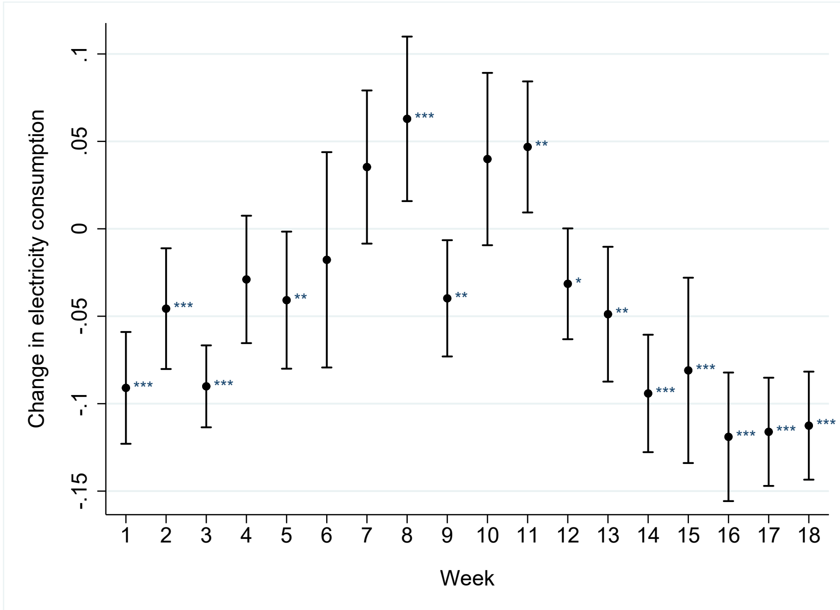
Notes: The figure shows the results of estimating Specification (10) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings. The dependent variable (hourly household electricity use, shown on the vertical axis) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 24: Alberta Internal Load and Wholesale Electricity Price Varying by Temperature Bins



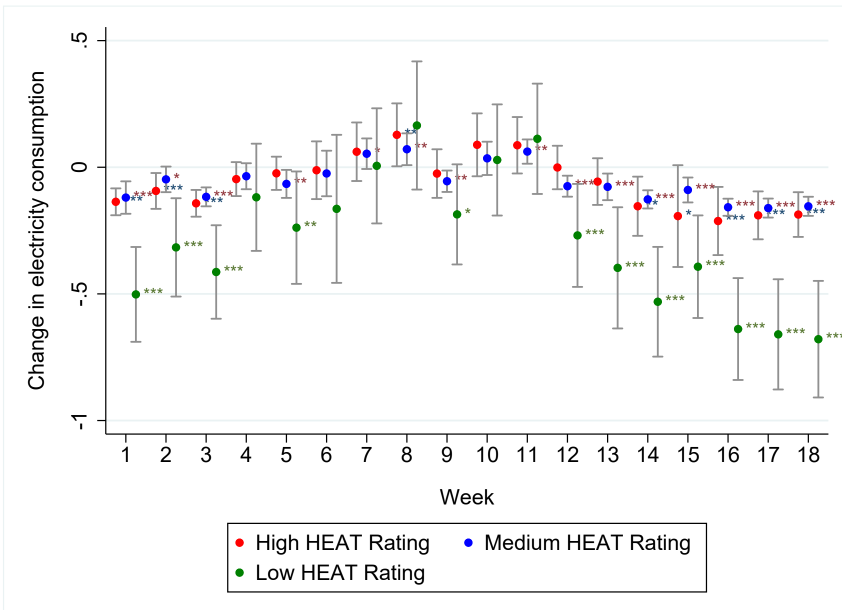
Notes: The figure shows the variation in the average hourly electricity load and wholesale electricity price across temperature bins during the summer months (June - September 2017 and June - September 2018). Source: Alberta Electric System Operator (2020); Government of Canada (2022b).

Figure 25: Hourly Electricity Conservation Changing During the Experiment



Notes: The figure reports the estimation results for Specification (11). The specification is the same as Specification (5), except that the hour-of-day dummy is replaced with the dummy showing the week number in the pre and post-treatment periods. The horizontal axis represents the week of the sample. 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 the total number of the weeks of the sample is 18. The dependent variable (hourly household electricity use, shown on the vertical axis) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. The graph displays point estimates and the corresponding 95% confidence intervals. For example, the coefficient for the 8th week, which is equal to approximately 5%, shows the change in electricity consumption per hundred dollars of non-zero estimated savings among the treated households in the 8th week of the post-treatment period relative to the 8th week of the pre-treatment period, compared to the corresponding post- versus pre-treatment change in the electricity consumption of the control group. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 26: Hourly Electricity Conservation Changing During the Experiment: HEAT Rating Groups



Notes: The figure shows the results of estimating Specification (11) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings. The horizontal axis represents the week of the sample. The dependent variable (hourly household electricity use, shown on the vertical axis) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

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

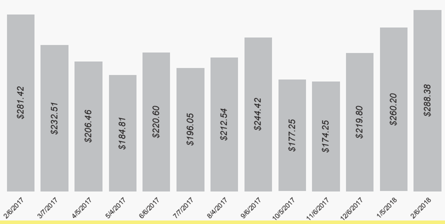
C-10

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

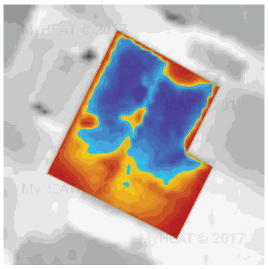
Amount on your last bill	260.20
Payment (Feb 1, 2018)	-260.20
Your balance forward	0.00

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: The table shows the results of re-estimating Specification (3) using various combinations of fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Based on the Wald test, the change in electricity consumption in the treatment group per hundred dollars of non-zero estimated savings, i.e. the coefficient of $D \times T \times P$, in the on-peak is not statistically significantly different from the corresponding change in the off-peak.

Table B2: Peak Hours Test

Dependent variable:	Hourly Electricity Use			
	(1)	(2)	(3)	(4)
Treatment, $T \times P$				
Off-Peak	0.063**	0.054**	0.091***	0.074***
	(0.025)	(0.023)	(0.033)	(0.028)
On-Peak	0.045**	0.059***	-0.001	0.027
	(0.019)	(0.022)	(0.019)	(0.017)
Treatment × Dollar Savings, $D \times T \times P$				
Off-Peak	-0.042***	-0.042***	-0.039**	-0.041***
	(0.014)	(0.014)	(0.015)	(0.014)
On-Peak	-0.040***	-0.040***	-0.044***	-0.041***
	(0.014)	(0.014)	(0.015)	(0.014)
Peak Hours	8 a.m. - 4 p.m.	6 a.m. - 4 p.m.	11 a.m. - 7 p.m.	9 a.m. - 5 p.m.
Observations	43,587,912	43,587,912	43,587,912	43,587,912
R-squared	0.498	0.498	0.498	0.498

Notes: The table shows the results of re-estimating Specification (3) using different definitions of peak hours. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Based on the Wald test, the change in electricity consumption in the treatment group per hundred dollars of non-zero estimated savings, i.e. the coefficient of $D \times T \times P$, in the on-peak is not statistically significantly different from the corresponding change in the off-peak.

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).

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[27]. The value of the electricity savings is very similar to the one reported for the summer data.

[Table C1 goes here.]

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). 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.

[Figure C1 goes here.]

[Figure C2 goes here.]

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.

[Table C2 goes here.]

Finally, Figure C3 contains the estimates of the coefficients δ_{1hw} from Specification (6)[28]. 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 behavior related to electricity consumption.

[Figure C3 goes here.]

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.

[27] 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).

[28] I was not able to estimate Specification (5) for the winter season due to insufficient computing power.

In such case, i.e. in the 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 unit fixed effects to evaluate a treatment effect might result in the estimate with quite nontrivial interpretation. More specifically, when groups of units are exposed to a treatment at different points in time, the estimate is the weighted sum of the average treatment effects in each group and time period, and some of the weights may be negative, which can lead to the two-way-fixed-effects estimator being biased. Currently, there are a number of approaches that are being proposed to solve the problem[29].

I have made an attempt to use the estimator developed by de Chaisemartin and D'Haultfoeuille (2022), which is unbiased and robust to heterogeneous treatment effects. 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[30] 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 i, which indexes a household, is the group variable, and the time period variable t represents 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} being a post-treatment dummy variable. The outcome variable, Y_{ith}, indicates the electricity consumption for household i on day t in hour h. The controls are CDH_{th} and HDH_{th} showing cooling degree hours and heating degree hours, respectively (I calculate heating and cooling degree hours using 18 °C as the reference point). The standard errors are clustered at the household level[31].

Although the command does not allow me to estimate how the treatment effect varies with respect to a certain variable, I 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

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

[29] The issue is examined for observational studies, but I do not see why heterogeneous treatment effects should not cause problems for experimental interventions.

[30] I do not use the estimator for the summer data since the treatment was not being sent out in the summer months, meaning that the households in the treatment group are technically all treated in the post-treatment period without any heterogeneity in the treatment dates.

[31] The command does not support two-way clustered standard errors.

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 using *reghdfe*, a Stata command that performs linear regressions absorbing many levels of fixed effects (Correia, 2014).

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) commands in Stata.

[Table C3 goes here.]

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.

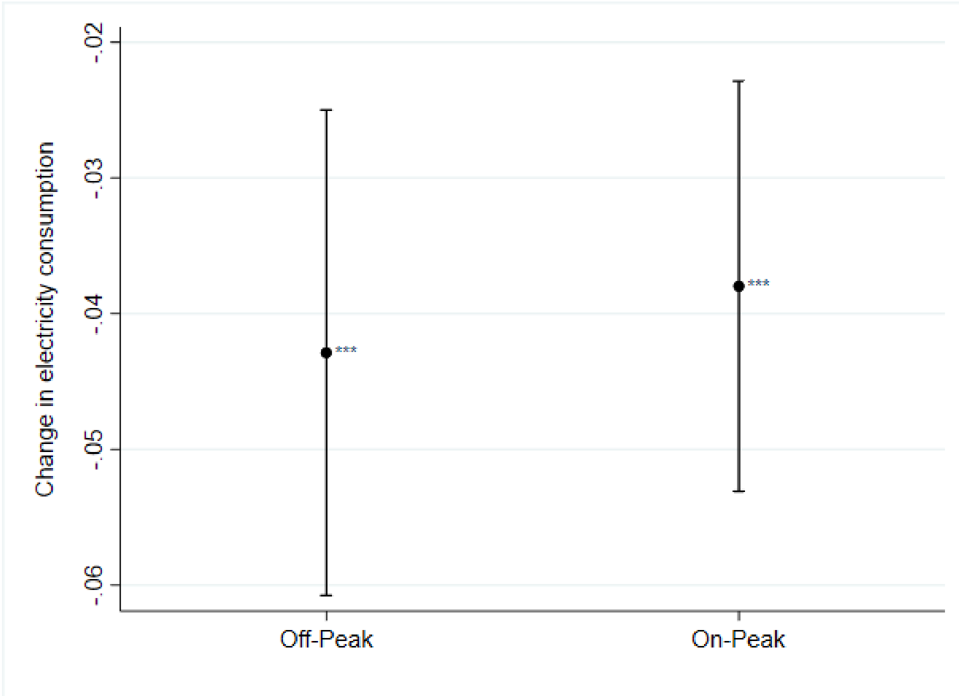
Research in the area of heterogeneous treatment effects is in progress. For example, Souza (2022) introduces a machine learning approach, which could reduce the biases related to the standard two-way-fixed-effects model for settings with staggered adoption. As the research develops, I will be updating the results reported in this section, including estimating the hourly variation in the electricity savings when possible.

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

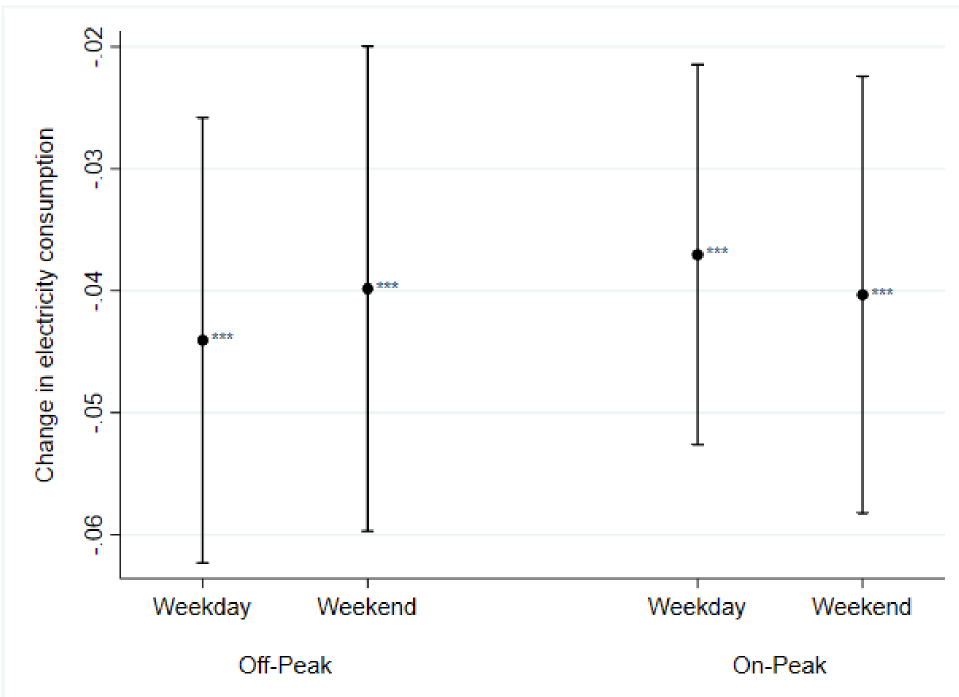
Notes: The table reports the results of estimating Specifications (1) – (2). The dependent variable represents hourly household electricity consumption. T is a dummy variable indicating a household's treatment status (i.e., whether a household belongs to the treatment group), P is a post-treatment dummy variable, D indicates the dollar savings estimate (in units of hundreds of dollars) for a household in the treatment group. The specifications include household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. In Column (2), the coefficient of the $D \times T \times P$ variable, -0.04144, implies that on average a household in the treatment group decreases 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. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure C1: Peak Regression Results (Winter)



Notes: The figure shows the results of estimating Specification (3). The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

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



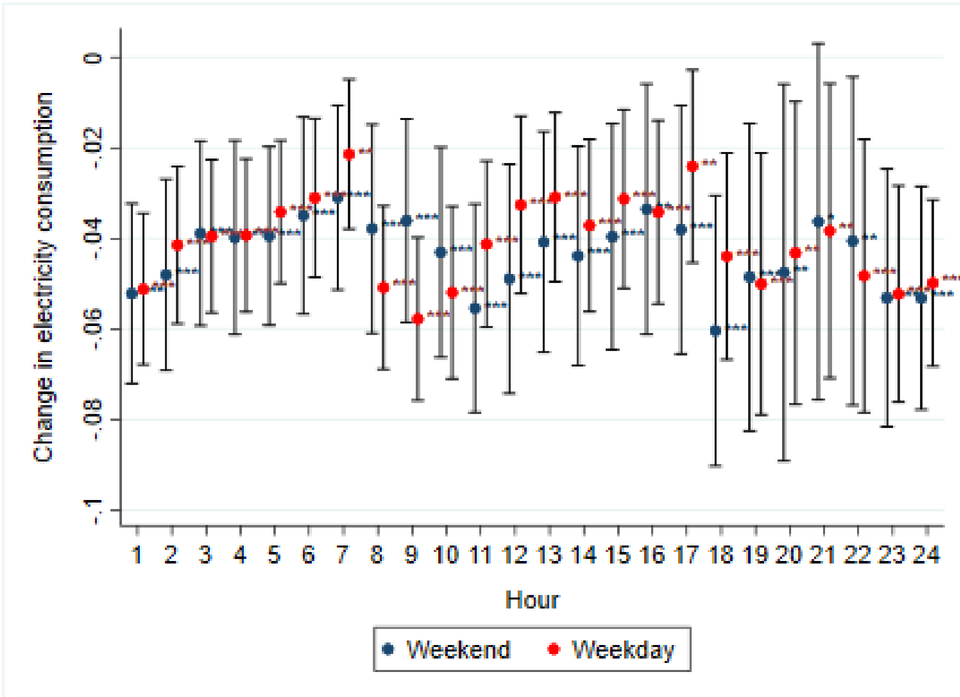
Notes: The figure shows the results of estimating Specification (4). The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** 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: The table shows the results of re-estimating Specification (3) using various combinations of fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the 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 reports the estimation results for Specification (6). The graph displays point estimates and the corresponding 95% confidence intervals. The specification includes household-by-hour-of-the-day and day-of-sample fixed effects. The dependent variable (hourly household electricity use) is normalized by average post-treatment consumption in the control group; the interpretation of the coefficients is identical to that in the models with a logged dependent variable. Standard errors are two-way clustered by household and day of the sample, shown in parentheses; *** 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: The first row and the second row of Column *reghdfe* contains the estimates from Specifications (C3) and (C4), respectively. The second column, *did_multiplegt*, shows the estimated treatment effect obtained after running the (C1) and (C2) commands in Stata. Standard errors are clustered by household, shown in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

CEWP 23-01

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

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