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, and accounting for the intraday distribution of the electricity savings is not important when measuring the social benefits of the program. As a policy recommendation, the study suggests implementing retail electricity prices fluctuating within a day.

Keywords: Peak Electricity Demand, Behavioral Nudge, Information Provision, 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 (Bulkeley, 2010; Broto and Bulkeley, 2013), including those 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). Residential electricity conservation programs frequently implement non-price information-based approaches that use insights from behavioral science. One of the reasons explaining the failure to engage in energy efficiency is imperfect information: consumers lack the relevant knowledge to demonstrate energy-saving behaviors, but the cost of obtaining such information could be high, which suggests that providing households with feedback on their electricity consumption can motivate them to undertake privately profitable investments in energy efficiency (Allcott and Greenstone, 2012; Delmas et al., 2013). Information interventions are cost-effective and demonstrate the reductions in electricity use equivalent to substantial electricity price increases (Allcott, 2011b; Allcott and Rogers, 2014; Brandon et al., 2019; Papineau and Rivers, 2022).

Not only the aggregate savings induced by an information nudge but also their distribution across hours of the day is important. 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. 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).

In the paper, 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.

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

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

periods.

My work builds on existing literature exploring the effectiveness of information provision to motivate electricity conservation. One strand of the research is focused on providing households with real-time feedback on their electricity consumption via in-home displays or smart thermostats. These studies present mixed evidence on whether the electricity savings from the adoption of real-time information are constant throughout the day (Harding and Lamarche, 2016; Martin and Rivers, 2018) or if the effect varies across hours (Houde et al., 2013; Jessoe and Rapson, 2014; Harding and Lamarche, 2016). The papers also show that the conservation behavior changes with outdoor temperatures (Harding and Lamarche, 2016; Martin and Rivers, 2018)[2]. Another group of studies tests the effect of information-based nudges targeted for overall electricity conservation as opposed to shifting usage to off-peak hours. Information about the environmental and health externalities of electricity production (Asensio and Delmas, 2015) or the arrival of an electricity bill (Gilbert and Zivin, 2014) induce the treatment effect that varies throughout a day and the outdoor temperature[3]. In addition, Brandon et al. (2019) simultaneously explore the effect of a social nudge promoting aggregate reductions in electricity use and the intervention motivating conservation during peak hours; the authors find that the two types of social nudges cause a decrease in peak load electricity consumption, and the effect of the nudges implemented in isolation is lower than when received in combination.

It is worth pointing out that 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).

My paper belongs to the second strand of the extant literature estimating the intraday impact heterogeneity of a behavioral nudge that does not explicitly aim at yielding this type of heterogeneity. Papineau and Rivers (2022) demonstrate that providing households with feedback on their energy use in the form of images (heat loss visualization[4]) induces larger aggregate energy conservation than the same information presented in figures and/or text (a 'traditional' home energy report). If the heat loss intervention promoted a stronger response at peak times, it would amplify its benefits even more. Evidence on the distribution of the heat loss treatment effects across hours is therefore particularly valuable.

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.

I find that households in Medicine Hat decrease their electricity usage due to the program

[2]The findings in Harding and Lamarche (2016) depend on a feedback technology: households with an in-home display do not show any variation in the savings across hours and outdoor temperatures, whereas the households receiving a smart thermostat engage in load shifting to off-peak hours and demonstrate treatment effects varying across days with different maximum temperatures.

[3]Asensio and Delmas (2015) do not study the effect across ambient temperatures. In addition, households in the second treatment group, which are provided with cost savings information, do not engage in any load-shifting behavior.

[4]Papineau and Rivers (2022) note that the intervention informs households about their energy consumption in terms of home heat loss, the approach to communicating energy use that is most customers are likely unfamiliar with. Due to the fact that the treatment combines visual depiction of information, heat loss framing and personalized energy efficiency messaging, the authors cannot point to which of the three components induces energy conservation and estimate the joint effect of the elements instead.

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. Contrary to the absence of the savings heterogeneity across hours, there exists a variation in the treatment effect across outdoor temperatures: relative to the control group, the treated households increase their electricity usage during periods of hot weather, which are associated with soaring electricity demand and wholesale prices. The findings suggest that the intervention fails to target the times that could potentially deliver the most socially efficient electricity conservation. To some extent, the results are consistent with the evidence in Martin and Rivers (2018) and Asensio and Delmas (2015). As a policy implication, incorporating time variation in the retail electricity rates could motivate households to shift their electricity usage to off-peak.

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.

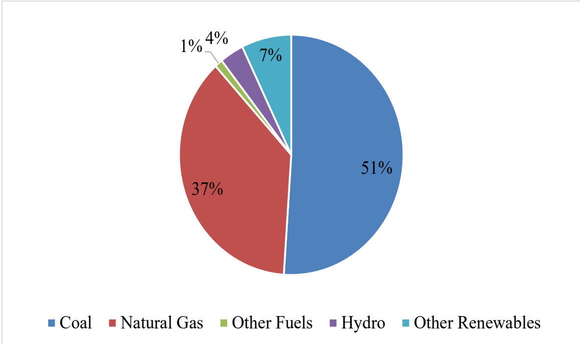
2 Background

2.1 Electricity Generation in Alberta

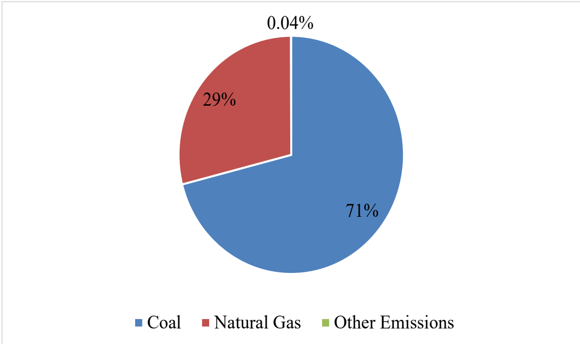
Fossil fuels are the primary source of electricity production in Alberta: as shown in Figure 1a, in 2018, the year overlapping the sample period, most of the electricity in the province was produced from coal (51%) and natural gas (37%). At the same time, fossil fuels, especially coal, are the main contributors 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 1b).

Figure 1: Electricity Generation and GHG Emissions from Electricity Generation by Source in Alberta in 2018

(a) Electricity Generation



(b) GHG Emissions



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

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)[5].

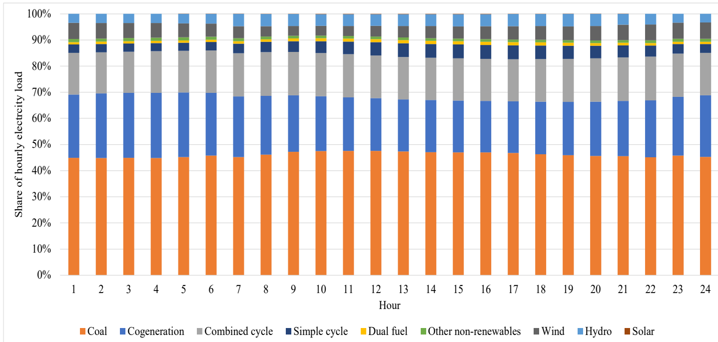
In Alberta, baseload technologies also include cogeneration and combined-cycle, both of which use natural gas as an energy source. In addition, there exist peaking generation technologies that operate using natural gas, such as combustion turbines used in simple-cycle gas generation (Alberta Electric 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, 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

[5]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.

hours (see Figure 2).

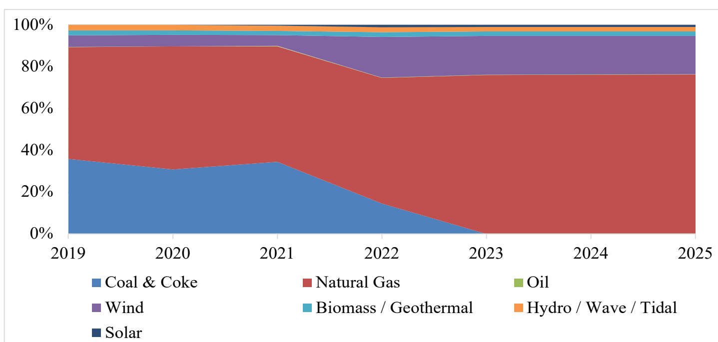
Figure 2: Hourly Electricity Generation by Source in Alberta in June - September 2018



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

However, coal-fired generation is scheduled to be gradually phased out by the end of 2023 (Government of Alberta, 2022b): Figure 3 shows that coal-fired power plants currently provide less than 20% of the province's electricity.

Figure 3: 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).

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 3). 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 off-peak and on-peak energy savings in terms of reducing pollution should become more prominent.

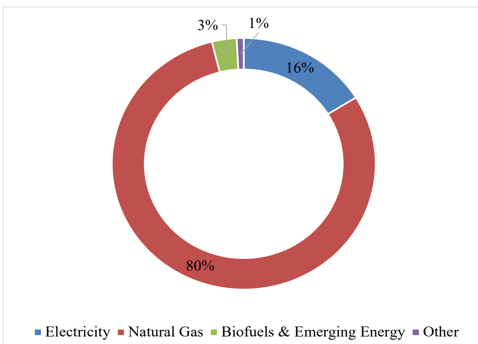
2.2 Electricity Consumption in Alberta

In Alberta, electricity comprised 7% of end-use energy demand in 2018, whereas natural gas with its 57% share was the largest fuel consumed in the province (Canada Energy Regulator, 2021). Most of the end-use energy demand was taken by the industrial sector, and the share of the residential sector was 6% (Canada Energy Regulator, 2021). Figure 4a shows that the residential sector primarily consumed natural gas, electricity was in the second place with its 16% share.

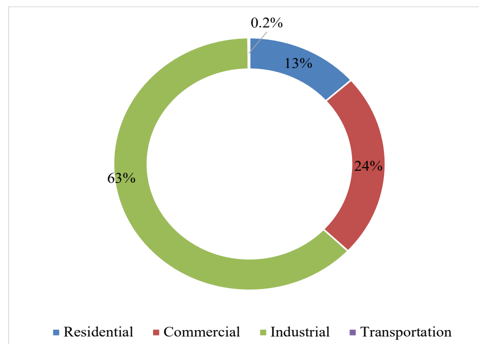
Overall, residential electricity consumption made up around 13% of the total electricity end-use in the province in 2018 (Figure 4b), and the share is predicted to increase to 15% by 2025 and 18% by 2050 (Canada Energy Regulator, 2021).

Figure 4: End-Use Demand in Alberta in 2018

(a) End-Use Energy Demand by Source in Residential Sector



(b) End-Use Electricity Demand by Sector

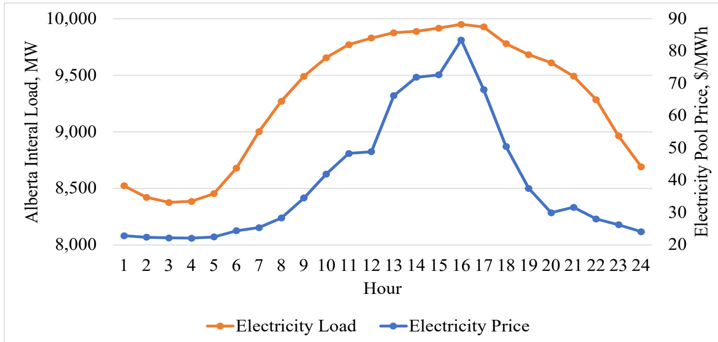


Notes: The residential sector primarily consumes natural gas; residential electricity consumption makes up 13% of the total electricity end-use. Source: Canada Energy Regulator (2021).

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 5). 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 5: 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).

So, with only constant retail electricity prices in place, studying if the information-based nudge, which aims for overall conservation, can also solve the problem of load curtailment during peak hours is of great interest. Most of the papers mentioned in Section 1 study the effect of information provision on electricity conservation across households that are not exposed to time-varying retail electricity rates. Only Martin and Rivers (2018) use the sample of residential customers on a time-of-use pricing schedule, and a time-of-use or critical-peak pricing scheme is part of the treatment in Harding and Lamarche (2016) and Jessoe and Rapson (2014), respectively.

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[6].

The experiment took place in Medicine Hat, Alberta, a mid-sized city with a population of about 60,000 people (Statistics Canada, 2021b) located in the southeast of the province (Appendix Figure A1).

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

Households in the treatment group were shown infrared images of their roof. Thermal images were acquired using the technology platform developed by a company called MyHEAT; they were taken at night in the heating season immediately before the experiment. Using the thermal images, each dwelling was assigned a heat loss score, or so-called HEAT Rating, ranging from 1 to 10, which indicates the amount of heat loss from the rooftop. The higher your home's

[6]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.

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 B 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[7] 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)[8]; this time range is chosen to capture the warmest part of the summer season in Medicine Hat.

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, 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 home-improvement rebates focus on changing the structural characteristics of the home and thereby improving a home's thermal envelope, so the households that have done these upgrades will benefit from them in summer too.

Recent literature also provides some insights on this matter. 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 main goal of the codes was heating savings (natural gas). However, the study region experiences higher summer temperatures compared to California as a whole, and the authors conclude that adopting the codes is also associated with electricity savings driven by reductions in cooling; moreover, the savings vary within a day (the savings are the largest in the afternoon and evening when demand for cooling is highest)[9].

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

[8] 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. Finally, I remove one household that has its treatment start date in December 2018. I drop around 6.6% of the total number of observations. Dropping the observations has not affected the balance statistics for the two groups.

[9] Murphy et al. (2021) show that building-envelope energy efficiency measures, including but not limited to installing

4 Analysis

4.1 Electricity Conservation by Hour

Before estimating the hourly distribution of electricity savings, I estimate the model that captures total electricity savings for the whole period of study[10]:

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

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_t is a post-treatment dummy variable[11]. The term μ_{ih} represents a household by an hour of the day fixed effect to account for any hour-specific differences between households, and the term λ_t indicates a day-of-sample fixed effect, which absorbs factors that shift over time and affect electricity demand (weather, seasonal changes, etc.). The error term is ϵ_{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[12]. The variable 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.

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):

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

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.

new windows, doors, or upgrading insulation, motivate hourly electricity savings that also vary within a day in both summer and non-summer seasons.

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

[11] The treatment started in the spring of 2018, and it 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. In addition, I do not observe the spring 2018 data.

[12] 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. Similarly, the post-treatment dummy, P_t, is omitted due to the presence of day-of-sample fixed effects in the model; its coefficient would represent how much the average electricity consumption of the control group has changed in the post-treatment period compared to the pre-treatment period.

The coefficient γ_1 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 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: General Regression Results

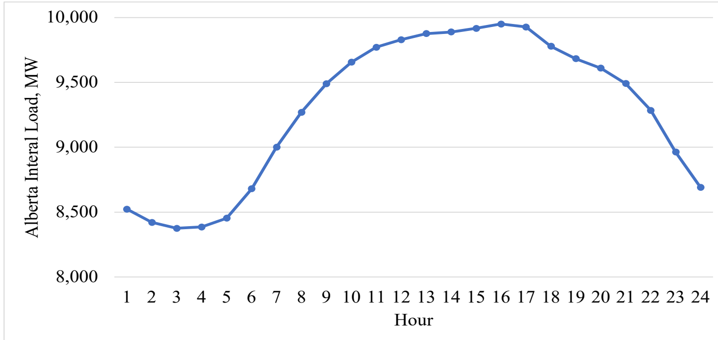
Dependent variable:	Hourly Electricity Use	
	(1)	(2)
Treatment, $T \times P$	-0.00672	0.05634***
	(0.00651)	(0.02118)
Treatment × Dollar Savings, $D \times T \times P$		-0.04128***
		(0.01390)
Observations	43,582,056	43,582,056
R-squared	0.49757	0.49766

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.

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 6 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 load[13], I define the on-peak period to be from 11 a.m. to 5 p.m.

[13] 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.

Figure 6: 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).

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:

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

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

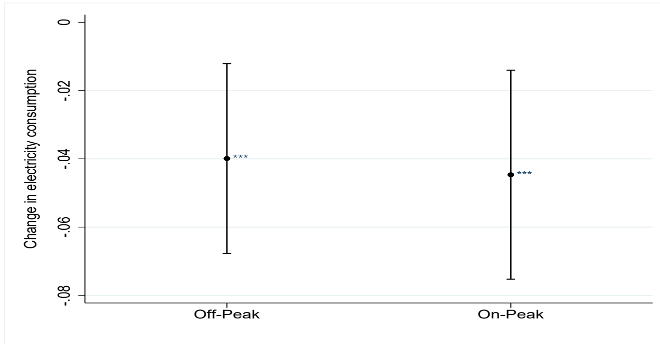
In Specification (3), I treat $D_{im} \times T_i \times P_t$ as a continuous variable due to the presence of the dollar savings D_{im}. So, when I interact the continuous variable with $TimeOfDay_{hd}$, I estimate the separate slope coefficients of $D_{im} \times T_i \times P_t$ for peak and off-peak 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 $T_i \times P_t$ even though $T_i \times P_t$ 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}).

Appendix Section C contains the results of the following robustness checks: in Table C1, I re-estimate Specification (3) using various combinations of fixed effects; in Table C2, 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[14].

Figure 7 shows the estimates of the coefficients θ_{1d} in Specification (3).

[14] In addition, estimating Specifications (1) - (4) 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.

Figure 7: 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.

Then, the Wald test is performed to see if the estimates shown in the figure are statistically significantly different from each other. The difference between the on-peak and off-peak savings shown in Figure 7 is not statistically significant. In other words, the treatment does not produce more electricity savings in on-peak hours than in off-peak times.

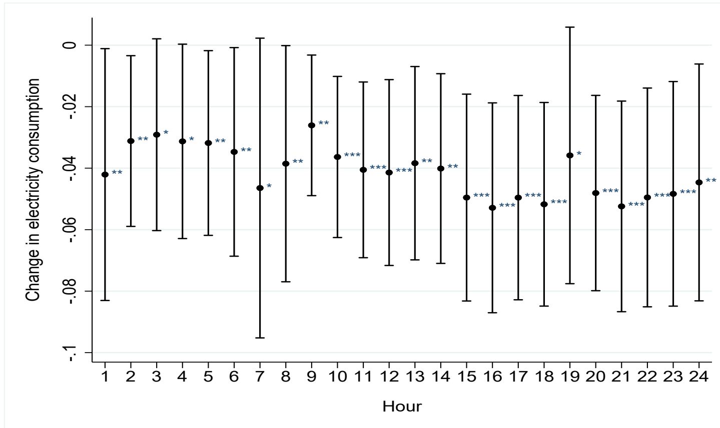
I then evaluate if consumers tend to use less electricity in some specific hours. Specification (4) is the same as Specification (3), except that the time-of-day variable is replaced with the indicator for each hour of the day:

$$Y_{ith} = \alpha_0 + \sum_{h=1}^{24} \alpha_{1h} D_{im} \times T_i \times P_t \times Hour_h + \sum_{h=1}^{24} \alpha_{2h} T_i \times P_t \times Hour_h + \mu_{ih} + \lambda_t + \epsilon_{ith}, \tag{4}$$

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.

The estimates of the coefficients α_{1h} in Specification (4) are presented in Figure 8.

Figure 8: Hourly Regression Results



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 (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.

I perform the multiple hypothesis testing of the pairwise difference between the hourly estimates with Holm-adjusted p-values[15]. The α_{1h} estimates are not statistically significantly different across 24 hours.

So, in addition to the fact that the households do not save more in peak hours, I do not observe any intraday variation in the electricity savings induced by the treatment[16]. This could be due to the fact that households respond to the treatment by forming electricity conservation habits as opposed to engaging in load-shifting behavior.

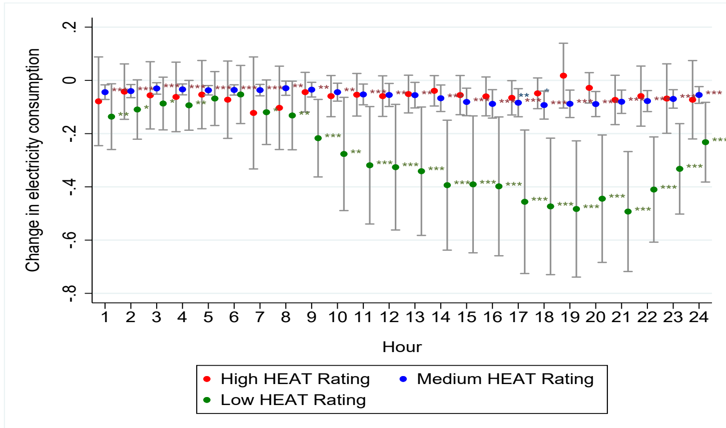
Let's see if this pattern changes depending on the heat loss score. I run Specification (4) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings[17]. The results of estimating the coefficient α_1, showing the change in electricity use in the treatment group per hundred dollars of non-zero estimated savings, are presented in Figure 9.

[15]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.

[16]In Appendix Section D, to further explore the behavioral pattern of the treated households, I check if the peak (hourly) electricity savings in weekends are different from those during weekdays. Households do not save more during weekends as opposed to weekdays, or vice versa.

[17]I am not able to include the HEAT Rating group as an interaction in Specification (4) due to the lack of computing power. This applies to all the specifications that test the treatment effect heterogeneity by the HEAT Rating group.

Figure 9: Hourly Regression Results by HEAT Rating Group



Notes: The figure shows the results of estimating Specification (4) 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.

Only the most energy-efficient households with the lowest HEAT Ratings save considerably more during peak and post-peak hours. Energy-efficient households may be more responsive to the treatment due to, say, being more environmentally conscious. 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. Figure 9 shows that households with high HEAT Ratings and the most populous medium HEAT Rating group still have relatively flat savings profiles, which explains why the treated households save the same amount of electricity across hours of the day on average.

4.2 Electricity Conservation by Temperature

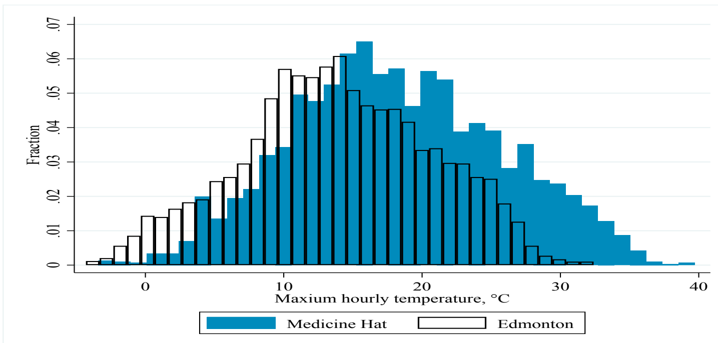
Next, I explore if households react to the heat loss information by adjusting their thermostats (changing the use of air conditioning) at certain times of the day. In particular, I estimate how the electricity savings in the summertime vary with ambient air temperature[18]. If the reductions in electricity use are due to thermostat adjustments, then I would expect the electricity conservation to be larger during the times with the highest average temperatures.

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). However, the study area is located in the southeast of the province (Appendix Figure A1), i.e. summers in Medicine Hat are warmer

[18]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; the temperature data is obtained from Government of Canada (2022b).

than those in Alberta as a whole, so the share of households using air conditioning could be higher than the provincial average According to Figure 10, during the summer months of 2017 and 2018, the maximum hourly temperatures in Medicine Hat went up to 39.7°C. For the sake of comparison, the figure also shows the outdoor temperature distribution for the City of Edmonton, located 500 km north of Medicine Hat, which saw cooler summers in 2017 and 2018.

Figure 10: Maximum Hourly Temperatures During Summer Months in Medicine Hat and Edmonton



Notes: The histogram shows the distribution of maximum hourly temperatures in Medicine Hat and Edmonton from June until September of 2017 and 2018. As seen in the figure, Medicine Hat has higher hourly summer temperatures than Edmonton, another city in Alberta, located approximately 500 km north of Medicine Hat.

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)[19] to the highest (40°C) temperature observed in the sample, and then I regress non-normalized hourly electricity use[20] on the hourly outdoor temperature:

$$Y_{ith} = \sum_{b=1}^{10} \phi_b TempBin_b + \mu_{ih} + \lambda_t + \epsilon_{ith}, \tag{5}$$

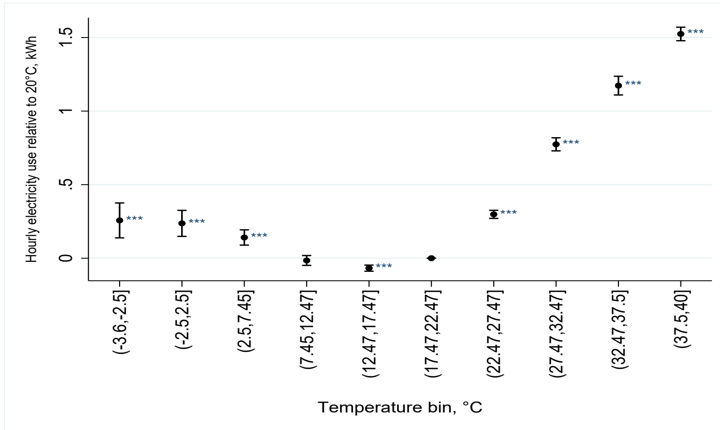
where $TempBin_b$ is a dummy variable for each temperature bin. The temperature bin $(17.5, 22.5]$ is the reference category, and I estimate the change in hourly electricity consumption relative to that category. The fixed effects and standard errors are the same as before.

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 11), which suggests that most of the households in the sample use air conditioning. For convenience, Appendix Figure A2 shows the average electricity consumption across the ten temperature bins.

[19] 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.

[20] In Specifications (5) and (7), I use hourly electricity consumption of the treatment and control 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.

Figure 11: Hourly Electricity Consumption and Outdoor Air Temperature



Notes: The figure shows the results of estimating Specification (5). 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 20°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.

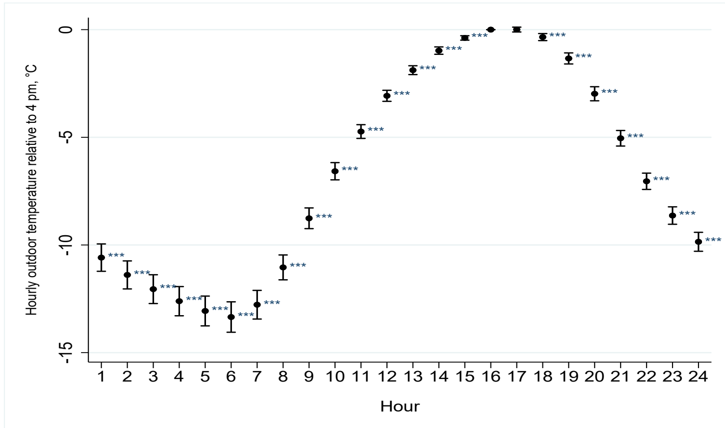
Then, I check how outdoor temperature changes within a day. I regress the average hourly outdoor temperature on a dummy that corresponds to each of the 24 hours of the day using day-of-sample fixed effects and clustering standard errors at the day-of-sample level:

$$T_{th} = \sum_{h=1}^{24} \omega_h Hour_h + \lambda_t + \epsilon_{th}, \tag{6}$$

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 12 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 Appendix Figure A3 presenting the variation in the average outdoor temperature within a day.

Figure 12: Outdoor Air Temperature: Hourly Variation



Notes: The figure shows the results of estimating Specification (6). 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.

Based on the results demonstrated in Figures 11 - 12, 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:

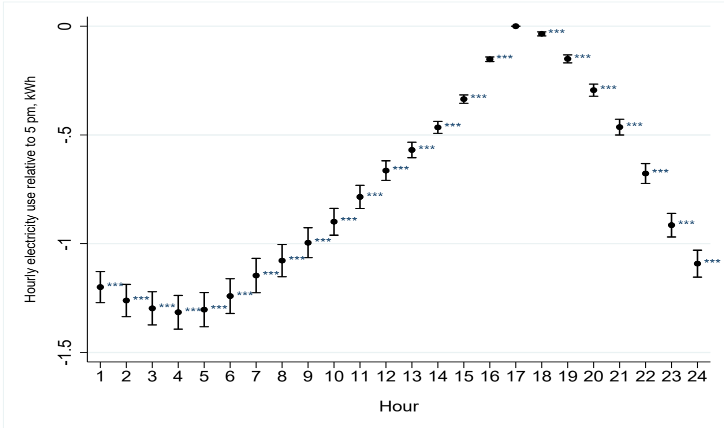
$$Y_{ith} = \sum_{h=1}^{24} \zeta_h Hour_h + \mu_i + \lambda_t + \epsilon_{ith}, \tag{7}$$

where the reference category is now $Hour = 17$, the hour with the highest average consumption during a day. The specification includes household (μ_i) and day-of-sample (λ_t) fixed effects.

Figure 13[21] confirms that electricity usage reaches its maximum around peak hours.

[21] Appendix Figure A4 shows the average electricity consumption for each of the 24 hours of the day.

Figure 13: Electricity Consumption: Hourly Variation



Notes: The figure shows the results of estimating Specification (7). 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.

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 peak hours. However, previously, I have found that households do not save more during peak periods.

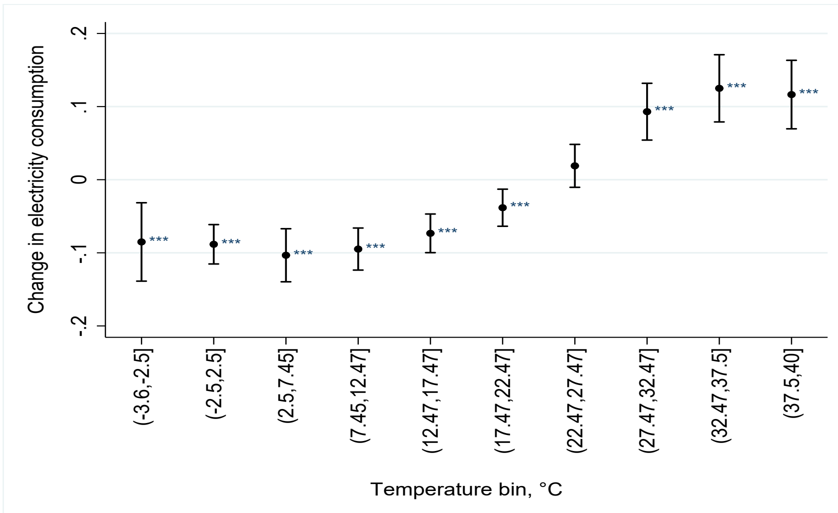
Finally, I re-estimate Specification (4) with the dummy for each hour of the day replaced by the dummy showing one of the 10 temperature bins generated above:

$$\begin{aligned} Y_{ith} = \chi_0 + \sum_{b=1}^{10} \chi_{1b} D_{im} \times T_i \times P_t \times TempBin_b \\ + \sum_{b=1}^{10} \chi_{2b} T_i \times P_t \times TempBin_b + \mu_{ih} + \lambda_t + \epsilon_{ith}, \end{aligned} \tag{8}$$

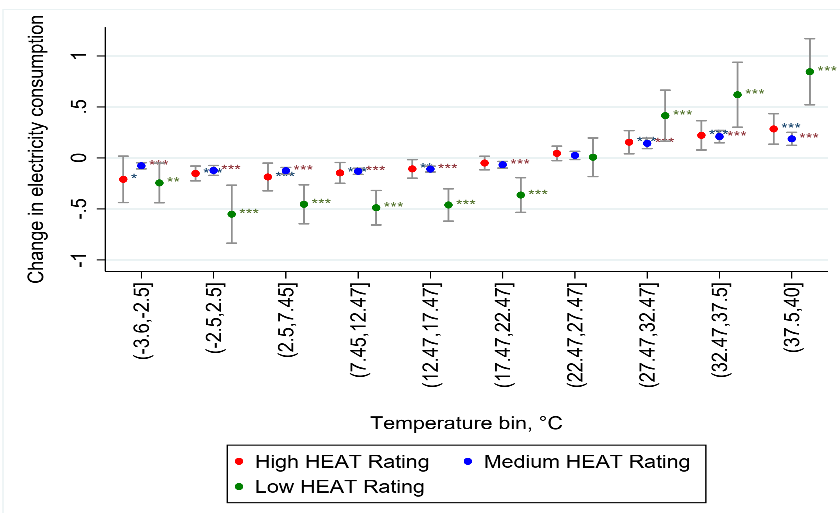
Figure 14a shows the estimated coefficients χ_{1b}. Previously, it was found that higher consumption corresponds to higher temperatures (Figure 11), and the latter concentrate around peak hours (Figure 12), so, naturally, households consume more electricity during times with warmer outdoor temperatures, i.e. in peak hours (Figure 13). 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 14a demonstrates the opposite. I observe that treated households save electricity relative to the control group when it is cooler outside, 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 (Appendix Figure A5). Figure 14b shows the results of re-estimating Specification (8) for households in each of the three HEAT Rating groups separately. One can observe that the pattern presented in Figure 14a is especially bright for the most energy-efficient households. Households respond to the electricity conservation during hours with relatively low to average temperatures by increasing their consumption when the outdoor temperature is high, and the most energy-efficient customers have the largest variation in electricity usage across temperature bins. As a possible explanation for this behavior, the treated households could be engaging in "moral licensing", i.e. performing an off-setting action triggered by a perceived good action (Harding and Lamarche, 2016), such as reductions in electricity use during milder temperatures. Households could also justify their 'bad' behavior by the fact that temperatures above 27°C are not common in the area (Figure 10).

Figure 14: Hourly Electricity Conservation and Outdoor Air Temperature

(a) Aggregate Electricity Conservation



(b) Electricity Conservation by HEAT Rating Groups



Notes: Figure 14a reports the estimation results for Specification (8), and Figure 14b shows the results of estimating Specification (8) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings. The specification is the same as Specification (4), 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.

4.3 Electricity Conservation by Week

Finally, 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 (Allcott and Rogers, 2014), which might give some insights into the nature of households' response to the information.

I again re-estimate Specification (4) with the hour dummy replaced by the dummy showing the week number in the pre and post-treatment periods:

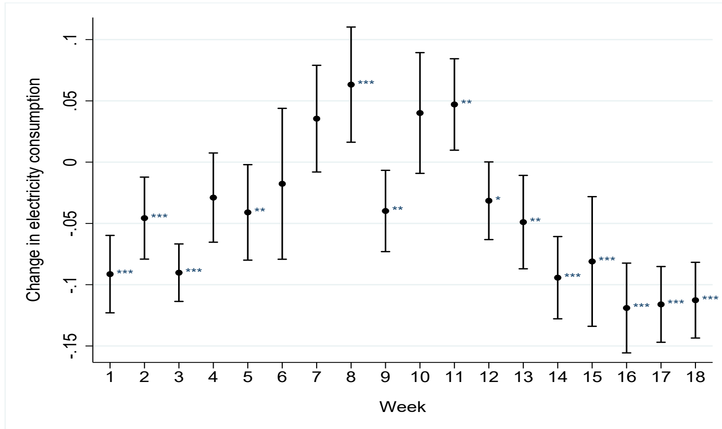
$$\begin{aligned} Y_{ith} = \eta_0 &+ \sum_{s=1}^{18} \eta_{1s} D_{im} \times T_i \times P_t \times Week_s \\ &+ \sum_{s=1}^{18} \eta_{2s} T_i \times P_t \times Week_s + \mu_{ih} + \lambda_t + \epsilon_{ith}, \end{aligned} \tag{9}$$

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.

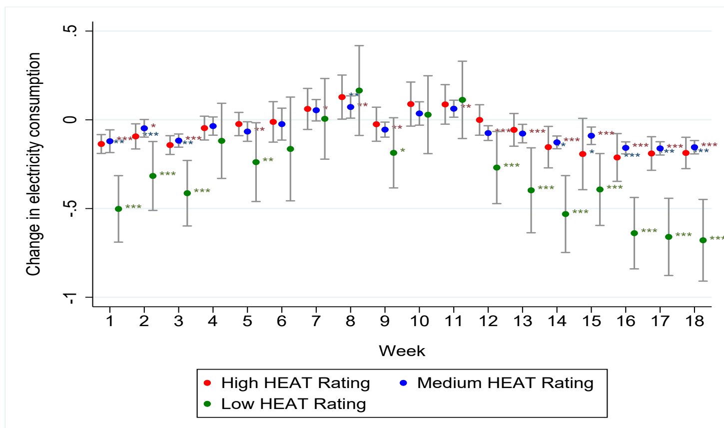
According to Figure 15a, the highest savings are concentrated around the first and the last weeks of the sample that correspond to the months of June and September, respectively. After I run Specification (9) for the three HEAT Rating groups of households separately, I observe that the pattern of increased electricity savings at the beginning and end of summer is the same across the three groups (Figure 15b) with larger effects for the most efficient households. The pattern observed in Figure 15a (Figure 15b) matches the one shown in Figure 14a (Figure 14b): 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 15: Hourly Electricity Conservation Changing During the Experiment

(a) Aggregate Electricity Conservation



(b) Electricity Conservation by HEAT Rating Groups



Notes: Figure 15a reports the estimation results for Specification (9), and Figure 15b shows the results of estimating Specification (9) separately for households with high (8-10), medium (4-7), and low (3 and less) HEAT Ratings. The specification is the same as Specification (4), 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.

Overall, as opposed to the savings heterogeneity across hours, there does exist temperature variation in the electricity conservation. The households save the same amount of electricity within a day demonstrating consistent electricity conservation. As for the outdoor temperature, although I do observe the variation in the savings across the temperature bins, this heterogeneity includes ‘anti-savings’ (i.e. the increase in electricity usage in the treatment group relative to the control 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 socially efficient consumption reductions.

4.4 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.

Boomhower and Davis (2020) 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% (the timing premium)[22]. The positive value of the timing premium indicates that accounting for timing increases the value of the estimated savings. 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[23].

The timing premium is calculated as follows:

$$
\begin{aligned}
Timing\ Premium &= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecAve \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}} \times 100\% - 100\% \\
&= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{PriceElecAve} \times 100\% - 100\% \qquad (10) \\
&= \frac{\frac{\sum_{h=1}^{24} PriceElecHour_h \times \alpha_{1h}}{\sum_{h=1}^{24} \alpha_{1h}}}{\frac{\sum_{h=1}^{24} PriceElecHour_h \times LoadElecHour_h}{\sum_{h=1}^{24} LoadElecHour_h}} \times 100\% - 100\%,
\end{aligned}
$$

where α_{1h} represents electricity savings in kWh in hour h; α_{1h} comes from re-estimating Specification (4) using non-normalized electricity consumption on the left-hand side[24]. $PriceElecHour_h$ 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

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

[23] 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).

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

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 \$41.21 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 1.28%. 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%[25]. 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.

5 Conclusion

By mid- and end-century, Canada will see a shift from winter-peaking to summer-peaking electricity grids due to climate change. All provinces are expected to exhibit a substantial increase in the range between minimum and maximum hourly electricity consumption within a day arising from larger air conditioner adoption and higher hourly temperatures in the peak of summer, making the flexibility of electricity consumption an important issue for the country in the long term (Rivers and Shaffer, 2020). In addition, achieving a net-zero electricity system requires continued decarbonization and electrification of Canada's economy, which may be associated with a supply adequacy risk due to increased peak capacity requirements. For example, in Alberta, 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). Therefore, identifying effective ways to lower electricity load during peak times is vital for Canada'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.

Even though there exists mixed evidence on the intraday electricity savings induced by information nudges (and this study adds more confusion to this body of research), social welfare is likely to increase from shifting to time-varying pricing. Exposing residential customers on

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

a flat retail electricity rate to exogenous within-day price changes is very likely to decrease electricity usage during peak hours (Allcott, 2011a; Jessoe and Rapson, 2014; Ito et al., 2018). 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). Switching residential customers to retail electricity prices varying within a day possibly coupled with some form of information 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).

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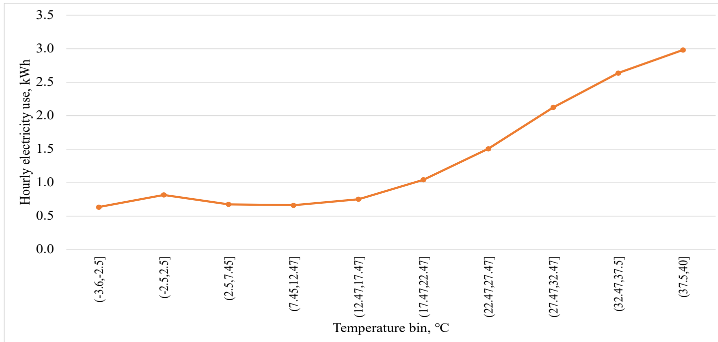
A Additional Figures

Figure A1: The Map of Alberta

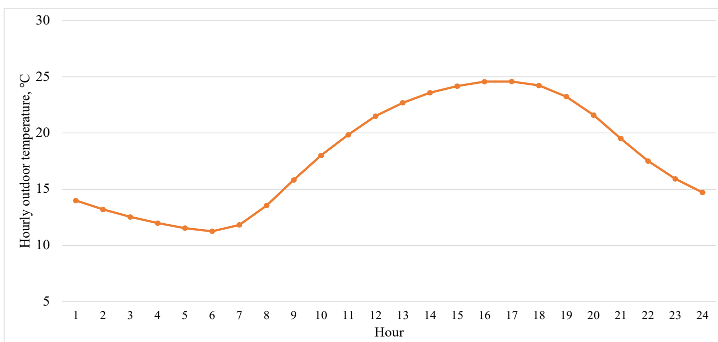
Notes: The map shows the province of Alberta. Medicine Hat is a mid-sized city located in the southeast of the province.

Figure A2: Average Hourly Electricity Consumption across Temperature Bins



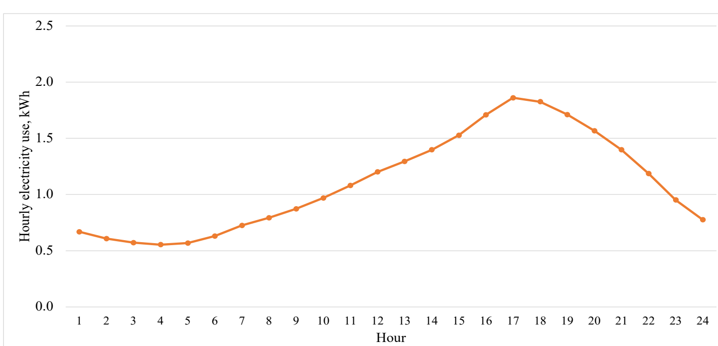
Notes: The figure shows the average electricity consumption across ten temperature bins. The average electricity consumption and the temperature bins are calculated for the period of June - September 2017 and June - September 2018. The pattern presented in the figure does not change if I use pre-treatment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

Figure A3: Average Outdoor Air Temperature across Hours



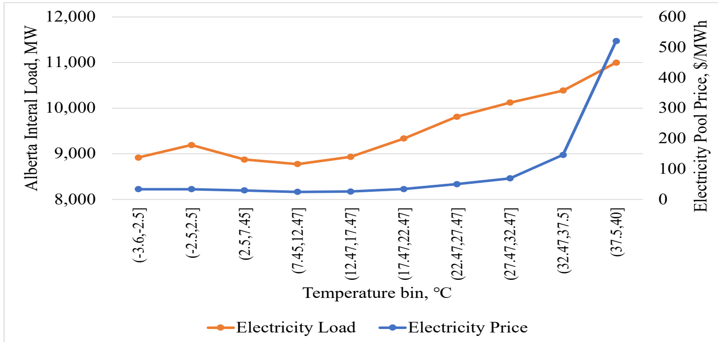
Notes: The figure shows the variation in the average outdoor temperature within a day. The average hourly temperature is calculated for the period of June - September 2017 and June - September 2018.

Figure A4: 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 A5: 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).

B Treatment Sample Bill

B.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

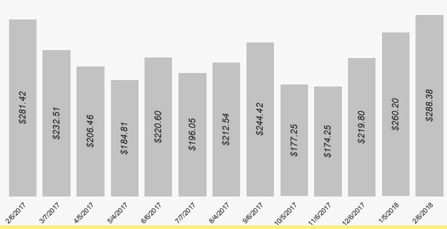
Utility bill for:

[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

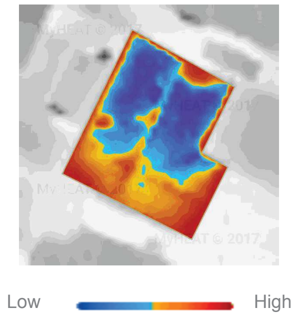
Amount on your last bill	260.20
Payment (Feb 1, 2018)	-260.20
Your balance forward	0.00

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

B.2 Page 2

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



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**.

C Robustness Checks

Table C1: 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)	(0.024)	(0.024)	(0.028)
On-Peak	0.059**	0.012	0.013	0.013
	(0.024)	(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)	(0.013)	(0.013)	(0.014)
On-Peak	-0.045***	-0.044***	-0.044***	-0.045***
	(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	43,582,056	43,582,056	43,582,056	43,582,056
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 C2: 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)	(0.022)	(0.033)	(0.028)
On-Peak	0.045**	0.060***	-0.001	0.028
	(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***	-0.042***
	(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	43,582,056	43,582,056	43,582,056	43,582,056
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.

D Weekends

I check how similar the peak electricity savings are in weekends as opposed to weekdays[26]:

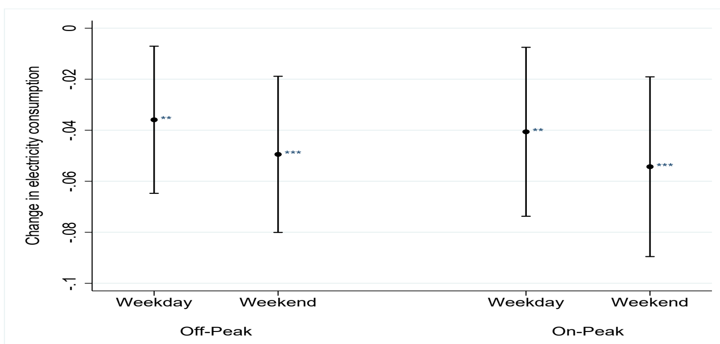
$$Y_{ith} = \kappa_0 + \sum_{w=1}^{2}\sum_{d=1}^{2} \kappa_{1dw} D_{im} \times T_{ik} \times P_t \times TimeOfDay_{hd} \times TimeOfWeek_{tw}$$
$$+ \sum_{w=1}^{2}\sum_{d=1}^{2} \kappa_{2dw} T_i \times P_t \times TimeOfDay_{hd} \times TimeOfWeek_{tw} + \mu_{ih} + \lambda_t + \epsilon_{ith}, \tag{D1}$$

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

Figure eports the estimation results for κ_{1dw} in Specification (D1).

Figure D1: Peak Regression Results: Weekends Vs. Weekdays



Notes: The figure reports the estimation results for Specification (D1). 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.

Then, the Wald test is performed to see if the estimates shown in the figure are statistically significantly different from each other. There is no statistically significant difference between the on-peak and off-peak savings during weekends or weekdays. In other words, households do not save more during weekends as opposed to weekdays, or vice versa.

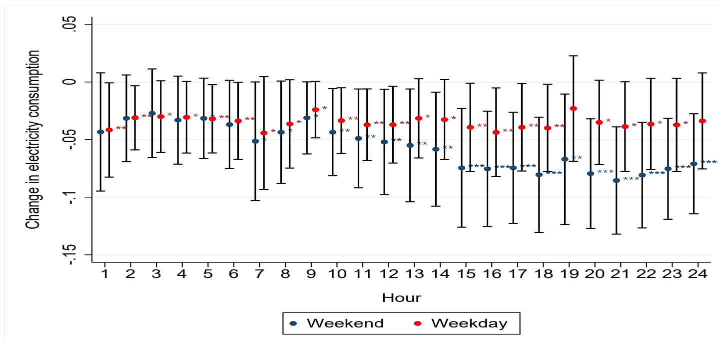
[26]There is no substantial difference in the electricity load dynamics during weekends compared to weekdays. As a result, the definition of peak hours stays the same.

In addition, I estimate Specification (4) separately for weekends and weekdays[27]:

$$\begin{aligned} Y_{ith} = \delta_0 &+ \sum_{w=1}^{2}\sum_{h=1}^{24} \delta_{1hw} D_{im} \times T_i \times P_t \times Hour_h \times TimeOfWeek_{tw} \\ &+ \sum_{w=1}^{2}\sum_{h=1}^{24} \delta_{2hw} T_i \times P_t \times Hour_h \times TimeOfWeek_{tw} + \mu_{ih} + \lambda_t + \epsilon_{ith}, \end{aligned} \tag{D2}$$

The estimates of the coefficients δ_{1hw} from Specification (D2) are shown in Figure

Figure D2: Hourly Regression Results: Weekends Vs. Weekdays



Notes: The figure reports the estimation results for Specification (D2), 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.

I perform the multiple hypothesis testing of the pairwise difference between the hourly estimates with Holm-adjusted p-values. Most of the δ_{1hw} estimates are not statistically significantly different across 24 hours during weekdays and weekends[28].

[27]Due to insufficient computing power, instead of using the interactions with $TimeOfWeek$ in Specification (D2), I have to estimate it separately for the weekend and weekday sub-samples of the data.

[28]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 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.

E Winter Data

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.

Table E1 contains the results of estimating Specifications (1) and (2)[29]. 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[30]. The value of the electricity savings is very similar to the one reported for the summer data.

Table E1: General Regression Results (Winter)

Dependent variable:	Hourly Electricity Use	
	(1)	(2)
Treatment, $T \times P$	-0.00204	0.05822***
	(0.00552)	(0.01255)
Treatment × Dollar Savings, $D \times T \times P$		-0.04072***
		(0.00849)
Observations	50,515,800	50,515,800
R-squared	0.46426	0.46440

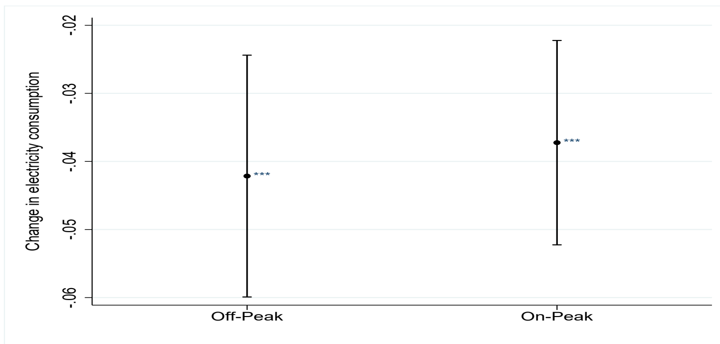
Notes: The table reports the results of estimating Specifications (1) – (2). The dependent variable represents hourly household electricity consumption. T is a dummy variable indicating a household's treatment status (i.e., whether a household belongs to the treatment group), P is a post-treatment dummy 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.

[29] The treatment messaging was first included on the February 2018 billing cycle. Due to differences in billing cycle schedules, different groups of treated households received their treatment on different dates. In such case, i.e. when heterogeneous treatment effects are present, recent academic literature (Goodman-Bacon, 2021; Sun and Abraham, 2021; de Chaisemartin and D'Haultfoeuille, 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. However, heterogeneous treatment effects could be less of an issue for a given study. The treatment effect is tested in an RCT, and the post-treatment dummy variable was generated considering the date when each of the treated households received their treatment messaging (in other words, staggered adoption is controlled in this experiment). In addition, the treated households first received the treatment bills during a relatively short period of time (several months in the spring of 2018).

[30] 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).

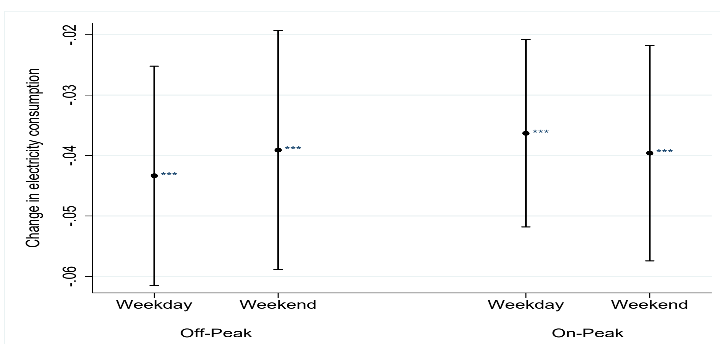
Figure E1 shows the estimates of the coefficients θ_{1d} in Specification (3), and Figure E2 reports the estimation results for κ_{1dw} in Specification (D1). On-peak hours are selected to be from 6 a.m. until 9 a.m. and from 4 p.m. until 6 p.m. The difference between the on-peak and off-peak savings shown in Figure E1 is not statistically significant; the same goes for the estimates in Figure E2 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 E1: 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 E2: Peak Regression Results: Weekends Vs. Weekdays (Winter)



Notes: The figure shows the results of estimating Specification (D1). 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.

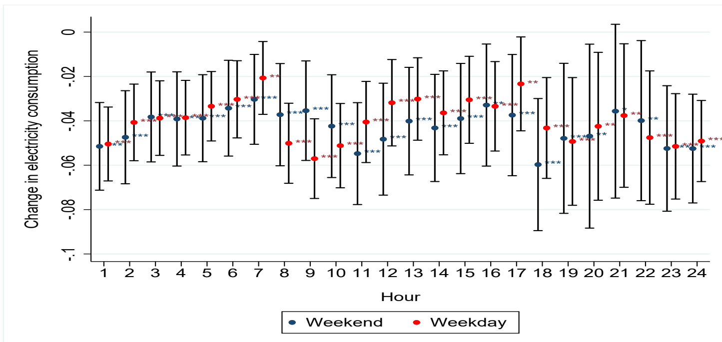
Table E2 reports the results of a robustness check. In particular, I re-estimate Specification (3) using different fixed effects. The coefficients of interest, θ_{1d}, are robust to changes in fixed effects.

Finally, Figure E3 contains the estimates of the coefficients δ_{1hw} from Specification (D2)[31]. In comparison to the results obtained using the summer data, there are some δ_{1hw} estimates that

[31] I was not able to estimate Specification (4) for the winter season due to insufficient computing power.

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 E3: Hourly Regression Results: Weekends Vs. Weekdays (Winter)



Notes: The figure reports the estimation results for Specification (D2). 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 E2: Peak Regression Specifications Test (Winter)

Dependent variable:	Hourly Electricity Use			
	(1)	(2)	(3)	(4)
Treatment, $T \times P$				
Off-Peak	0.059***	0.025	0.046***	0.053***
	(0.013)	(0.017)	(0.016)	(0.013)
On-Peak	0.057***	0.016	0.037*	0.070***
	(0.012)	(0.020)	(0.020)	(0.012)
Treatment × Dollar Savings, $D \times T \times P$				
Off-Peak	-0.042***	-0.035***	-0.036***	-0.042***
	(0.009)	(0.011)	(0.011)	(0.009)
On-Peak	-0.039***	-0.026**	-0.027**	-0.037***
	(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	0.511	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.