Just Shut It: Investigating the Effect of a Fume-hood Contest on Building Energy Consumption

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Abstract

Christopher John Ryan for Economics Undergraduate Honors Thesis

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Fume-hoods are often the most energy intensive pieces of equipment within science laboratories. A contest, designed at Harvard University, to encourage energy efficient use of fume-hoods is implemented on the University of Colorado Boulder campus, but how effective is this contest at reducing energy consumption? This paper employs a difference-in-differences, event study, and synthetic controls framework to determine the energy savings created by a building participating in this contest. The estimates generated by these methods all produce overestimates of the treatments effect, making it is difficult to distinguish an actual effect of the contest from bias.

1 Introduction

Energy efficiency is an increasingly relevant topic in the United States. Between 1980 and 2005 the amount of commercial building space and the number of residential homes in the United States increased by 50 percent and 40 percent, respectively. Additionally, buildings account for 72 percent of all the electricity consumption in the United States (U.S. Department of Energy, 2008). A rapid increase in electricity consumption is not an issue that is unique to the United States. Between 1970 and 2009 the global per-capita electricity consumption has more than doubled (International Energy Agency, 2012), and without proper action global energy demand is predicted to rise an additional 50 percent from 2013 to 2050 (International Energy Agency, 2013).

Efforts to improve energy efficiency are not just in response to the increase in the use of a particular resource. They are also in response to the various negative externalities caused by electricity consumption. The energy sector is the second leading cause of greenhouse gas emissions, only slightly behind the transportation sector (US EPA, 2019). The reduction of greenhouse gases is critical to achieve the goal set by the United Nations of limiting global temperature rise to 2° C, or 1.5°C (Britannica, 2019). Electricity used in buildings accounts for 38 percent of carbon dioxide emissions (U.S. Department of Energy, 2008), so finding effective and low-cost ways to reduce energy consumption in buildings is essential.

Science laboratories are designated as one of the three most energy-intensive buildings by the U.S Department of Energy. This comes as no surprise considering that laboratories contain fume-hoods, which have fans constantly running, ultra-low temperature freezers, industrial ovens, and are almost always temperature-controlled environments. Additionally, science laboratories are usually much more focused on safety standards than on energy efficiency. Universities typically have a high concentration of laboratories. A study conducted in 2011 determined that university laboratories in the United Kingdom use three to four times more energy per square foot than office space (Hopkinson et al., 2011). Despite this massive source of energy consumption, energy conservation in science laboratories has not been well studied.

My thesis evaluates the effectiveness of an energy conservation initiative within laboratories at the University of Colorado Boulder. In 2017 the University of Colorado Boulder reported that laboratory research buildings occupy 22% of the campus's square footage but are responsible for 43% of campus energy use (Green Labs, 2017). To combat this disproportionate use of electricity the University of Colorado Boulder has a program to increase laboratory efficiency. The program, CU Green Labs, attempts to minimize the use of water, material goods, hazardous chemicals, and most importantly for this research, energy. In 2017 CU Green Labs held a contest to encourage laboratory users to close their fume-hood sashes. Fume-hoods are an excellent opportunity for energy conservation within laboratories because of the sheer amount of energy they consume. A single fume-hood is estimated to use the same amount of energy as three average U.S. homes (Matthew et al., 2007). North Carolina State University estimates that one fume-hood on its campus can cost the school up to $6,000 per year. University campuses can have hundreds of fume-hoods, significantly contributing to the total energy costs of the school.

Fume-hoods are enclosed and ventilated workspaces used in science laboratories, which safely remove harmful vapors, gasses, and partials from the building. There are two types of fume-hood systems that may be in place in a building: constant air volume (CAV) and variable air volume (VAV). A building with a CAV fume-hood system will always exhaust the same amount of air, whether the fume-hood sash is open or closed, by pulling more or less air through vents, depending on the height of the sash. However, in buildings with a VAV fume-hood system, the fume-hoods will exhaust more air when the sash is left open and less air when the sash is left only an inch or two from fully closed (often you cannot fully close the sash for safety reasons). This change in ventilation in a building with a VAV system can save energy in two ways. First, the fume-hood fan will not have to work as hard when exhausting less air, and second, the fume-hood will exhaust less heated or cooled air out of the building.

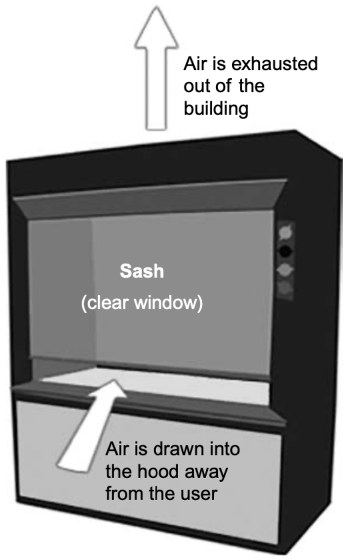

Figure 1: A diagram of a typical fume-hood. (Credit: Feder et al., 2012).

The “Just Shut It!” contest implemented by CU Green Labs was initially designed by Harvard University. The contest operates by participating laboratories being checked at random throughout the contest. At each check a laboratory has an opportunity to earn a sticker. A sticker can be earned if the sash of a fume-hood is below two inches when not in use or below 14 inches when in use. If earned, the sticker is placed on a card above the fume-hood. At the end of the contest the card is turned in to be converted to raffle tickets (one ticket per sticker) which are entered into a drawing for a prize.

At the University of Colorado Boulder, the contest was held in the Sustainable Energy and Environment Laboratories (SEEL) building, a building with a VAV fume-hood system in place, from April 3rd to May 25th 2017. Ten random checks of the laboratories that chose to participate occurred during this time. At each check student volunteers assigned stickers based on the rules explained above. The volunteers also taped one of three graphics directly on to the fume-hood sash.

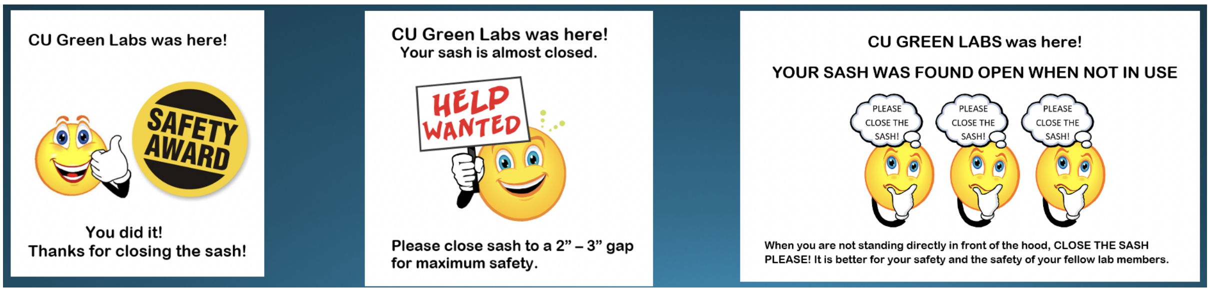

Figure 2: The graphics that were placed on the fume-hood. (Credit: CU Green Labs)

If the fume-hood was fully compliant the first smiley face graphic would be taped on the sash. If the fume-hood sash was lowered but not within the desired two-to-three-inch range, the second "help wanted" graphic would be taped on the sash. Finally, if the sash was well above the desired range the fume-hood would receive the third graphic providing some encouragement to keep the sash closed. The student volunteer made a judgment call in awarding the second vs. third sticker; it was not based on a hard-set measurement. The graphics served as a form of feedback and provided some instruction when needed. At the end of the contest there was a drawing for one 75-dollar and two 50-dollar gift cards to local restaurants (up to one per participating laboratory).

My research question is: What is the effect of this contest on a building's energy[1] consumption?

To answer my research question, I model energy usage of laboratory buildings on the University of Colorado Boulder campus by exploiting data on monthly energy consumption per building. Data on the time and location of CU Green Labs treatment are vital in determining the effect the program has on building energy consumption. In addition, various control data are needed to account for variation in energy consumption not due to the contest. With this data I use three strategies to determine the effect the contest has. First, is a difference-in-differences framework which estimates the average treatment effect my comparing mean energy consumption before and after treatment. Second, is an

[1]Throughout the paper the objective is to determine "energy" savings. Both electricity savings in kWh and natural gas savings in therms are estimated. When ever you see "energy", it can be replaced with "electricity in kWh and therms in natural gas".

event study which estimates the immediate effect of the treatment. Finally, a synthetic controls design is used to create the hypothetical monthly energy consumption of the SEEL building if it had never been treated. This can be used to estimate the individual monthly effect of the contest and say something about its longevity.

The most closely related paper to this research is (Feder et al., 2012), which investigates the same "Just Shut It!" campaign at a different university campus. Feder et al. uses a pairwise comparison to determine how effective the contest is at getting laboratory workers to lower their fume-hood sash. The main difference between this research and Feder et al. is using energy consumption as the dependent variable. The use of energy consumption as a dependent variable improves this analysis in two ways. First it eliminates the issue of cheating. In Feder et al. there were reports of word getting around that student volunteers were coming to check fume-hood sashes, allowing laboratory workers to close their fume-hood sashes in preparation. Second, using building energy consumption as the dependent variable instead of the height of the fume-hood sash measures the contest's efficacy in its intended way, reduction of energy consumption, not just changing behavior.

The three different approaches used to evaluate the contest aim to estimate the average, immediate, and monthly effect. While all estimates are likely overstating the effects of the contest, Figure 10 does support the idea that there was some reduction in natural gas consumption beyond just a biased estimate.

1.1 Literature Review

There is extensive literature that information and behavioral intervention can have a significant effect on reducing energy consumption. In (Allcott & Mullainathan, 2010), a paper on behavior and energy policy, the authors argue that non-price based behavioral interventions are effective at reducing energy consumption and have merit in the global push to reduce emissions.

Not only do people alter their decisions when given new information, they do so at higher rates when they are given information comparing their actions to the actions of their peers. In a study conducted by Ornaghi and others, participants were sent emails to remind them to keep their windows closed. One group of participants was told to merely close their windows; a second group was told of the environmental benefits of closing their windows; and a third group was informed how much energy they were wasting compared to coworkers. Findings suggest that people respond the best (that is, keep their windows closed most often) when they are given feedback relative to their peers (Ornaghi et al., 2010). The idea that individuals are most likely to change their habits when compared to their peers is supported by (Nolan et al., 2008) who find that residents are more likely to be energy conscious when compared to other neighbors as opposed to just being given more general claims about environmental benefits.

Furthermore, it has been determined that individuals respond well to information on energy use when they receive it from other people within the same organization (Gulbinas & Taylor, 2014). Giving people non-price-based information about externalities caused by energy use is effective at reducing consumption, as discussed above, but non-price-based information is also crucial to alter the behavior of people in public and commercial buildings who cannot be motivated by the marginal price of electricity. (Masoso & Grobler, 2010) suggest this when they discovered office buildings are using over 50 percent of their electricity during non-work hours. A large part of the issue was employees carelessly leaving lights, air conditioning, and other equipment on when it did not need to be. The employees did not face any financial repercussions for leaving equipment on. Their findings highlight the usefulness of energy awareness campaigns in public buildings.

Fume-hoods in laboratories are large consumers of energy and their consumption is largely determined by the day-to-day habits of the people using them (Woolliams et al., 2005). This makes them a perfect candidate for an informational campaign that could lead to major energy savings. An experiment conducted by (Aldred & Wells, 2020) investigates the use of a sticker to remind people to close their fume-hood sash. The sticker was in the form of a smiley face that was cut in half; the halves would match up when the fume-hood door was at the optimal height for energy savings. Participants were also given feedback in the form of either a smiley face, neutral face, or frowny face to rate their performance. It was found that the stickers alone did reduce the number of times fume-hood doors were left open but not by a statistically significant amount. After feedback was given to the participants, the number of times fume hood doors were left open did drop by a statistically significant amount (9.3 times on average to 5.5).

The study done by Aldred and Wells is similar to the paper (Feder et al., 2012), both of which are similar to this study in that they investigate programs intended to reduce energy consumption caused by fume-hoods in laboratories. However, neither of them uses a similar methodology to what will be used to evaluate the contest held on the University of Colorado Boulder campus. The event study design that is used to estimate the immediate effect of treatment is similar to the approach used in (Davis, 2008) and (Auffhammer & Kellogg, 2011). Both papers use a polynomial in time to control for factors that smoothly vary over time to account for seasonal variation in their dependant variable. For example, (Davis, 2008) examines legislation in Mexico City that restricts driving by license plate number. The goal of this legislation was to reduce pollution and improve air quality. It is hard to estimate the effect of the legislation because of the overall downward trend of pollution caused by other legislation aimed at improving air quality that begin before and after the legislation of interest. The aim of the using the polynomial in time in the event study is to overcome this issue and only estimate the immediate effect of the legislation (or treatment), instead of observing a difference overtime which could be skewed by an overall trend. How applicable this method is under the conditions of this study will be discussed further in the methodology section.

The synthetic controls framework is most similar to (Abadie et al., 2010) who use a synthetic controls method to estimate the effects of Proposition 99 in California, which was intended to reduce tobacco sales. The synthetic controls framework was used in this paper because it is well suited for the scenario of aggregate data where only one unit is treated. Once again, the use of this method in this setting is discussed more in the methodology section.

Aside from differences in methodology, there are gaps in the research surrounding fume-hoods and information interventions to reduce energy consumption. Only a limited number of studies have evaluated the use of behavioral intervention is non-residential buildings (Masoso & Grobler, 2010). In addition, very few studies investigate energy conservation in buildings that contain laboratories (Kaplowitz et., al 2012). Sophisticated building technology is a main focus to creating energy efficiency, but those technologies often exhibit a gap between their estimated and actual returns (Newsham et al., 2009).

2 Data

This analysis will use a panel data set of monthly electricity and monthly natural gas consumption of the buildings on the University of Colorado Boulder obtained from the campus facilities management database. The electricity data is measured at the building level in kilowatt hours per month and is restricted to a group of twenty buildings that are classified as laboratory research buildings by the school. This electricity data is restricted to the time-frame April 2016 – April 2019 (37 months). The natural gas data is measured at the building level in therms (one therm is equal to 100,000 BTUs) per month. This natural gas data is only available for seven of the twenty buildings but fortunately SEEL is included in that subset. Both the electricity and the natural gas data are reported as the consumption between the first and last day of the month. In reality, it is often never like this, varying by a few days on either end of the month. Even though this varies from month to month and even building to building, the variation is small enough, and random enough, that it is unlikely that there is any impact on this analysis. Information from CU Green Labs is used to construct two dummy variables that are added to the data set. The first is the variable "treated", which takes on a value of one if the building is ever treated and zero otherwise. The second is the variable "after", which takes on a value of one in every month after treatment and zero in every month before treatment. Given how the energy consumption is reported and that the consent begins on April 3rd, 2017, April 2017 is considered the first treated month.

Various control data are needed to account for all the different determinants of a building's energy consumption. These determinants, include the weather, daylight, square footage, the year the building was constructed or of its most recent renovation, the number of fume hoods in each building, and a dummy variable for whether the building contains a VAV fume-hood system. Here, the weather data is measurements of the daily average temperature (an average of the daily minimum and maximum) taken from a weather station just North-West of campus and downloaded from the Colorado State University - Colorado Climate Center. These data will be used for the standard practice of calculating the average heating degree days (AHDD) and average cooling degree days (ACDD) per month.

$$ACDD = \frac{\sum_{t=1}^{n}[\frac{T_{min,t}+T_{max,t}}{2} - 65]}{\text{num. days above 65 F}} \qquad AHDD = \frac{\sum_{t=1}^{n}[|\frac{T_{min,t}+T_{max,t}}{2} - 65|]}{\text{num. days below 65 F}}$$

Here, ACDD is calculated using the days in a month where the average temperature is above 65 degrees and AHDD is calculated using the days in a month where the average temperature is below 65 degrees. In other words, ACDD (AHDD) is the average number of degrees above (below) 65 degrees Fahrenheit, for a particular month.

All the data available for this analysis is either building invariant or time invariant, which is a major limiting factor that is elaborated more upon in the following discussion of the methodology.

Table 1: Dataset Summary Statistics

Variable	Mean	S.D.	Minimum	Maximum
Electricity (kWh)	184040	162883.4	2585	844267
Natural gas (therms)	7266	8825.5	240	43950
Year - month	201736	94.3	201604	201904
Square footage	105084	89596.0	8306	417014
Number of hoods	27.30	44.3	0	169
Effective year built	1990	21.7	1951	2020
VAV	0.3	0.459	0	1
Treated	0.05	0.218	0	1
After	0.6757	0.468	0	1
AHDD	15.29	11.1	0	34.07
ACDD	2.811	3.3	0	9.672
Daylight (hours)	12.223	1.9	9.375	14.971

Table 2: Building Electricity Summary Statistics

Building Code	Mean	S.D.	Minimum	Maximum
ARL	116227.89	42171.41	51680	258040
BESC	141857.19	28564.88	57924	24019
BIOT	635578.84	104519.98	436103	844267
CHEM	268534.92	35554.89	178147	325978
CIRE	44686.89	6120.42	27115	56749
DLC	61597.35	8414.25	39062	77460
DUAN	338661.97	43287.56	223123	420637
GBB	286366.03	39248.32	173843	364690
ITLL	75083.38	27436.49	34459	140594
JILA	251776.65	105356.60	157230	486817
LITR	26836.30	8227.27	14499	46979
LSRL	29414.05	6519.77	16480	44480
MUEN	175491.78	22361.09	102026	217351
NPL	49068.19	22971.72	31412	68089
OBSV	4550.78	1185.21	2585	7274
PORT	207844.46	62467.14	76226	292971
RAMY	163717.59	22218.89	103360	208601
SEEL*	212175.35	42690.92	141503	312357
SPSC	454577.95	23547.05	407366	502202
WILD	122105.95	33937.36	18720	189200

Note: * is the treated building

Table 3: Building Natural Gas Summary Statistics

Building Code	Mean	S.D.	Minimum	Maximum
ARL	2833.37	1128.72	1343	5773
BIOT	24474.46	9205.95	14410	43950
LITR	3513.72	2096.71	300	6910
LSRL	977.48	423.40	336	1990
NPL	1318.65	934.87	240	3210
SEEL*	8202.89	3551.15	666	18889
WILD	8244.96	3588.83	670	14580

Note: * is the treated building

3 Methodology

3.1 Difference in Means Calculation

The first approach to determine the effect that the "Just Shut It!" contest has on energy consumption is to calculate the difference in means before and after treatment using a basic difference-in-differences framework. This can be imagined as:

$$\text{Difference-in-Differences} = (D - B) - (C - A)$$

Where:

A. Average energy consumption for <u>untreated</u> buildings <u>before</u> the treatment date.

B. Average energy consumption for <u>treated</u> buildings <u>before</u> the treatment date.

C. Average energy consumption for <u>untreated</u> buildings <u>after</u> the treatment date.

D. Average energy consumption for <u>treated</u> buildings <u>after</u> the treatment date.

This difference-in-differences estimate could also be represented as:

$$E_{it} = \beta_1 treated_i + \beta_2 after_t + \beta_3 (treated \times after)_{it} \tag{1}$$

This model cannot be expanded upon due to covariates in the data set being either time invariant or building invariant. This means that no new information is added to the regression equation by including any of the available control variables, because the available controls are already absorbed in $treated_i$ or $after_t$. When estimating the difference in energy consumption using this difference-in-difference framework, it is important to keep in mind the key assumptions that are required to produce an accurate estimate. The two most important assumptions here are the parallel trends assumption and the constant treatment assumption.

3.1.1 Parallel Trends Assumption

The parallel trends assumption states that the treated units would have experienced the same proportional change (measured by the change in the dependent variable) as the untreated units, in the scenario where the treated units are not treated. This assumption is important because only the treated energy consumption can be observed for a treated building; the untreated consumption of a treated building is impossible to know. The effect of treatment is calculated by the change in outcomes for treated buildings minus the change in outcomes for the untreated buildings. It is important that the only unique change is the treatment. It is acceptable if there are changes in energy consumption not due to the treatment, but those changes need to be constant among all buildings to produce an unbiased estimate of the treatment effect. For example, if there is some unusual event that occurs in many untreated buildings, after treatment has occurred to the treated building, that increases (decreases) energy consumption, then this difference-in-differences framework will produce an over (under) estimate of the effect of treatment (assuming this unusual event does not affect the treated building).

Based on a visual inspection of Figure 3, the parallel trends assumption likely does not hold to be true. The treated building's (SEEL's) electricity consumption is following a downward trend in the pre-treatment period - a trend that is not similar to the other control buildings. This will cause the mean consumption in the pre-treatment period (for the treated building) to be higher than the mean consumption in the post-treatment period for reasons other than the treatment. This means that our estimate of the treatment effect will be an overestimate of savings. This downward trend is likely a result of SEEL being a building relatively new to the University of Colorado campus. The building was originally built in 1994 and was not affiliated with the school. In 2013 the building was vacated and acquired by the school. It was then renovated to include laboratories, offices, and classrooms, reopening in 2015. It can take time for a building's energy consumption to stabilize after renovations like this.

Figure 4 show the natural gas consumption. Here, the parallel trends assumption seems to be a much more reasonable assumption. There is some cause for concern due to the sudden drop in consumption in SEEL at the end of the sample, so the difference-in-differences framework will still overestimate the savings of natural gas consumption. However, this will not be nearly as much of an overestimate as produced with the electricity data.

3.1.2 Constant Treatment Assumption

The constant treatment assumption is the assumption that all units are treated the same in magnitude and that once a unit is treated it remains treated. In this study, the constant treatment assumption likely does not hold. The SEEL building is given the treatment of running a contest that incentivizes people to close their fume-hood sashes. In a perfect world the lab workers that participate in this contest would be incentivized during the two-month period to lower their sash and then have the simple task become habit, continuing it after the end of the contest. However, this does not seem to happen in practice. In (Feder et al., 2012), which ran the "Just Shut It!" campaign in virtually the same fashion, only 3.1% of fume-hood sashes were at the optimal height when not in use before running the contest. During the contest this was improved to 61.3%, and eight months after the end of the contest this number had dropped to 14.5%. This is still much better than the 3.1% before the contest, but significantly worse than performance during the contest.

It is speculated that the act of a contest could reduce long-term effectiveness. The drop in performance after eight months is likely due to the habit not being fully engrained in laboratory workers, so once the contest ended and there was no incentive to keep hoods closed, people stopped shutting them. Over a longer year-to-year time frame the issue of turnover also arises. Many people in university laboratories are undergraduate or graduate students who will graduate and be replaced. This means it is likely that after a year the people working in the laboratory will not be the same ones that experienced the contest.

3.2 Event Study

The aim of the event study design is to examine the immediate effect the contest has on building energy consumption. This is a more appropriate approach at estimating the effect of the treatment because the constant treatment assumption, which likely fails, does not need to hold like in the difference-in-differences framework. This approach could also be thought of as a regression discontinuity with time as the running variable, similar to the implementation in (Davis, 2008) and (Auffhammer & Kellogg, 2011), who also use a polynomial in time to flexibly control for any determinants of the dependent variable that smoothly vary overtime, these are mostly seasonal variations. Variables accounted for by this polynomial include AHDD, ACDD, and daylight, so those covariates will not be included in the regression. More importantly it includes things like campus being busier at different times of year, which is very hard to obtain data for.

This event study takes the form of:

$$E_{it} = \beta_1 Treat_{it} + \boldsymbol{\beta}\mathbf{D}_{it} + f(Date_t) + u_i + \varepsilon_{it} \tag{2}$$

where the dependent variable, E_{it}, is electricity in kilo-watt hours or natural gas in therms consumed by building i in month t; $Treat_{it}$ is an indicator variable for whether building i is treated in month t; $\boldsymbol{D}_{it}$ contains several interaction terms between building invariant and time invariant covariates; $f(Date_t)$ is a 5th order polynomial in time; u_i is individual building fixed effects; and ε_{it} is the error term. The key coefficient here is β_1 which can be interpreted as the change in energy consumption in the first month of treatment.

The interaction terms within $\boldsymbol{D}_{it}$ are all interactions that could create sharp jumps in energy consumption that would not be fully captured by the polynomial; $\boldsymbol{\beta}$ contains the corresponding coefficients. Specifically, building square footage interacted with both ACDD and AHDD. The suspected relationship here is that smaller buildings will have a harder time maintaining their set temperature, whether being heated or cooled, because of their higher surface area relative to size. The number of hoods per building interacted with ACDD and AHDD could also explain additional variation in energy consumption. Fume-hoods exhaust already heated or cooled air, requiring building temperature control systems to work harder to replace the conditioned air that is removed. Finally, the dummy variable VAV, indicating whether a building has a variable air volume fume-hood system or a constant air volume fume-hood system, is interacted with ACDD and AHDD.

The coefficients of these interaction terms are not of particular interest but including them is important to see the effect they have on the key coefficient β_1. Unfortunately, because only one building is treated, it is not possible to identify differences in energy consumption, due to time invariant differences, across treated buildings. It is possible to identify a difference in energy consumption across treated months, but this effect is likely absorbed by the polynomial in time. The interaction between $Treat_{it}$ and AHDD or ACDD is not included for it does not produce a significant result or even a sizable coefficient.

3.3 Synthetic Controls

Equation (1) estimates the average effect of treatment and Equation (2) estimates the immediate effect of treatment, but still nothing is known about the long-term effects of treatment. With a synthetic controls design the individual savings in each month can be estimated, answering this question.

The synthetic controls design is best suited for settings where there is a singular, or small number of, treated units and only aggregate unit data is available (Abadie, 2021). In this study, data for individual laboratories within a building are not available; only the aggregate building energy consumption can be use. The synthetic controls framework selects the group to be used as the comparison through quantifiable characteristics, as opposed to the more subjective method of selecting a comparison group used in the difference-in-differences model. Recall that in Equation (1) the parallel treads assumption, which did not seem to hold true, was important to produce an accurate estimate of the treatment effect. This assumption is normally satisfied or rejected by a visual inspection of the data, like is done here with Figure 3 and Figure 4. The difference in means estimate of the treatment effect generated by the difference-in-differences framework is calculated with all untreated buildings equally contributing to the expected path that the treated building would have taken if it had never been treated. There may be a better subset of buildings that more accurately predict the energy consumption of the treated building. The synthetic control approach uses a weighted average of the available control observations to construct the counterfactual for the treated building. The untreated buildings that are the most similar to the treated building will contribute the most, while the untreated buildings that are the least similar will contribute the least. Creating this counterfactual of the monthly energy consumption in the treated building as opposed to a counterfactual of the average consumption after treatment, which is what is done in the difference-in-differences framework, makes it possible to estimate the energy savings in each month. These monthly estimates can be used to investigate the expected diminishing returns found in (Feder et al., 2012).

This synthetic controls design can be estimated with the equation:

$$\alpha_{1t} = Y_{1t} - \sum_{j=2}^{J+1} \boldsymbol{W} Y_{jt}$$

where α_{1t} is an estimate of the change in energy consumption for the treated building in each year-month t (t_0 = first month of treatment); Y_{1t} is the observed energy consumption in the treated building in year-month t; $\boldsymbol{W}$ is a $(J \times 1)$ vector of positive weights that sum to one. That is, $\boldsymbol{W} = (w_2 + \ldots + w_J + 1)$ with $w_j \geq 0$ for $j = 2, \ldots, J + 1$ and $w_2 + \ldots + w_{J+1} = 1$. The weights within $\boldsymbol{W}$ are calculated to create a synthetic control that best resembles the treated unit based on a set of predictor variables. Here, the predictor variables are total building square footage, the number of fume-hoods in the building, the effective year built, and whether the building has a VAV fume-hood system in place. Finally, Y_{jt} is the energy consumption in building j in period t. The term $\sum_{j=2}^{J+1} w_j Y_{jt}$ essentially serves as the "synthetic" treated building, representing a prediction of the monthly energy consumption of the SEEL building, if it had never been treated.

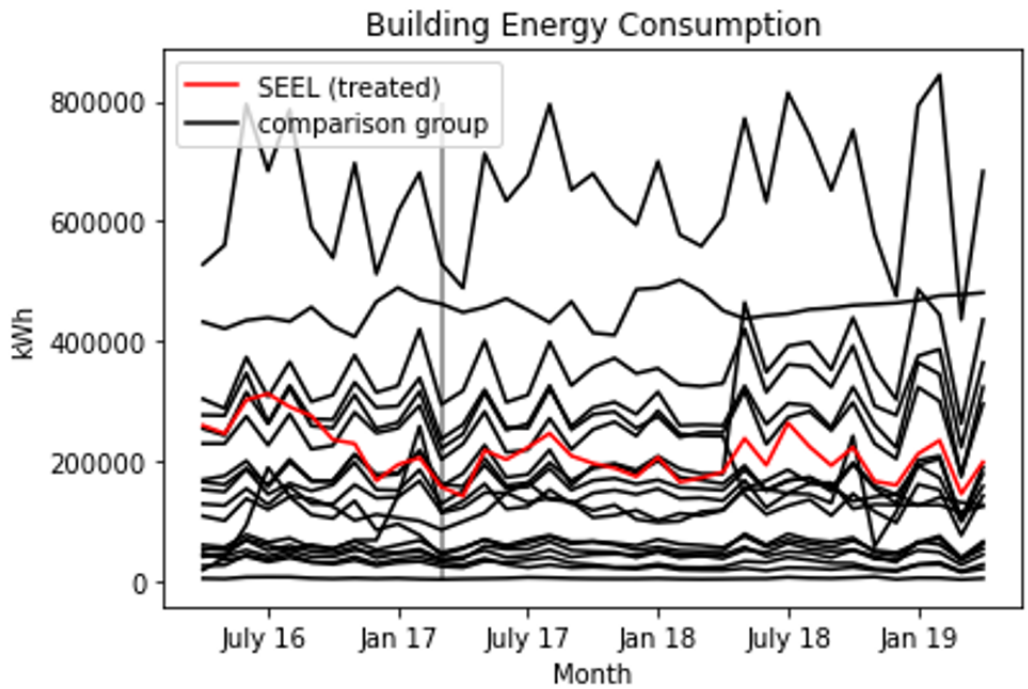

Figure 3: Plot of electricity consumption over time.

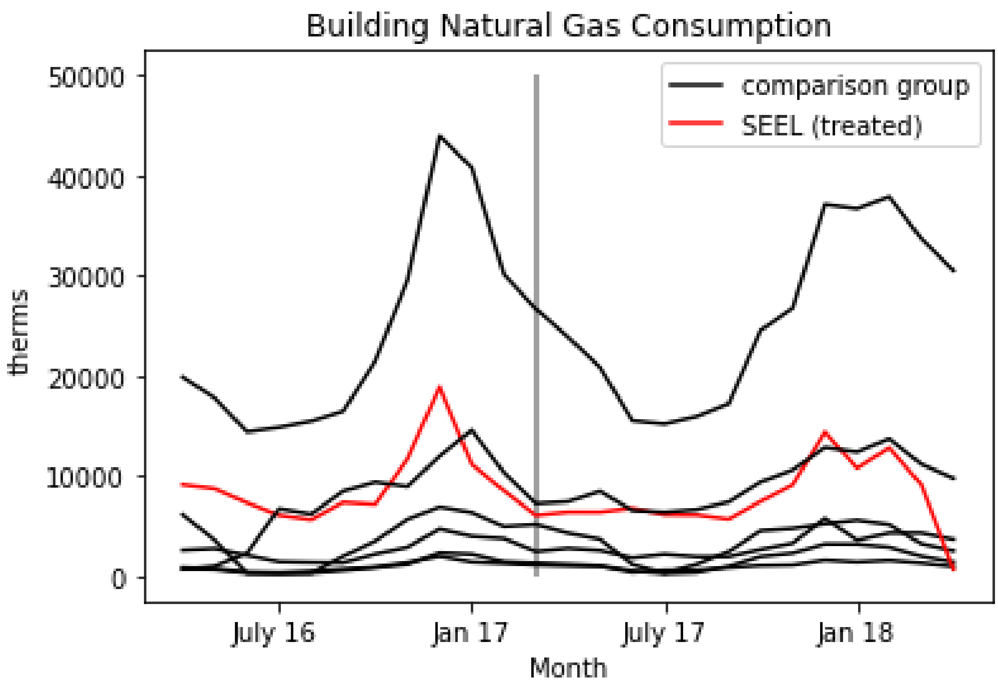

Figure 4: Plot of natural gas consumption over time.

4 Results

4.1 Difference in Means Results

Table 4 shows the results of the difference in means estimation for electricity consumption. It is clear to see that the difference-in-differences here is -45783.07 kilowatt hours. Meaning that the average electricity consumption in SEEL after the contest is 45783.07 kilowatt hours less than the average electricity consumption before the contest, compared to changes in consumption in other laboratory buildings. As discussed before this is likely a large overestimate of the electricity savings generated by the contest, due to the abnormally high electricity consumption in SEEL before the contest that can be seen in Figure 3.

Table 5 shows the results of the difference in means estimation for natural gas consumption. It is clear to see that the difference-in-differences here is -1898.61. Meaning that the average natural gas consumption in SEEL after the contest is 1898.61 therms less than the average natural gas consumption before the contest, compared to changes in consumption in other laboratory buildings. The natural gas data does not violate the parallel trends assumption nearly as severely as the electricity consumption does. However, this is likely still a slight overestimate of savings due to the sudden drop in natural gas consumption at the end of the time frame that can be seen in Figure 4.

Table 4: Mean Electricity Consumption of Treated and Untreated Group

	Before	After	Difference
Treated	239561.25	199030.12	-40531.13
Untreated	179010.52	184262.46	5251.94
Difference in Differences			-45783.07

Table 5: Mean Natural Gas Consumption of Treated and Untreated Group

	Before	After	Difference
Treated	8985.583	7838.231	-1147.353
Untreated	6663.014	7414.2696	751.2553
Difference in Differences			-1898.61

4.2 Event Study Results

Unfortunately, there is not a great method to choose the optimal order of the polynomial used. This analysis uses the 5th order polynomial in time, but also reports the 4th and 6th to show the differences. Table 6 contains the results from Equation (2) for electricity consumption. Column 2 and column 5 are the results of the 5th order polynomial without and with the inclusion of additional interaction terms. The coefficient on $Treated_{it}$ is an estimate of the immediate effect of the contest, this estimate is of the savings generated in first month of treatment. Without the inclusion of any additional interaction terms this estimate is -43950 kilowatt hours. With the interaction terms the estimate is -44120 kilowatt hours. The coefficients on the interaction terms can be interpreted as the additional change in electricity consumption under the corresponding conditions, however these do not change the interpretation of the key coefficient. Many of the coefficients on the interaction terms do not follow what was expected. For example, the coefficient on VAV x ACDD is 2080, this means that a VAV building uses 2080 more kWh for each extra ACDD per month. It was expected that this coefficient would be negative because a VAV fume-hood would use less electricity in times of cooling when compared to a CAV fume-hood.

These estimates of the immediate effect of the consent are also not very different from the estimate of electricity savings generated by the difference-in-differences framework. This is because by including the polynomial that controls for things smoothly varying overtime, it can control for an overall trend in the electricity consumption. This would look like electricity consumption steadily increasing or decreasing over the entire time frame. As can be seen in Figure 5 this is not the case here, electricity consumption does not appear to be trending up or down overall, even though there was abnormally high electricity consumption in SEEL before treatment. Because there is no overall downward trend for the polynomial to correct for, the estimate is still a large overestimate.

Table 6: Event Study Results Electricity

	Without Interactions			With Interactions		
kWh	4^{th}	5^{th}	6^{th}	4^{th}	5^{th}	6^{th}
Treated_{it}	-44310^{**}	-43950^{**}	-44450^{**}	-44410^{**}	-44120^{**}	-44230^{**}
	(15730)	(15730)	(15730)	(15200)	(15200)	(15220)
SQFT × ACDD				0.0194	0.0197	0.0193
				(0.0114)	(0.0114)	(0.0115)
SQFT × AHDD				0.0051	0.0054	0.0053
				0.0033	(0.0033)	(0.0034)
Hoods × ACDD				6.172	5.862	6.296
				(27.80)	(27.80)	(27.89)
Hoods × AHDD				-14.70	-14.95	-14.84
				(8.159)	(8.166)	(8.187)
VAV × ACDD				2080	2091	2075
				(1806)	(1807)	(1809)
VAV × AHDD				144.0	153.0	148.9
				(529.9)	(530.1)	(530.8)
Intercept	116000^{***}	114000^{***}	112900^{***}	112000^{***}	110300^{***}	110200^{***}
	(7559)	(7770)	(7841)	(7812)	(8054)	(8020)
$B-FE$	Y	Y	Y	Y	Y	Y
Polynomial	Y	Y	Y	Y	Y	Y
AR^2	0.9277	0.9278	0.9278	0.9327	0.9327	0.9326
N	740	740	740	740	740	740

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

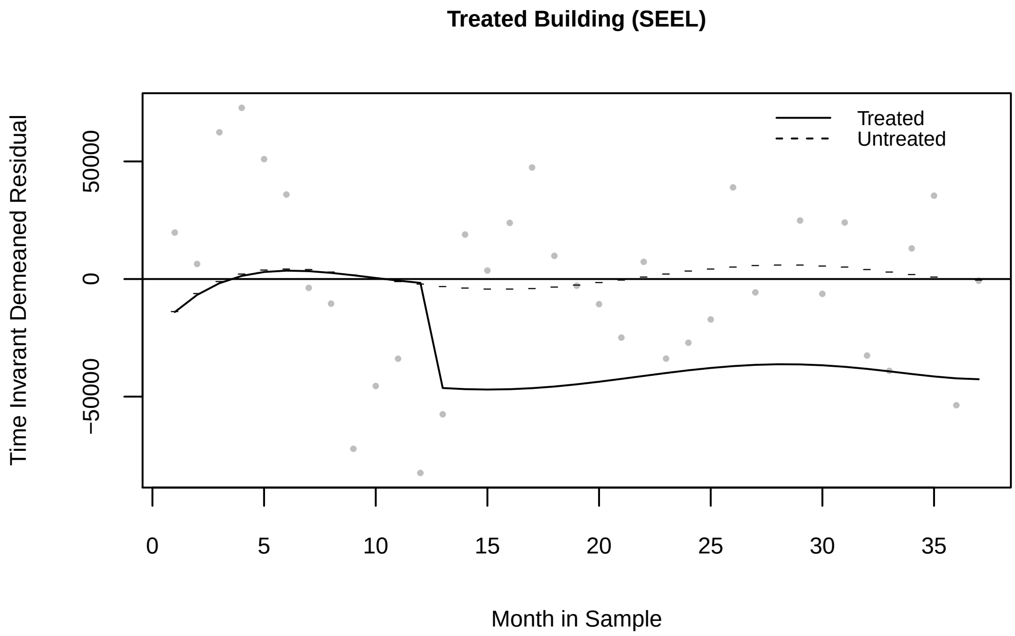

Figure 5: Plot shows the estimate of the immediate effect and no sign of an overall trend in electricity consumption.

Table 7 reports the results of Equation (2) for the natural gas consumption. Columns 2 and 5 contain the results for the 5th order polynomial. -1990 therms is the estimate of savings without the inclusion interaction terms and -1701 is the estimate of savings when interaction terms are added to the regression. The interaction terms serve the same purpose as described above. You may notice that the magnitude of the coefficients on the interaction terms are proportionally larger when compared to the results in Table 6. This is likely because natural gas is mainly used for heating, causing a much stronger correlation with temperature, while electricity is used for cooling along with many other general uses that can dilute the trend.

Just like in the electricity results, the natural gas estimates generated from the event study are not very different from the difference-in-differences estimates. Once again, this is because there is no overall trend, evident in Figure 6, for the polynomial to correct for. The results in Table 7 are likely overestimates of savings.

Table 7: Event Study Results (Natural Gas)

	Without Interactions			With Interactions		
therms	4^{th}	5^{th}	6^{th}	4^{th}	5^{th}	6^{th}
Treated_{it}	-2889	-1990	-1996	-1689^{*}	-1701^{*}	-1698^{*}
	(1658)	(1434)	(1439)	(680)	(559)	(685)
SQFT × ACDD				-0.0032	-0.0032	0.0193
				(0.0017)	(0.0017)	(0.0018)
SQFT × AHDD				$(0.0022)^{***}$	0.0022^{***}	0.0022^{***}
				0.0033	(0.0005)	(0.0005)
Hoods × ACDD				5.50	5.55	5.53
				(4.19)	(4.20)	(4.22)
Hoods × AHDD				-1.51	-1.65	-1.66
				(1.25)	(1.30)	(1.30)
VAV × ACDD				499.3^{**}	497.7^{**}	498.2^{**}
				(164.1)	(164.6)	(165.2)
VAV × AHDD				182.0^{***}	186.5^{***}	186.8^{***}
				(49.1)	(50.4)	(50.5)
Intercept	2788^{**}	2781^{***}	2838^{***}	1999^{***}	1967^{***}	1930^{**}
	(905)	(780)	(835)	(552)	(559)	(580)
$B-FE$	Y	Y	Y	Y	Y	Y
Polynomial	Y	Y	Y	Y	Y	Y
AR^2	0.8060	0.8558	0.8550	0.9678	0.9676	0.9674
N	175	175	175	175	175	175

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

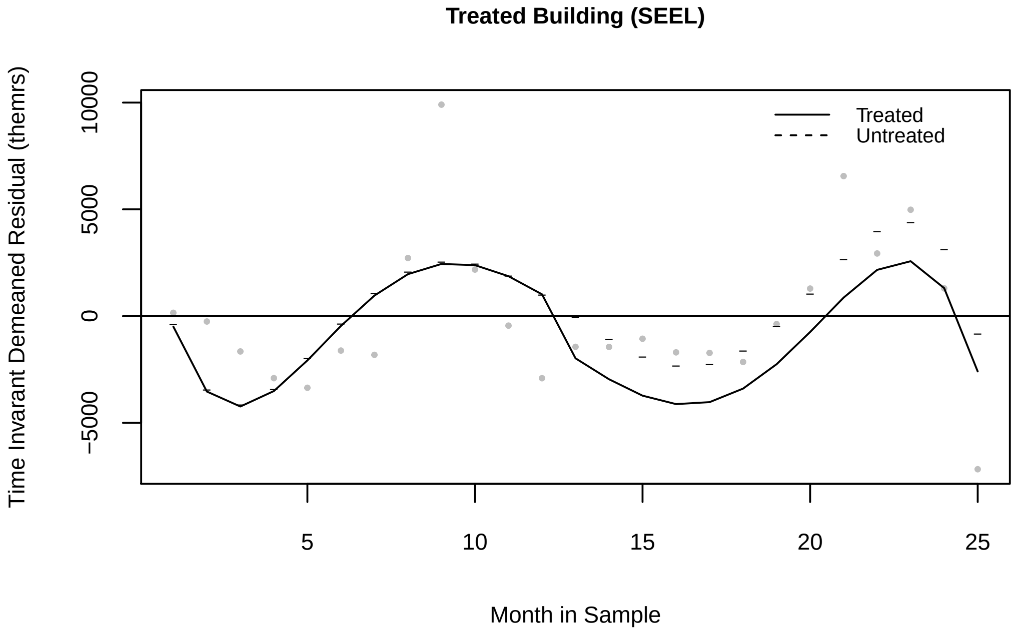

Figure 6: Plot shows the estimate of the immediate effect and no sign of an overall trend in natural gas consumption.

4.3 Synthetic Control Results

As explained in the methodology section, the synthetic SEEL that is produced with the synthetic controls design is calculated using the best subset of the available buildings to create a counterfactual that most closely resembles what energy consumption would have looked like in SEEL if it had never been treated. The comparison between the real and synthetic SEEL, along with the average of the comparison group is shown in Table 8 and Table 9. These tables highlight an important aspect of synthetic controls which is the difference between comparing the treated unit to an arbitrary control group versus comparing it to a subset based on quantifiable characteristics. The synthetic SEEL is clearly much more similar to the real SEEL than the average of the nineteen other laboratory buildings when analyzing electricity and natural gas.

Table 8: Synthetic SEEL Electricity Consumption

	Real	Synthetic	Average of 19 controls
SQFT	142343	142961.4	103122.8
Number of hoods	84	54.25	24.32
VAV	1	0.885	0.263
Effective year built	2015	2015.97	1988.58

Table 9: Synthetic SEEL Natural Gas Consumption

	Real	Synthetic	Average of 6 controls
SQFT	142343	161385.5	107480.4
Number of hoods	84	54.53	38.43
VAV	1	0.976	0.429
Effective year built	2015	2015.03	1987.71

Shown in Figure 7 and Figure 8 below are the plots of SEEL's consumption verses the synthetic SEEL's consumption for electricity and natural gas respectively. The pre-trends are not perfect, but the synthetic counterfactual does a decent job or predicting consumption before treatment for electricity and natural gas. The difference between the real and synthetic SEEL after treatment is the estimated effect of savings in each month. Followed by the figures are the weights used to construct the synthetic counterfactual for both electricity and natural gas consumption.

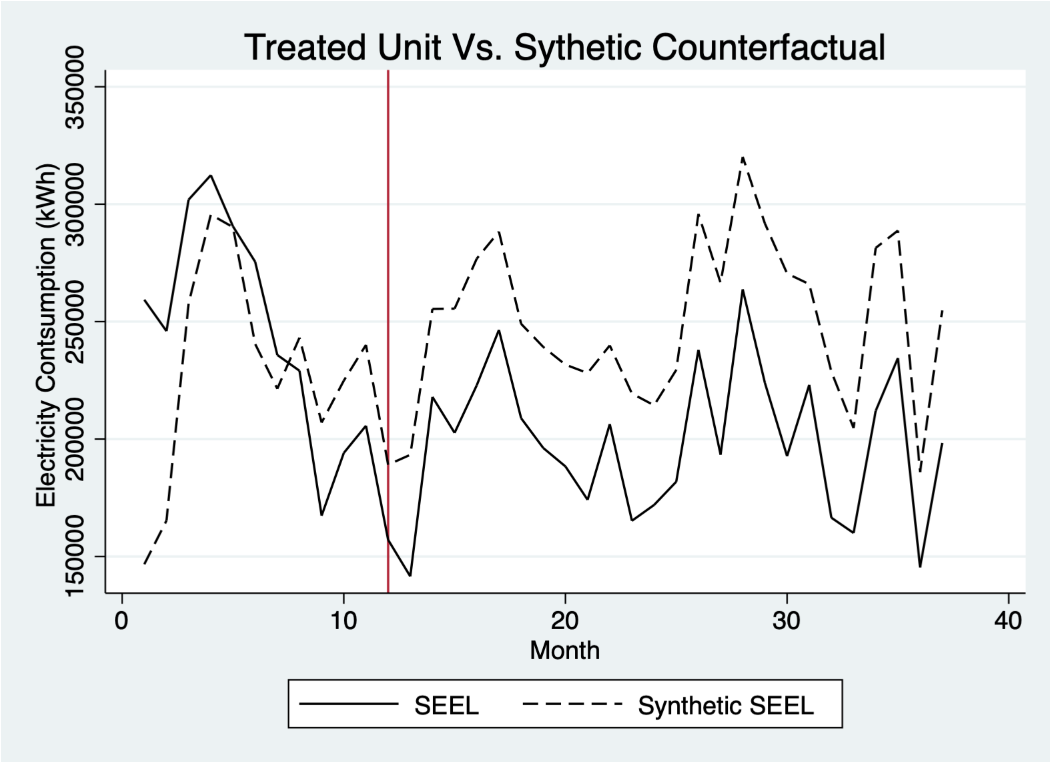

Figure 7

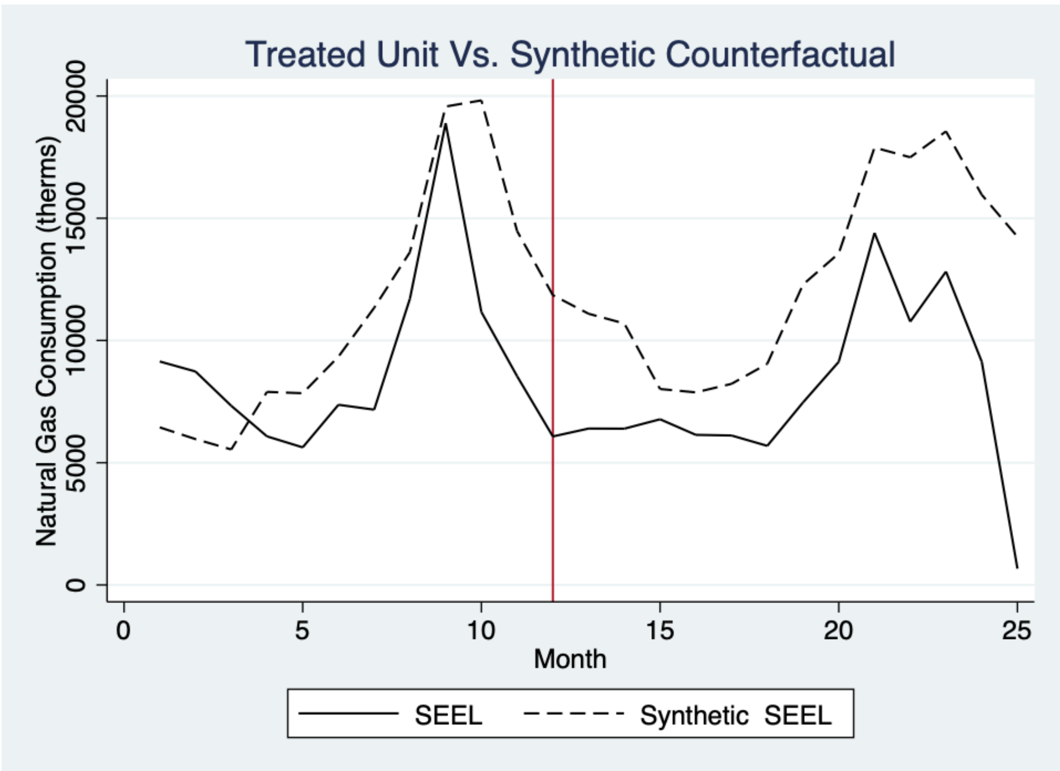

Figure 8

Table 10: Synthetic Control Weights

Building Code	Weight	Building Code	Weight
ARL	0	LITR	0
BESC	0	LSRL	0
BIOT	0.198	MUEN	0
CHEM	0.115	NPL	0
CIRE	0	OBSV	0
DLC	0	PORT	0
DUAN	0	RAMY	0
GBB	0	SEEL*	-
ITLL	0	SPSC	0
JILA	0	WILD	0.687

Note: * is the treated building

Table 11: Synthetic Control Weights

Building Code	Weight
ARL	0
BIOT	0.281
LITR	0
LSRL	0.024
NPL	0
SEEL*	-
WILD	0.695

Note: * is the treated building

It can be difficult to visually see the difference between the real and synthetic building. Figures 9 and 10 plot this difference to make it easier to see and also visualise the trend of the effect.

Figure 10 shows evidence of anticipation of the contest. If the contest was announced a few months before it actually started it is reasonable to assume that workers in the laboratories were reminded of the proper fume-hood behavior and the contest played a part in this effect. However, there is no evidence of anticipation in Figure 9. If anticipation truly is occurring, it would effect electricity and natural gas consumption. As discussed before, because electricity is used for things other than heating or cooling, this could attribute to the anticipation being seen the natural gas consumption but not electricity.

In regards to diminishing effects of the "Just Shut It!" contest that were found in (Feder et al., 2012), a trend similar to this can be seen by the dip in Figure 10 between months 9 and 15. This dip is most likely the extent of the contest, the change between the start of the contest and next few months more accurately represents the effect, as opposed to the absolute change from zero.Similarly, in Figure 9, the estimate of the effect of the contest is largely overestimated if it is taken at face value.

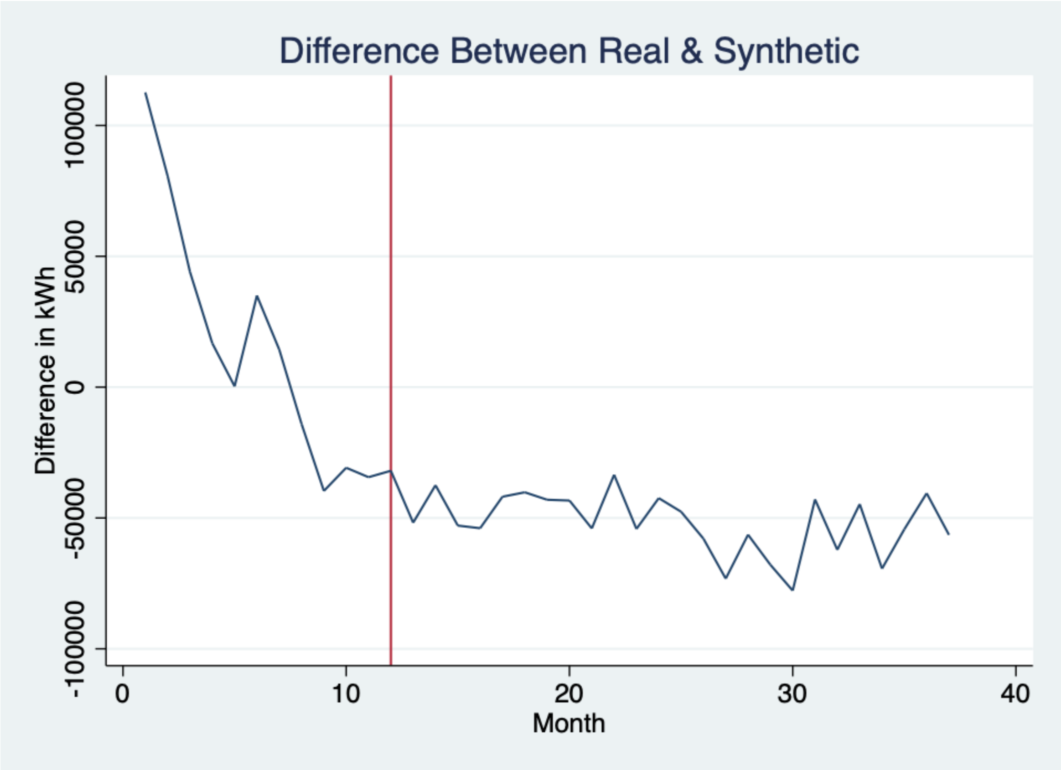

Figure 9

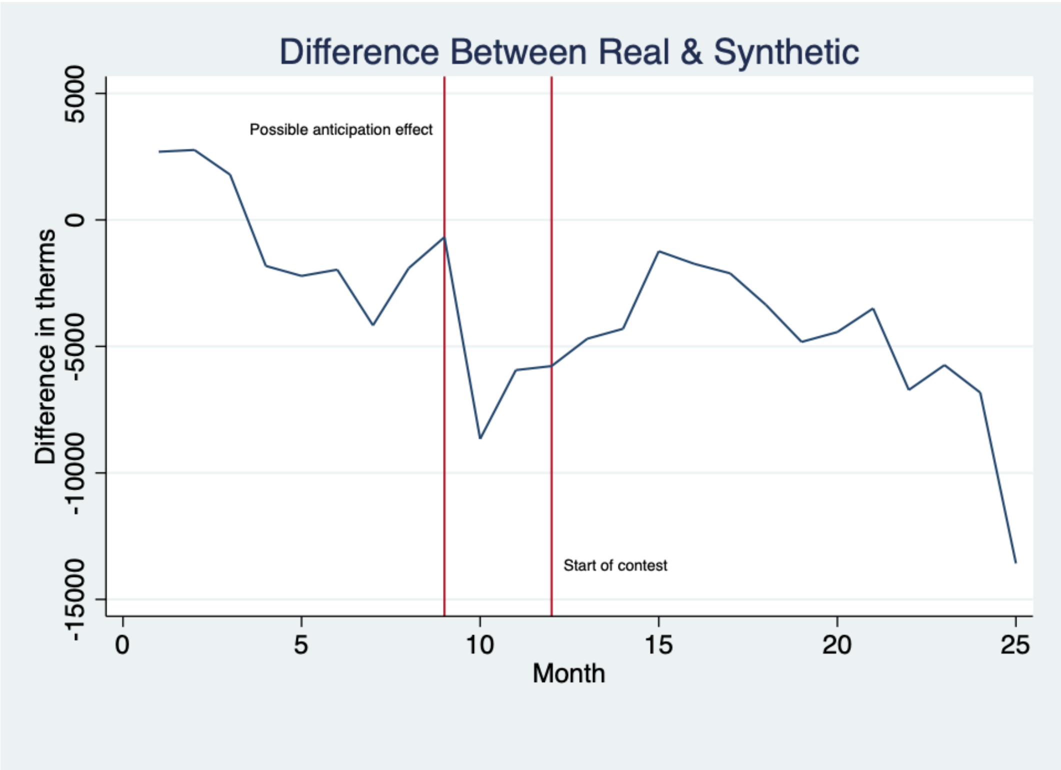

Figure 10

5 Conclusion

The estimates of the effect of the "Just Shut It!"contest held on the University of Colorado Boulder campus do show evidence of a reduction in energy consumption. However, all these estimates likely overestimate the effect. In the estimates generated by the difference-in-differences and event study frameworks this is largely due to the violation of the parallel trends assumption. The evidence suggesting that the estimates generated from the synthetic controls design are overestimates is that the synthetic counterfactual is already above the actual consumption before treatment occurs. This is most likely because there are not enough buildings in the comparison group, especially for natural gas, and/or that the predictor variables used are not enough to adequately model energy consumption. The dip between months 9 and 15 in Figure 10 seems to suggest that this contest does provide savings beyond the bias. The contest is so inexpensive to operate that virtually any savings are enough to justify it.

Interestingly, the building that contributed the most, 68.7%, significantly more than any other building, to the synthetic counterfactual is the WILD building. This building exhibits very similar electricity consumption to SEEL in the period before treatment. The WILD building underwent a large renovation that started in May 2015 and ended in June 2016. The building appears to exhibit the same settling effect that takes place in SEEL, which underwent a major renovation in 2015. That renovation was a possible explanation for the settling and seems to be a good one considering the similar occurrence in WILD.

The greatest limitation in this analysis is certainly the data. It would improve the validity of the results if there were multiple treated buildings. It would also be better if the energy consumption data was of individual laboratories instead of the aggregate building consumption. This would reduce the variation in energy consumption caused by everything outside of the laboratories themselves. While this would make it easier to identify the reduction in energy consumed by fume-hoods, there may still be little to know effect because of building safety requirements. Laboratories will usually have some minimum ventilation requirement, so even if excess fume-hood ventilation is reduced, systems else wear in the building may have to work harder for the safety of the people inside.

There is also the possibility that these estimates suffer from omitted variables bias, an issue that could be solved by having the proper data. For example, some measure of the building occupancy could be very crucial because different buildings are be used more or less at varying times through out the sample. None of the methods used in this study can do anything to account for that variation without the proper data.

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