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Engineering Estimates versus Impact Evaluation of Energy Efficiency Projects: Regression Discontinuity Evidence from a Case Study

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Abstract
Energy efficiency upgrades have been gaining widespread attention across global channels as a cost-effective approach to addressing energy challenges. The cost-effectiveness of these projects is generally predicted using engineering estimates pre-implementation, often with little *ex post* analysis of project success. In this paper, for a suite of energy efficiency projects, we directly compare *ex ante* engineering estimates of energy savings to *ex post* econometric estimates that use 15-minute interval, building-level energy consumption data. In contrast to most prior literature, our econometric results confirm the engineering estimates, even suggesting the engineering estimates were too modest. Further, we find heterogeneous efficiency impacts by time of day, suggesting select efficiency projects can be useful in reducing peak load.

JEL codes: Q4
Keywords: energy efficiency, engineering-economic evaluation, peak load

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1 Introduction

Improving energy efficiency is an increasingly important component of energy policy in the United States and around the world. As a result, substantial resources are being funneled into energy efficiency projects and programs. For instance, two-thirds of the $825 million in revenue generated by Regional Greenhouse Gas Initiative in the Northeast United States through permit auctions since its inception through 2011 was directed into energy efficiency programs (RGGI Inc. 2012).

While many believe that improving energy efficiency is a cost effective way of reducing energy consumption, others (often economists) have found little empirical evidence of unexploited, profitable investments in energy efficiency – the so-called energy efficiency gap. Granade et al. (2009), in a report for McKinsey & Company, describe energy efficiency as a vast, low-cost resource worth over $1.2 trillion if upfront investment in efficiency measures through 2020 were executed at scale. However, Allcott and Greenstone (2012) argue that the gap is likely very small, in the order of 1-2% of energy use.

One of the sticking points at the heart of this debate centers on discrepancies between engineering estimates and econometric impact evaluations of energy savings. Dubin et al. (1986) and Nadel and Keating (1991) both found engineering estimates to be greatly overstated compared to ex post measurements, and hypothesized the discrepancy was due to price effects and inaccurate engineering estimation techniques. These early studies have proven highly influential in shaping economists' and others' perceptions of this debate, and there is a dearth of similar studies despite many years of programs since.

This paper seeks to augment the literature comparing engineering and econometric estimates by examining a case study for which we have *ex ante* engineering estimates of savings and we can estimate *ex post* savings using building-level energy use ("smart meter") data. Specifically, we examine three lighting equipment upgrades undertaken at the Naval War College in Newport, Rhode Island. In October 2009, Secretary of the Navy Ray Mabus announced five ambitious energy targets, and as result the Navy is now paying close attention to the energy factors of its operations (Mabus 2009). Among the targets was a goal to ensure that at least 40 percent of the Navy's total energy consumption comes from alternative sources by the year 2020. The high price points of current alternative energy sources led naval institutions to first minimize existing energy footprints.[1] To this end, over the past three years the Naval War College has been implementing various small scale projects—primarily lighting equipment upgrades—to reduce their electrical load. In addition to upgrading to more efficient bulbs, the suite of projects implemented at the War College employ technologies such as occupancy sensors, ambient light sensors and timers in order to reduce usage.

To empirically measure electricity consumption changes, we collected smart meter recordings of kilowatt hours (kWh) in 15 minute intervals over the span of 15 months for each project building on the Naval War College campus. The high frequency nature of the data enables two critical aspects of the present research. First, we are able to implement a regression discontinuity (RD) research design, with time as the forcing variable and the time of installation marking the discontinuity, to estimate reductions in electricity demand caused by lighting upgrades. Given that energy use is a function of many unobserved factors, RD is ideal for measuring the impacts of an installation.

The second critical aspect that the 15 minute interval data allow is an examination of how project impacts vary over the course of a day. While reducing total energy consumption is perhaps the most frequent goal of energy policy, reducing peak demand is another valuable objective. On a typical summer New England day, Joskow (2012) reports peak load production costs being over six times greater than at base load.[2] It is unknown to what extent the two goals of reducing total consumption and reducing peak load can be simultaneously achieved through energy efficiency projects, or if there are substantial tradeoffs, and our case study addresses this.

Our results suggest that measurable reductions in energy consumption can be achieved through simple lighting upgrades as demonstrated by three energy efficiency projects implemented and tracked at the Naval War College. The econometric results confirm the engineering estimates, even suggesting the engineering estimates were too modest for two of the three projects. We attribute the additional energy savings to behavioral spillovers in other parts of the building, such as employees and students being more mindful of turning off lights and computers, though we are unable to test this hypothesis.

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[1] Having achieved many reductions in energy use, the Naval War College is now planning to build 9 megawatts of wind capacity on or near campus to continue their renewable energy goals (Hence 2013).

[2] Seasonal and daily peak load require the existence of power plants that only produce during those times of need. Beyond the inefficiencies of having capital that is rarely in use, peak load is when the costs of supplying electricity as well as marginal CO_2 emissions per kilowatt hour are highest. Thus, there is an economic and a social imperative to reduce peak load consumption.

Our analysis of heterogeneous impacts by hour of day finds that energy reductions can vary substantially throughout the day. For one of the projects that we analyze, monetizing peak load reductions leads to a 25% increase in estimated benefits of the project compared to the estimated benefits using a flat electricity rate. While current research tends to emphasize the importance of dynamic pricing (e.g., Wolak 2011) and load management (e.g., Newsham et al. 2011) to reduce peak demand, our results suggest that certain efficiency projects can also address peak load. We discuss in detail the characteristics of these lighting projects that are determinants of peak demand reductions.

The main contribution of this paper is to offer new evidence on the relationship between engineering and econometric estimates of energy savings. Our results stand in contrast to the findings of many papers that find *ex ante* engineering estimates of benefits to be overstated when compared to their empirically derived *ex post* counterparts (Dubin et al. 1986, Nadel and Keating 1991, Joskow and Marron 1992, Metcalf and Hassett 1999). While we only present evidence from a case study, it is an important benchmark that these two types of estimates can indeed match. One possibility to explain consistency in estimates here but not in prior papers is that in this case there is not a significant possibility for a countervailing behavioral response. Further, there may have been methodological improvements over the past 25 years in the way engineers estimate savings (for our case study, these methods are described in Section 2). However, it is also likely easier to estimate savings from lighting compared to heating and cooling because leakage is not an issue.

A second contribution of this paper is to highlight methods and data for calculating energy savings from energy efficiency investments. When there is a discrete time of implementation, regression discontinuity is an ideal framework because identification of the treatment effect allows for unobserved variables – of which there are many when it comes to energy use. This method lends itself particularly well with high frequency readings from smart meters, which are becoming increasingly available and affordable. Further, RD, in conjunction with difference-in-differences or another approach that can examine long term adjustments, may prove valuable for disentangling immediate impacts versus behavioral changes that occur at a lag.

Lastly, our paper may contribute to the growing literature and understanding of the energy efficiency gap. Because the engineering and econometric estimates align, it appears that prior to the implementation of these three energy efficiency projects, there were unexploited, profitable investments that the Naval War College had at its disposal. One of the avenues by which the energy efficiency gap exists is through imperfect information. Anecdotally, it seems that the ambitious energy agenda set forth by Secretary Mabus initiated facilities managers to understand energy use better and seek out projects for reductions. However, there may be hidden costs such as administrative or managerial time or inconvenient changes in energy services that caused the Naval War College not to adopt these efficiency improvements earlier, and our data and analysis cannot speak to these hidden costs.[3]

The paper proceeds as follows. In Section 2, we describe in detail each of the three projects undertaken at the Naval War College, discuss key information about our data, and outline the empirical models used. Section 3 presents results and compares the *ex ante* engineering estimates with our *ex post* data driven estimates. Section 4 concludes with generalized discussion of the results and their implications.

2 Setting, Data, and Methodology

2.1 Description of Projects

In response to Secretary of the Navy Ray Mabus' aggressive energy reduction goals, the Naval War College of Newport, Rhode Island implemented a series of three energy efficiency projects. Each of the projects sought to improve efficiency via enhanced lighting technologies, lamp upgrades or through the implementation of occupancy and daylight sensors. Refer to Table 1 for a summary of the three projects undertaken.

To complete cost benefit analyses of these three projects, the facilities engineer led an engineering study of energy savings. The engineering estimation technique evaluated existing lighting loads directly by counting fixtures in the project areas, and recording the wattage of those fixtures. Average daily usage was estimated by planting logging devices that continuously monitored lighting activity throughout the week. Occupancy loggers were also used to map human activity in the project spaces throughout the day. All three lighting conservation projects

[3] Gillingham, Newell and Palmer (2009) identify and discuss a host of potential market and behavioral failures that are attributable to the existence of the energy efficiency gap. They offer a nice discussion of how investments can appear profitable to outsiders, but unmeasured physical costs, risks and opportunity costs may lead to non-adoption. As an example of this, Anderson and Newell (2004) analyze technology adoption decisions of manufacturing firms following energy audits and find that the firms adopt only half of the recommendations due to factors unaccounted for by the auditors.

called for occupancy sensors to switch lighting, so e*x ante* savings estimates were calculated by finding the average time difference between current lighting activity, and actual occupancy trends. One project also incorporated photo sensing technology in the switching solution alongside motion sensors. For this project, estimated savings also considered the temporal windows where spaces were occupied, but external lighting through windows was sufficiently high enough to safely hold internal lighting off. In another project where some fixtures were removed, these changes to maximum load were taken into account. Finally, the appropriate electrical rate was applied to calculate cost savings.

<u>Project A</u>

The first project implemented was a lighting upgrade in a large section of the college's library. The lighting within 27 library stacks was automated using infrared occupancy sensors. This was an ideal location for implementing motion sensors for several reasons. Firstly, routine observation suggested that occupants traffic this particular section of the library infrequently. Furthermore, banks of lighting were not being turned off before workers returned home in the evenings, before weekends or even long holidays. Infrared sensors with a narrow viewing angle and long range were installed on opposite sides of each library stack. Chains of fluorescent tube lighting contained within each stack would then switch on only after that particular stack was accessed by an individual either viewing or returning a book. The lights would remain on while the stack was occupied, and switch off one minute after the stack was vacated. One time installation costs of $5,492 for this project primarily constitute electrician labor, but also include the cost of the new sensors. *Ex ante* engineering estimates predicted an annual savings of 42,357 kWh and $4,725, using a flat electricity rate of 11.1¢ per kWh.[4] This project was implemented July 26th-30th, 2010.

<u>Project B</u>

The second project involved an overhaul of the lighting systems within a 17,700 square foot office building. This project entailed the removal of excessive lighting (140 lamps; 4,296 kW

[4] The rate of 11.1¢ per kWh does not reflect the true rate the Naval War College has negotiated, which is currently at 9.8¢ per kWh. We use 11.1¢ instead because this is the average cost of the production cost curve presented in Joskow (2012), which we importantly use to value energy reductions at different times of day. In order for our comparisons to be on equal footing, we use 11.1¢.

under load) as well as a reallocation of remaining lighting to maximize balance and occupant comfort.[5] Also included in the lighting upgrades was the installation of a series of occupancy sensors. The sensors employed infrared and ultrasonic technologies to switch lamps on as spaces became occupied, and hold them in that state for 15 minutes after being triggered. Sensors were installed in strategic locations to ensure intended function while minimizing the occurrence of false triggers. Installation costs for this project were $6,605, which were relatively high given the scale of this project due to more electrician labor hours. *Ex ante* engineering estimates indicated an annual savings of 9,223 kWh and $1,029. This project was implemented August 2-6, 2010.

<u>Project C</u>

This project improved lighting infrastructure in a long walkway connecting three of the college's buildings, and was designed to take advantage of the fact that the walkway was well lit on sunny days via numerous floor-to-ceiling windows. Despite the abundant daylight during most work hours, the hallway was lit continuously by 195 four foot fluorescent bulbs. Further, there was no ability to shut off the lights other than through a secured breaker box. The energy efficiency upgrade selected to address these issues featured two technologies. First, standard occupancy sensors send a trigger for lamps to switch on when human presence is detected. These lamps remain lit for 15 minutes to ensure safe passage throughout the walkway during evening hours. Second, a daylight sensor was installed, which blocked the switching trigger if ambient light from the windows met the safe-lighting level standard without the need for artificial lighting. Installation costs for this project were $6,768, which again was due mostly to electrician labor. *Ex ante* engineering estimates predicated an annual savings of 42,362 kWh and $4,726.[6] The sensors for this project were installed between August 21st-22nd, 2011. However, calibration of the multiple types of sensors persisted through September, with small adjustments made as late as December.

2.2 Data

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[5] Instead of just being about energy efficiency, this project may have changed the energy services and theoretically could have reduced worker utility. However, given our knowledge of the lighting before and after and anecdotal conversations with employees, we are confident that worker utility was unlikely to decline and may have increased.
[6] While the estimated impacts for the library and walkway projects are near identical, this is simply a coincidence. Each space is lit by the same style 4' 32 watt fluorescent lamps; the library saw lighting load reductions for 151 lamps, and the hallway for 181 lamps. Additional predicted reductions came from sensor type and use estimates.

The critical data needed to measure the impacts of the energy efficiency projects described in Section 2.1 are accurate measures of energy use before and after the implementation of the projects. While energy use data for just the section of buildings targeted by the projects were not available, we were able to attain energy consumption data at the building level. In-situ recording devices were built into the electrical meters feeding each project building on the Naval War College's campus. These smart meters recorded energy consumed, in kWh, over fifteen minute intervals, for every fifteen minute interval in a day, seven days a week. This energy consumption data is available for each project building from May 27, 2010 (the date of smart-meter installation) until March 2, 2012 (the date we downloaded the data.) This span of data covers a temporal window before and after the three projects were implemented.

In addition, we downloaded weather data, specifically daily average temperature and rainfall, for the town of Newport, Rhode Island from an online data center called Weather Underground.[7] Weather data may be an important control in our regression analysis for two reasons. First, Project C specifically has sensors related to sunlight, and we use rain as a proxy for scarce sunlight. Second, because we have building level energy consumption data, this aggregate measure includes HVAC distribution, as well as private heating and cooling behavior if the building set point is undesirable.

2.3 Empirical Models

Our empirical analysis seeks to estimate the impacts in terms of energy savings of the three energy conservation projects implemented on the Naval War College campus. The building-level energy consumption data downloaded from the modified electrical meters for periods of time both preceding and following the installation of each project are used to identify the respective impacts of those projects.

Since the energy conservation projects were implemented at a known point in time and the impacts of the projects are expected to be in full effect directly following implementation, we employ a regression discontinuity design to estimate project impacts, with time as the forcing variable and the date of implementation marking the discontinuity (Lee and Lemieux 2010). Our methodology is similar to Bento et al. (2012), who assessed the impacts of a temporal

[7] Website is www.wunderground.com

discontinuity in the high occupancy vehicle lane access policy on interstate travel times. Our first RD specification is

$$kwh_t = \beta \cdot post\_treatment_t + f(t) + \boldsymbol{X_t}'\boldsymbol{\delta} + \varepsilon_t \qquad (1)$$

where kwh_t is the fifteen-minute kilowatt-hour reading and $post\_treatment_t$ is a binary variable equal to one after the implementation. β is our coefficient of interest as it estimates the average kWh savings per 15 minute interval due to the project. Next in the equation is a polynomial function of time, $f(t)$, where

$$f(t) = \sum_{k=1}^{P} \gamma_{1k} \cdot t^k + \sum_{k=1}^{P} \gamma_{2k} \cdot t^k \cdot post\_treatment_t \qquad (2)$$

We include this term to flexibly capture time trends in kWh before and after implementation. The time variable was created such that time is continuous before and after implementation of the project, and the days in which the project was undergoing implementation have been removed. Further, we define time such that the project was completed at time zero, which guarantees that the full treatment effect will be captured by β since the second set of terms in Equation (2) will equal zero. Since each project was implemented at a different time, we essentially have different time variables for each project. We estimate models for both P=3 and P=4, i.e., cubic and quartic time trends before and after the installation, to allow flexibility and test robustness of results.

Lastly, Equation (1) includes a vector of controls, $\boldsymbol{X}$, to combat several potentially confounding factors. First, $\boldsymbol{X}$ includes a cubic polynomial for daily average temperature. While the energy projects examined have nothing to do with heating or cooling, our dependent variable captures energy use for an entire building, which will reflect heating and cooling needs. At the Naval War College warm and cool air is not directly generated by any of the three buildings, but energy is still consumed by the HVAC infrastructure distributing this air. Further, it is not uncommon for occupants to also use personal fans, heaters, coolers, humidifiers or dehumidifiers with variable frequency in response to temperature changes. Second, $\boldsymbol{X}$ includes an indicator variable equal to one when school is in session and an indicator variable equal to one when it is a weekend or federal holiday. These variables are intended to control for varying levels of human presence. Third, $\boldsymbol{X}$ includes an indicator variable term for each hour of the day. This captures normal variability in energy consumption experienced throughout the day.

We estimate Equation (1) for temporal window sizes of one, two, three and four months. We construct the windows such that equal portions of observations fall before and after project implementation. Due to the intrinsic complexity of energy use patterns within buildings, reducing window size aids in minimizing variation that is otherwise difficult to model. This is especially true for buildings where significant human presence, and thus human behavior, make up for a substantial portion of energy consumed. For these reasons, we generally prefer small window sizes that allow us to estimate project impacts while reducing the presence of variation attributable to unmodeled behavior.

The second model we estimate is:

$$
\begin{aligned}
kwh_t = &\sum_{k=0}^{23} \beta_{1k} \cdot I(hour = k) \cdot post\_treatment_t \\
&+ \sum_{k=0}^{23} \beta_{2k} \cdot I(hour = k) \cdot post\_treatment_t \cdot weekend\_holiday_t \\
&+ \sum_{k=0}^{23} \alpha_k \cdot I(hour = k) \cdot weekend\_holiday_t + f(t) + \boldsymbol{X_t}'\boldsymbol{\delta} + \varepsilon_t \qquad (3)
\end{aligned}
$$

This model allows the treatment effect to vary for each hour of the day for both weekdays and weekends. β_{1k} and β_{2k} are the coefficients of interest in this model and measure average kWh savings per 15 minute interval due to the project for days of typical and reduced human presence. $\boldsymbol{X_t}$ is the same as in Model 1. This heterogeneity enables us to examine if these projects designed for energy efficiency may additionally have benefits in terms of peak load reductions. By pairing the hour of day impacts with the true variable costs of providing electricity during the day, we can monetize the additional impacts of peak load reductions.[8]

While RD is ideal for measuring the energy impacts of Projects A and B, we evaluate Project C using a simple before-after estimator. As a result of an elongated sensor adjustment period, expectations of full impact directly following implementation are unrealistic, and use of a regression discontinuity framework to explore project impacts is questionable. Using before-after estimation, we make use of a much larger time horizon and include more controls. We estimate treatment effects for Project C using the model:

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[8] Full accounting of social benefits of these energy efficiency projects would take into account the social cost of power plant generation, including criteria pollutants and carbon dioxide, but that is beyond the scope of this paper.

$$kwh_t = \beta \cdot post\_treatment_t + \boldsymbol{X_t}'\boldsymbol{\delta} + \boldsymbol{Z_t}'\boldsymbol{\varphi} + \varepsilon_t \qquad (4)$$

As in the previous models, we regress our 15 minute energy consumption readings on an indicator variable for treatment and a vector of controls. In addition to $\boldsymbol{X}$, which is the same as in Equations (1) and (3), we introduce a set of controls unique to the analysis of Project C, labeled above as $\boldsymbol{Z}$. Included in this new term is a cubic function of daily precipitation. Because this project relies on daylight sensors, we use precipitation to control for the outdoor light levels entering through the windows. $\boldsymbol{Z}$ also includes month fixed effects to capture seasonal variation in energy use, as well as seasonal variation in ambient light.

Lastly, we additionally estimate a heterogeneous treatment effects model for Project C:

$$\begin{aligned} kwh_t = & \sum_{k=0}^{23} \beta_{1k} \cdot I(hour = k) \cdot post\_treatment_t \\ & + \sum_{k=0}^{23} \beta_{2k} \cdot I(hour = k) \cdot post\_treatment_t \cdot weekend\_holiday_t \\ & + \sum_{k=0}^{23} \alpha_k \cdot I(hour = k) \cdot weekend\_holiday_t + \boldsymbol{X_t}'\boldsymbol{\delta} + \boldsymbol{Z_t}'\boldsymbol{\varphi} + \varepsilon_t \qquad (5) \end{aligned}$$

3 Results

In this section, we present our empirical estimates for the energy savings of the lighting equipment projects, including models that allow for heterogeneous impacts by time of day. Finally, we compare our estimates of energy savings to the *ex ante* engineering estimates, and compare both to the costs of the projects.

3.1 Ex post estimates of energy savings

Project A

Table 2 presents the main results for Project A using Model 1. We run separate regressions for window sizes of one month, two months, three months and four months, with varied control suites. Results are shown for regressions using cubic and quartic polynomials of time. Each coefficient is interpreted as the average kWh reduction per 15 minutes due to the implementation of the project.

The first three columns of Table 2 use the one month time window and explore the impact of including various covariates, starting with none in Column 1, then adding a cubic of temperature and dummy variables for weekends, holidays, and whether school is in session in Column 2, and finally adding hour of day fixed effects in Column 3. Adding covariates increases R-squared, dramatically in the case of hour of day fixed effects, and tends to decrease the size of the treatment coefficient.

Columns 3 through 6 present models for time windows ranging from one to four months, each including all covariates. The results show large variability in the point estimates, ranging from -2.18 to -11.29.[9] However, five of the eight point estimates are in the smaller range -4.53 to -6.85, and each of these are statistically significant at the 1% level. We choose the three month window as preferred over the other windows since the point estimates are fairly consistent between the cubic and quartic time trend, and from that we choose the specification with the cubic time trend as preferred. Thus, our preferred estimate of the treatment effect is -4.53, which is interpreted as building-level energy consumption declining by 4.53 kWh after the implementation of the project. This is a 9% reduction in the average energy use for this building. Figure 1 presents a graphical form of the discontinuity for Project A. This graph was created by fitting a cubic curve to residual errors from a regression of kWh on all covariates except the time polynomial.

Figure 2 visually presents results for the second model, Equation (3), which allows for heterogeneous treatment effects by hour of day for both weekdays and weekends.[10] We use our preferred specification of a three month window with a cubic time polynomial. The figure plots estimated usage for every hour of the day before and after implementation of the project, and the difference between the two lines is the estimated savings. The results suggest that the largest impacts occurred during evening and weekend hours, which is consistent with intuition. On

[9] In an attempt to combat the substantial volatility in the treatment estimates from Table 2, we estimate similar models but additionally include lagged kWh in the specification, similar to Chen and Whalley (2012). The motivation with this model is threefold. First, lagged kWh is likely to have an enormous effect on current kWh due to the persistence of activities that occur in these campus buildings (and any building or residence). Second, to the extent that our covariates do not model variation in kWh well, including lagged kWh will substantially improve the fit of the model and perhaps decrease the volatility of the coefficient estimates. Third, the errors in Equation (1) may suffer from serial autocorrelation that clustering by day does not address. The results show that lag kWh is an extremely strong predictor of current kWh, however the total treatment effects are quite similar with the estimates in Table 2. Inclusion of lagged kWh had only a modest impact on the volatility of the treatment effect. These results, as well as results from models including lagged kWh for Projects B and C are available from the authors by request.

[10] We choose not to present the results in table form as there are an unwieldy 96 coefficient estimates that result from Equation (3). Regression output used to construct these figures can be obtained from the authors.

weekdays during typical working hours, human occupancy is at its highest and the book stacks are accessed with the highest level of frequency. During these hours, reductions in energy use are small or non-existent because the human presence is forcing lights on. The greatest reductions occur throughout the night and on weekends and holidays where the sensors are triggered less frequently.

Figure 2 additionally plots real-time energy prices in order to gauge how the reductions associated with this project correspond to peak load. The price curve was constructed by Joksow (2012) for July 7th, 2010 in New England and reveals the sheer magnitude (a factor of six) in which energy prices can deviate throughout the day as a result of increasing marginal costs of production. Additionally, the energy use patterns for this building display similar fluctuations through the course of the day, thus confirming intuition about peak demand. Matching the estimated reductions to the cost curve, we can calculate the benefits of the project in terms of the true cost of production. As Project A's largest reductions tend to occur during off peak hours, accounting for the variable cost of energy generation actually decreases the monetary benefits of this project by 10% (see Table 5 and the discussion in Section 3.2).

Project B

Table 3 presents the main results for Project B using Equation (1). As with Table 2, Columns 1 through 3 explore the impact of including different control variables. Including a cubic of temperature and the indicator variables for weekends, holidays, and school in session has a dramatic effect on the treatment effect coefficients, in one case changing the sign from positive to negative, in the other case just making the coefficient more negative, and in both cases making the coefficient statistically significant. This confirms intuition that covariates are more important with Project B as this is where there is the most human influence over energy consumption. Including hour of day fixed effects increases R-squared and decreases the size of the treatment coefficient, consistent with the results from Project A.

Columns 3 through 6 present models for time windows ranging from one to four months, each including all covariates. The eight coefficients presented in those four models range from -0.74 to 0.36. As the time window grows, the coefficients become less negative, even becoming positive in some cases, and lose statistical significance. We interpret these findings as our empirical model being inadequate to control for human behavior (again because of human behavior) through changing seasons. Consequently, we choose one month for our preferred time window for Project B, and in addition choose the cubic polynomial. Thus, our preferred estimate of the treatment effect is -0.53, which is interpreted as building-level energy consumption declining by 0.53 kWh after the implementation of the project. This is a 13% reduction in the average energy use for this building. Figure 3 presents a graphical form of the discontinuity for Project B. This graph was created by fitting a cubic curve to residual errors from a regression of kWh on all covariates except the time polynomial.

Figure 4 visually presents results for Equation (3), which allows for heterogeneous treatment effects by hour of day for both weekdays and weekends/holidays. We use our preferred specification of a one month window with a cubic time polynomial. The results suggest that the largest impacts occurred during daytime hours. These results fit in with our intuition, given some previous knowledge of the project building. In this small office, occupants reported having turned lights off lights when leaving the office at the end of the day manually before the installation of Project B. For this reason, we did not expect to see savings from the automated system throughout the night. However, we do notice savings throughout the day, which suggests that occupants were not turning off lights while stepping away from their workspaces throughout the day, and that the removal of fixtures had some impact.

Comparing the heterogeneous treatment effects with the variable energy prices suggests that the benefits of this project increase as Project B’s largest reductions tend to occur during peak hours. Monetizing the peak load reductions causes estimated benefits to increase by 14% over a flat electricity rate (see Table 5 and the discussion in Section 3.2).

Project C

Table 4 presents the main results for Project C using Equation (4). Similar to Tables 2 and 3, the columns of Table 4 explore the impacts of including various covariates. In contrast to earlier results, however, the coefficient estimates are remarkably stable. Excluding Column 1, which does not include any covariates, treatment effect estimates range from -1.65 to -1.51. Further, all estimates are statistically significant at the 1% level. We choose Column 5, the model with all covariates, as preferred. Thus, our preferred estimate of the treatment effect is -1.51, which is interpreted as building-level energy consumption declining by 1.51 kWh after the implementation of the project. This is a 7% reduction in the average energy use for this building.

Figure 5 visually presents results for Equation (5), which allows for heterogeneous treatment effects by hour of day for both weekdays and weekends/holidays. We use our preferred specification which includes temperature cubic, precipitation cubic, a school in session term, and monthly fixed effects. The results suggest that the largest impacts occurred during daytime hours, both on weekdays and weekends. These results are in line with intuition. We see the greatest savings during the brightest hours of the day, which suggests that the daylighting controls are effective at keeping lights off while the hallway is bright enough not to necessitate them. However, we see few energy reductions throughout the night. Information we gathered on the influence of human behavior for this project helps to explain this occurrence. The hallway is the main point of access to several buildings on base, and it is regularly frequented by security guards who perform rounds throughout the night. For this reason, lights are being triggered, and savings during nighttime and early morning hours are minimal.

Comparing the heterogeneous treatment effects with the variable energy prices suggests that the benefits of this project increase as Project C's largest reductions tend to occur during peak hours. Monetizing the peak load reductions causes estimated benefits to increase by 25% over a flat electricity rate (see Table 5 and the discussion in the next section).

3.2 Comparing engineering to econometric estimates

Table 5 compares *ex ante* engineering estimates to *ex post* econometric estimates of kWh and dollar savings for each project. Empirical treatment effects are given for 'Total', which is derived from Equations (1) and (4), and 'Hourly', which is derived from Equations (3) and (5). kWh savings are converted into dollar savings using a flat cost of electricity for all entries except the last in each group, 'Hourly (variable energy prices)', where Joskow's (2012) typical daily cost curve is used.

For each of the three projects, we see that the empirical total treatment effect exceeds the engineering estimate. By confirming the engineering estimates, the empirical results offer support that implementation was cost-effective. For Project C, the engineering and econometric estimates are very similar, however, for Projects A and B, the econometric estimates are substantially larger than the engineering estimates. We know that the engineering estimates were made to be conservative, but not erroneously so. One possibility is that implementation of high profile projects led to energy conserving behavioral spillovers in other parts of the building.

Given the psychology of the Navy and the fact that the Secretary of the Navy proclaimed ambitious energy goals, these projects may have caused individuals to try and conserve energy in other ways.

Of the three projects, Project A and C offered the highest returns on the initial investments, as estimated by both engineering and empirical estimates of savings. The swift payback period for Project A, as shown in Table 1, was achieved because simple, inexpensive sensors switching several lights were employed in a space with very low human traffic. Similar savings were achieved in Project C, despite more frequent foot traffic, because photosensors ensured that lights would remain off during daylight hours, regardless of human presence. We see a much longer payback in Project B, which had a lower sensor-to-lights-controlled ratio, in a higher traffic location, and wasn't able to incorporate photosensors. Also, as sensors were installed in small office rooms, electricians had to constantly relocate their tools and supplies which proved tedious.

The engineering cost savings were calculated using a constant price of electricity because that is how the Naval War College pays. However, if these efficiency investments can also reduce energy use during peak demand hours, the projects offer additional social benefits and, in a larger sense, speak to whether efficiency and peak load goals can be simultaneously achieved. First, comparing empirically estimated savings for Total and Hourly, we see that the kWh estimates are nearly identical. This is as it should be since the models are nearly the same. The important difference is that the Hourly model allocates the Total savings to the correct hours of the day. Second, we can compare the dollar savings from the Hourly model with flat energy prices to the Hourly model with variable energy prices in order to monetize the hourly allocation of reductions. For Project A, savings in dollars decline by about 10% when accounting for variable energy costs. However, Projects B and C show increases in dollar savings of 14% and 25%, respectively, suggesting these projects offer substantial additional social benefits beyond the reduced kWh. The key to the daytime-weekday energy reductions for these projects were daylight sensors coupled with abundant ambient light (for Project C) and motion sensors in an environment where lights may be needed only intermittently through the day (Project B). In both cases, but certainly in the case of Project C, these technologies could be employed elsewhere to achieve similar results.

4 Conclusions

This paper takes advantage of a unique opportunity to compare *ex ante* engineering estimates to *ex post* econometric estimates of energy savings for three energy efficiency projects at the Naval War College. Our econometric estimates suggest that each project succeeds in reducing energy consumption in their respective buildings, and the magnitudes of savings are actually higher than their respective *ex ante* engineering estimates. By confirming the engineering estimates, the results contrast to the findings of other authors who find that engineering estimates overstate realized savings (e.g., Dubin et al. 1986, Nadel and Keating 1991, Joskow and Marron 1992, Metcalf and Hassett 1999) and may help update conventional wisdom about disparities between these types of estimates.

We use 15 minute interval energy consumption data, and the high frequency nature of the data allows us to go beyond validating the engineering estimates and assess the extent of peak load reductions. Because the marginal costs of energy production are highest during typical working hours, energy reductions during these times offer additional social benefits. We estimate models that allow for heterogeneous treatment effects by hour of day for both weekdays and weekends and find substantial differences in energy reductions across time. Using cost of electricity production data, we were able to monetize the additional benefits from peak load reductions and found that two of our three projects caused peak load reductions that could be valued at up to 25% of annual savings. Consideration of such social benefits in project development would be a meaningful step in the right direction towards addressing important global energy and economic challenges.

While our ability to access accurate, high-frequency recordings of building-level energy consumption as well as *ex ante* cost benefit analysis data allowed us to meaningfully pursue advances in the current literature, our data did present us with limitations. Separating project impacts from normal building-level variability and human behavior presented a challenge. The regression discontinuity framework is ideal to address unmeasured variables related to human behavior, but some of the results were still curious. Future studies could benefit from the collection of site-level human behavior data such as work schedules, computer use practices and some measure of personal reaction to the implementation of energy reduction projects within the workspace, the introduction of which could modify occupant behavior in either beneficial or destructive ways.

While this paper provides a rare comparison of engineering and economic estimates of energy savings, it is only a case study. However, due to the prominence of energy efficiency at the local, state, and national level and the increasing availability and affordability of smart meters, we hope and expect that this type of *ex post* verification will become more common. Through a wealth of experience, researchers can disentangle various factors that drive realized benefits and the efficacy of energy efficiency projects can increase. Further, methods of calculating *ex ante* estimates of energy savings may be refined if through experience it is found that some methods of evaluation lead to over- or under-estimates.

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Table 1: Project summaries

Project description	Average 15-minute kWh reading pre-installation	Engineering estimates			
		Installation costs	Annual kWh savings	Annual dollars saved	Payback period (years)
(A) Library: 27 library stacks were populated with infrared occupancy sensors. Pre-implementation, lamps remained lit. Post-implementation, lamps within a bookstack are lit only when human presence is sensed within the stack. The project was implemented July 26-30th, 2010.	51.00	$5,492	42,357	$4,725	1.32
(B) Office: A small office was populated with occupancy sensors. Excessive lighting was removed, and remaining lighting was reallocated to provide an even balance. The project was implemented Aug. 2-6th, 2010.	5.21	$6,605	9,223	$1,029	7.31
(C) Hallway: A long hallway with many windows was populated with occupancy and daylight sensors. Pre-implementation, lamps remained lit. Post-implementation, lamps will energize for fifteen minutes when the hallway is both occupied, and internal lighting conditions including sunlight from windows, are dimmer than the Navy lighting standard. The project was implemented Aug. 21-22nd, 2011.	20.33	$6,768	42,362	$4,726	1.63

Source: Authors' data.

Table 2: Regression Discontinuity estimates of energy savings for Project A

	Time Window					
	1 month			2 months	3 months	4 months
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Third order polynomial						
post_treatment	-7.69	-7.99	-6.85	-5.38	-4.53	-2.18
	(4.48)	(2.12)***	(2.11)***	(1.58)***	(1.48)***	(2.10)
R-squared	0.04	0.19	0.85	0.84	0.84	0.83
Panel B: Fourth order polynomial						
post_treatment	-5.73	-4.38	-3.12	-11.29	-6.26	-5.69
	(7.53)	(2.27)*	(1.96)	(2.75)***	(1.52)***	(1.63)***
R-squared	0.11	0.19	0.85	0.84	0.84	0.83
Observations	2880	2880	2880	5760	8640	11459
Temperature cubic, weekend, holiday and school in session	N	Y	Y	Y	Y	Y
Hour of day fixed effects	N	N	Y	Y	Y	Y

Notes: Each coefficient comes from a separate regression of Equation (1). Standard errors are shown in parentheses and are estimated using the Eicker-White formula to correct for heteroskedasticity and are clustered at the day level. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 3: Regression Discontinuity estimates of energy savings for Project B

	Time Window					
	1 month			2 months	3 months	4 months
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Third order polynomial						
post_treatment	0.32	-0.80	-0.53	-0.21	0.36	0.22
	(1.34)	(0.32)**	(0.28)*	(0.28)	(0.28)	(0.28)
R-squared	0.04	0.21	0.68	0.65	0.65	0.65
Panel B: Fourth order polynomial						
post_treatment	-0.36	-0.94	-0.74	-0.23	-0.20	0.25
	(1.93)	(0.39)**	(0.24)***	(0.43)	(0.30)	(0.30)
R-squared	0.12	0.21	0.68	0.66	0.65	0.65
Observations	2880	2880	2880	5760	8640	11520
Temperature cubic, weekend, holiday and school in session	N	Y	Y	Y	Y	Y
Hour of day fixed effects	N	N	Y	Y	Y	Y

Notes: See notes to Table 2.

Table 4: Before-after estimates of energy savings for Project C

	(1)	(2)	(3)	(4)	(5)
post_treatment	-2.63	-1.65	-1.65	-1.51	-1.51
	(0.31)***	(0.25)***	(0.25)***	(0.29)***	(0.29)***
R-squared	0.03	0.17	0.17	0.24	0.40
Temperature cubic, weekend, holiday and school in session	N	Y	Y	Y	Y
Precipitation cubic	N	N	Y	Y	Y
Month FE	N	N	N	Y	Y
Hour of day FE	N	N	N	N	Y

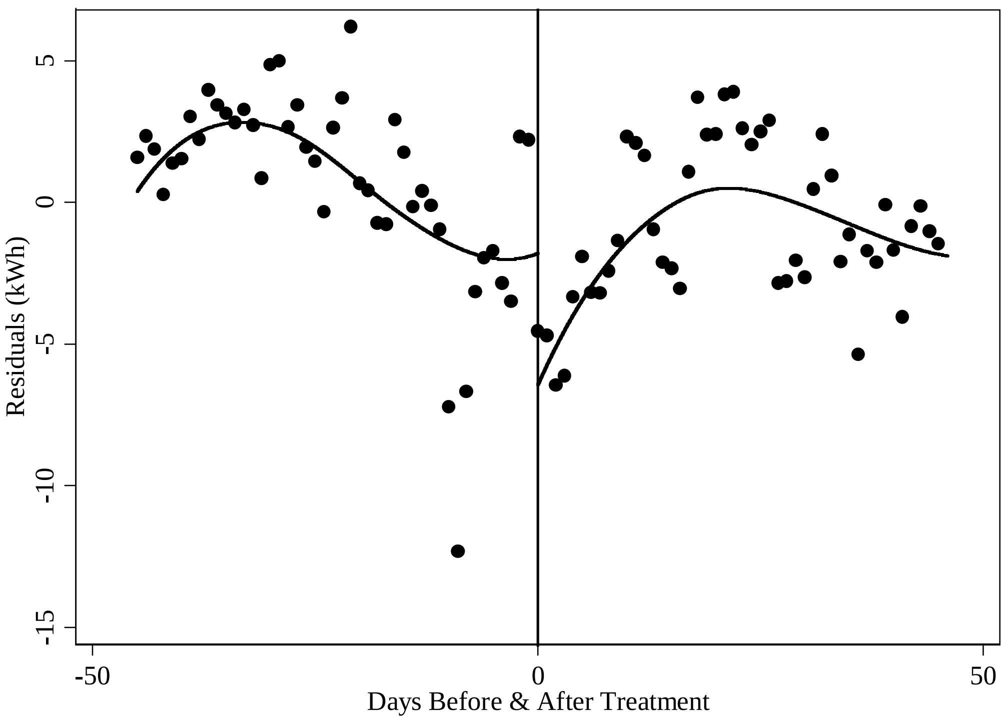
Notes: All regressions come from an Equation (1) specification. There are 61,627 observations. Standard errors are shown in parentheses and are estimated using the Eicker-White formula to correct for heteroskedasticity and are clustered at the day level. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 5: Result summaries

Project	Estimating method	Treatment effect measurement	Estimated annual savings	
			kWh	dollars
(A) Library	Engineering	Total	42,357	$4,725
	Empirical	Total	158,865	$17,723
		Hourly (flat energy price)	158,531	$17,686
		Hourly (variable energy prices)	158,531	$15,950
(B) Office	Engineering	Total	9,223	$1,029
	Empirical	Total	18,608	$2,076
		Hourly (flat energy price)	18,977	$2,117
		Hourly (variable energy prices)	18,977	$2,419
(C) Hallway	Engineering	Total	42,362	$4,726
	Empirical	Total	52,910	$5,903
		Hourly (flat energy price)	52,968	$5,909
		Hourly (variable energy prices)	52,968	$7,365

Notes: Empirically derived 'Total' savings come from our preffered specification of Equation (1) detailed in the text for Projects A and B and Equation (4) for Project C. Estimated "Hourly" savings come from Equation (3) for Projects A and B and Equation (5) for Project C. kWh savings are translated into dollar savings using a flat rate of 11.2¢/kWh for "Total" and "Hourly (flat energy price)" and the Jaskow (2012) hourly prices for "Hourly (variable energy prices)".

Figure 1: Regression discontinuity diagram for Project A



Notes: Points on the graph are daily averages of residuals from a regression of kWh on all covariates in Equation (1) except the time polynomial. The curve is a third order polynomial interacted with an indicator variable for after treatment fit to the residuals.

Figure 2: Hourly kWh reductions for Project A

Figure 2A: Weekdays

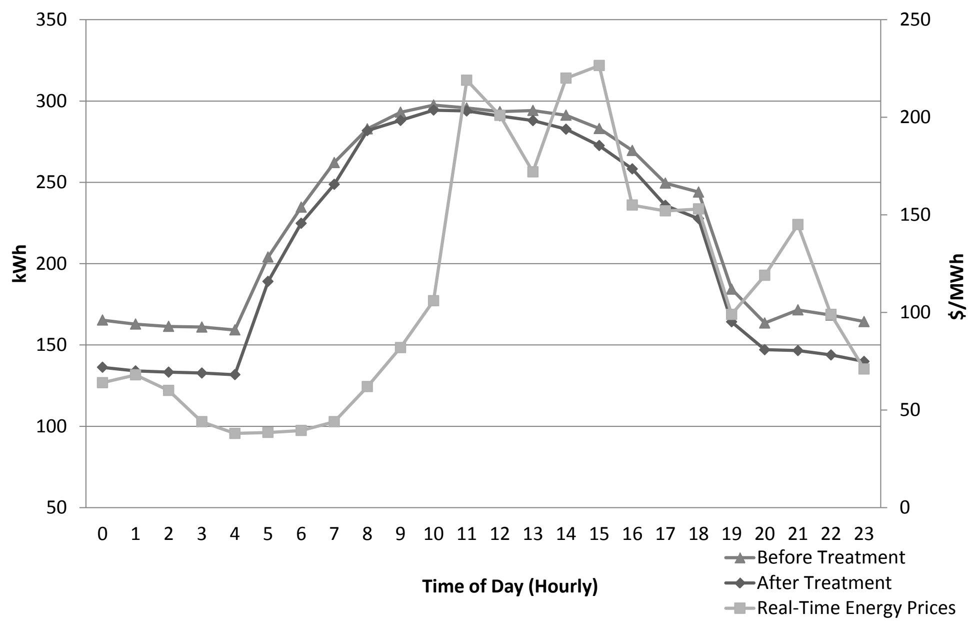
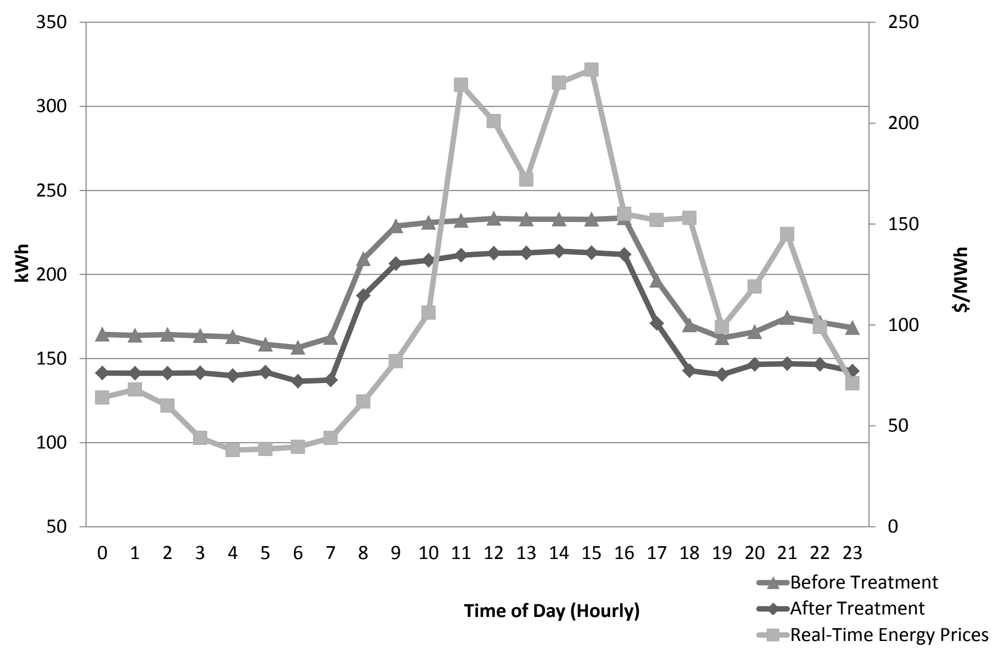
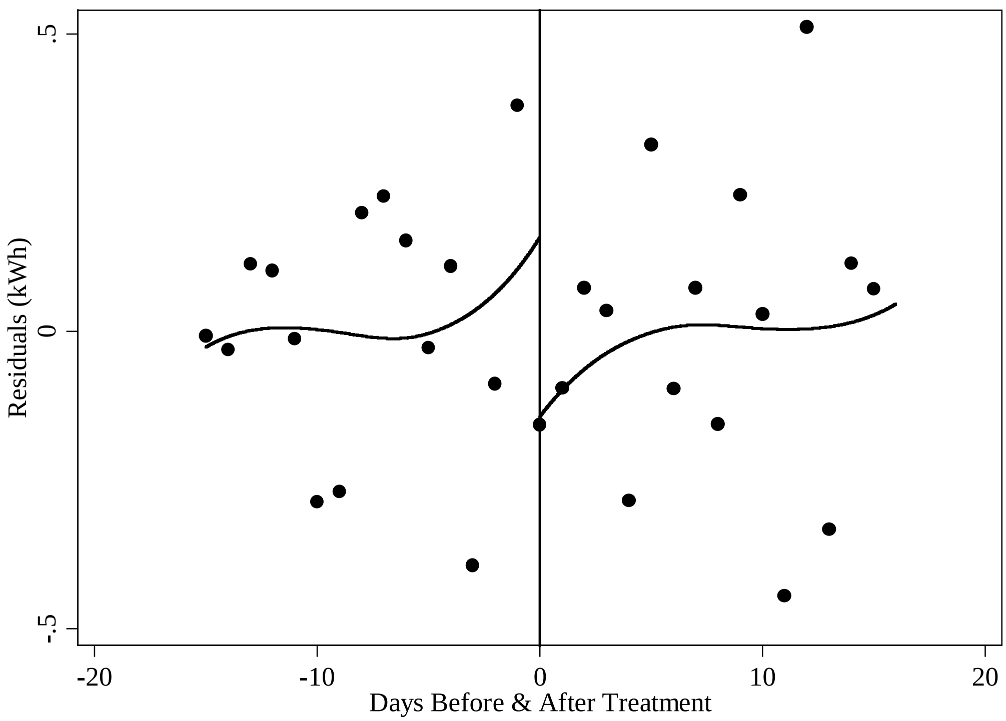


Figure 2B: Weekends and Holidays



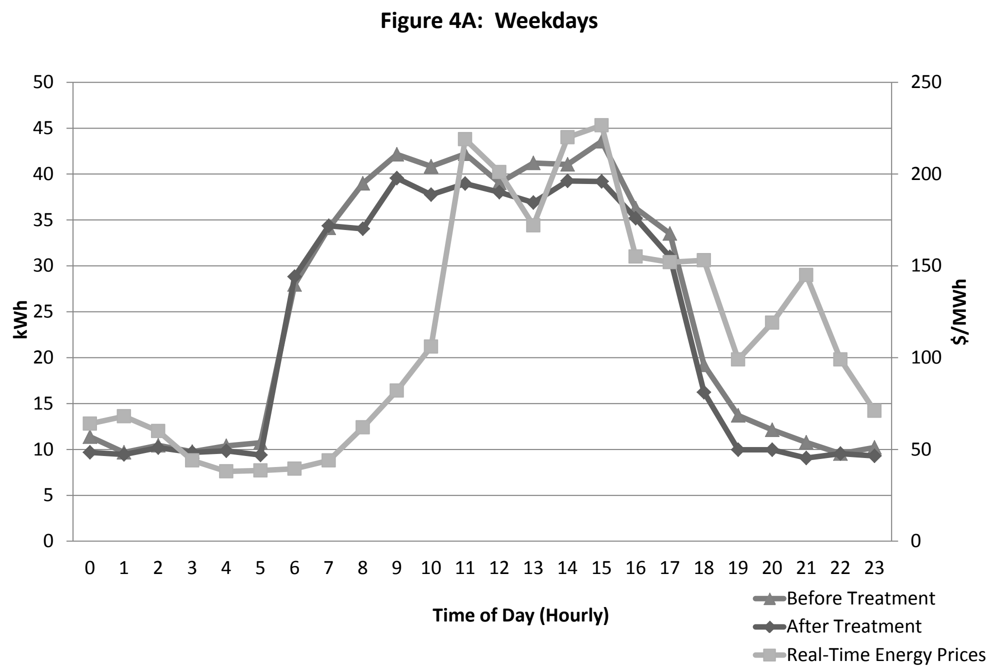
Notes: Plotted points for before and after treatment are derived from coefficient estimates of Equation (3) using a three month window. Coefficients are multiplied by four in order to get kWh on an hourly basis. Real-time energy prices for a summer's day in New England borrowed from Joskow (2012).

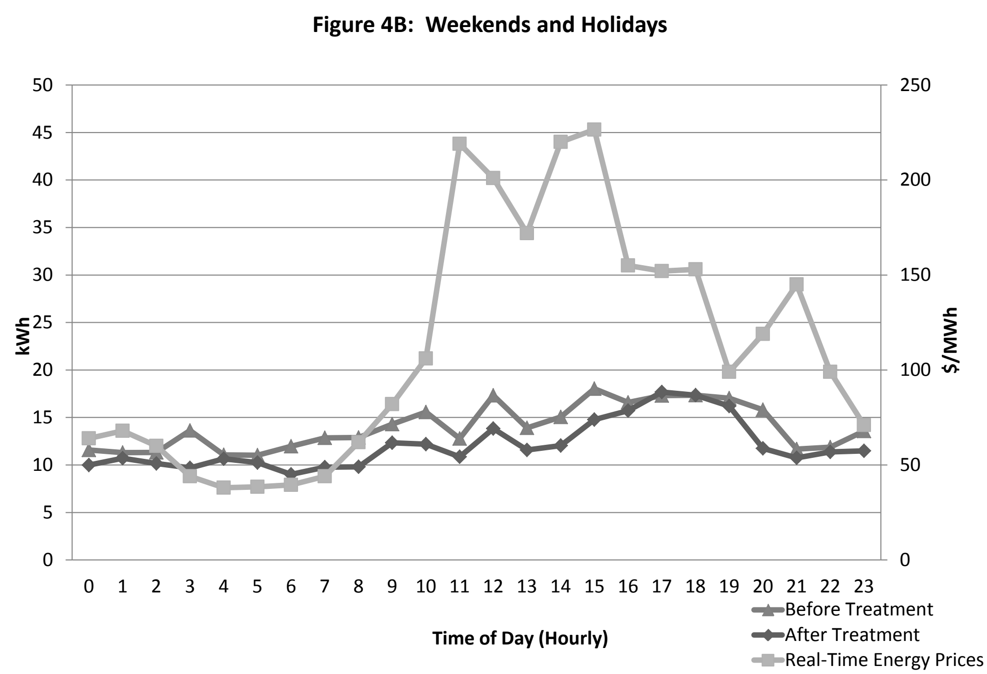
Figure 3: Regression discontinuity diagram for Project B



Notes: See notes to Figure 1.

Figure 4: Hourly kWh reductions for Project B





Notes: Plotted points for before and after treatment are derived from coefficient estimates of Equation (3) using a one month window. Coefficients are multiplied by four in order to get kWh on an hourly basis. Real-time energy prices for a summer's day in New England borrowed from Joskow (2012).

Figure 5: Hourly kWh reductions for Project C

Figure 5A: Weekdays

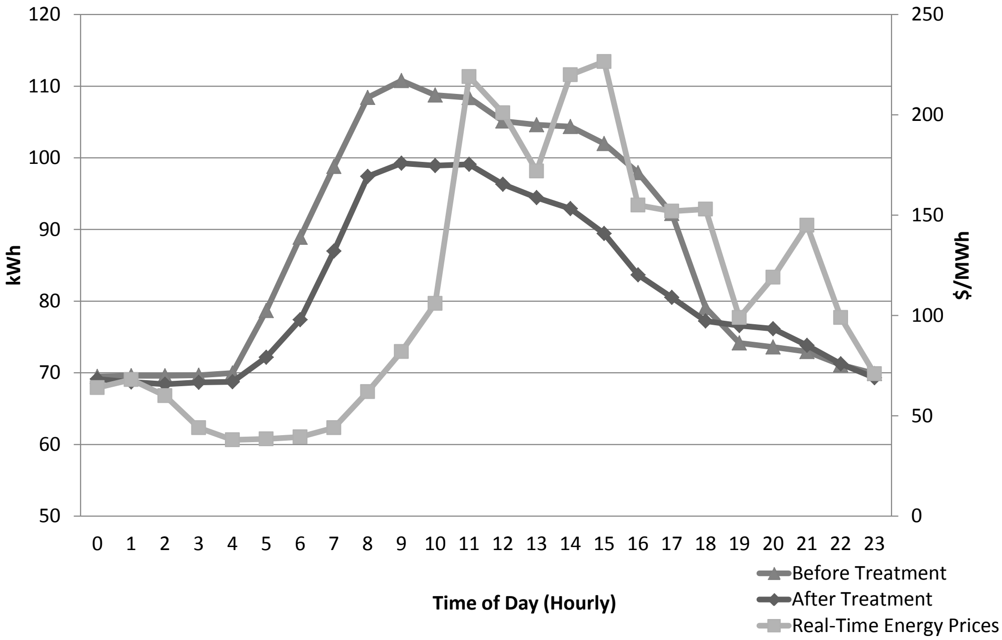
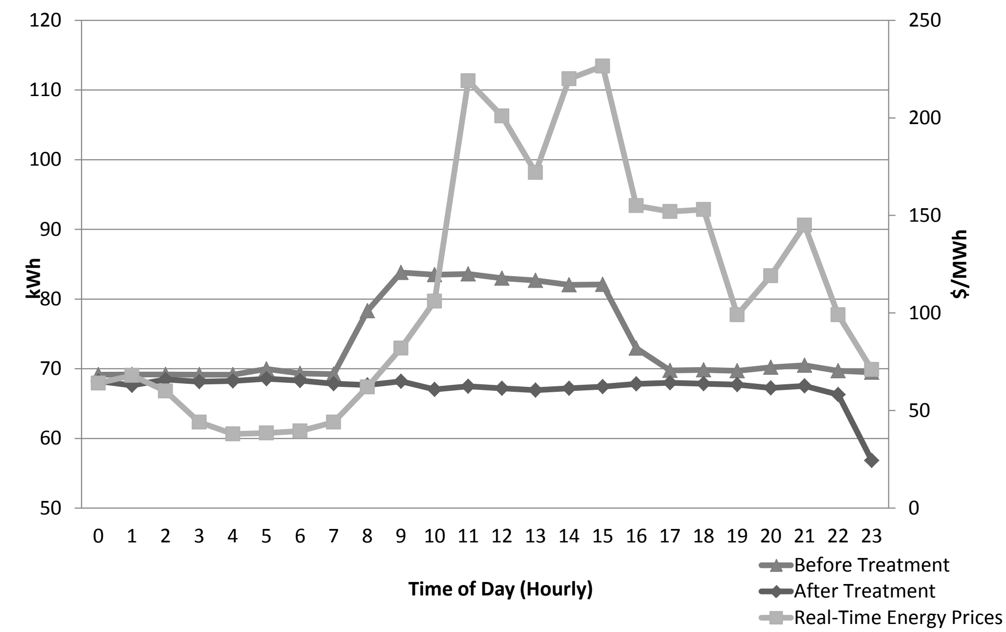


Figure 5B: Weekends and Holidays



Notes: Plotted points for before and after treatment are derived from coefficient estimates of Equation (5). Coefficients are multiplied by four in order to get kWh on an hourly basis. Real-time energy prices for a summer's day in New England borrowed from Joskow (2012).