Evaluation of building policies, programs, and potential for energy efficiency in the United States

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Oluwatobi Gbemisola Adekanye
B.Sc, Electrical and Electronics Engineering, University of Lagos
M.Sc., Energy Science, Technology, and Policy, Carnegie Mellon University

Carnegie Mellon University
Pittsburgh, PA

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Abstract

In the United States, buildings i.e. both residential and commercial are responsible for about 40% of total U.S. energy consumption, and as a result, a large amount of greenhouse gas and criteria air pollutants. Energy efficiency has been identified as a low-cost resource of reducing energy use and hence the carbon footprint in the buildings sector. As a result, a myriad of policy actions has been put in place to ensure that energy reduction goals can be achieved through energy efficiency. This dissertation performs a critical examination of some of these programs and policies that have been put in place with the aim of ensuring that their intended efforts are indeed achieved. This work also provides a prospective look into other considerations e.g. the inclusion of broader health and environmental benefits needed to be made when making the decision about building energy efficiency.

In Chapter 2, I use a panel data approach to measure the association of policy implementation at different levels of the government with increases in green building adoption. I find that the effectiveness of green building policies is dependent on both the nature of the policy as well as the background federal policy context. I corroborate existing research by finding that local policies especially requirement and density bonuses are essential in driving green building certification. I also highlight the importance of federal policies (e.g. federal funding like the American Recovery and Reinvestment Act – ARRA) and private actions (e.g. through improvements to the building rating system process) in driving green building adoption. These findings highlight that local policy, federal policy, and private actions need to work in tandem to drive green building growth.

In Chapter 3, I explore a similar line of questioning, however, focusing on the associations of different energy efficiency programs with reductions in electricity and gas usage. Using the difference-in-difference and event history modeling approaches, I find that behavioral programs are associated with the largest increases in energy reductions even when compared to financial incentive programs. I also provide a means of detecting unexpected program impacts (i.e. changes that occur at the same time as the introduction of a new technology leading to biased estimates of program impacts) using electricity and gas usage data. I find gas reductions for some electricity-only programs thereby indicating that energy reductions may have occurred in the absence of the program. I highlight here that energy efficiency programs have the potential to significantly reduce electricity and gas use in buildings. However, the ex-post evaluation of these programs need to be appropriately measured to ensure that these reductions are indeed associated with policy implementation as significant amounts of money and time is invested in program implementation.

While Chapters 2 and 3 focus on the evaluation of past energy efficiency programs and policies, in Chapter 4, I focus on other considerations that need to be made when making the decision about building energy efficiency. Specifically, I focus on the incorporation of other health and climate impacts when addressing the issue of climate change in the building sector. I investigate the energy reductions, greenhouse gas and other air emission reductions, as well as the private net costs and benefits of implementing a myriad of energy efficiency measures using the case study of the state of Pennsylvania. I find significant energy reductions compared to 2017 baseline levels - 36%, 44%, 19%, and 43% reductions of electricity, gas, propane, and fuel oil. More importantly, I estimate significant social

benefits of $2.4billion per year and highlight the energy efficiency measures which maximize both the private and social benefits for the state.

In Chapter 5, I discuss overarching conclusions and some considerations for policy revealed in Chapters 2 to 4. Findings in Chapters 2 and 3, for example, show the benefits of non-economic programs and incentives in driving building energy efficiency. I corroborate the nascent research on behavioral programs on energy reductions and recommend that utility evaluators examine non-financial program and policy approaches to reducing energy use as it also offers a low-cost alternative to promoting energy use reductions. More specifically, In Chapter 2, I learn that policy actors i.e. local and federal policy makers, as well as private bodies, need to work together in driving green building adoption. However, highlighted is the need for more transparency in ensuring that green building certifications are indeed translating to energy reductions. In Chapter 3, I learn the importance of more robust analyses when using data-driven approaches in the energy measurement and verification process of energy efficiency programs. In Chapter 4, I find that energy efficiency measures which yield the highest private benefits may not necessarily yield the highest social benefits therefore highlighting the need for a more holistic look when making the decision between competing energy efficiency measures.

Table of Contents

List of Tables

List of Figures

Glossary of Acronyms

AP3	3rd version of the Air Pollution Emission Experiments and Policy analysis model
ARRA	American Recovery and Reinvestment Act
CEDM	Center for Air, Climate, and Energy Solutions
CI	Confidence Interval
CI	Commercial Interiors (if used as a suffix to "LEED")
CO_2	Carbon Dioxide
CPA	City of Palo Alto
CS	Core and Shell
DHP	Ductless Heat Pump
DOE	Department of Energy
EB	Existing Buildings
EDC	Electric Distribution Company
EE	Energy Efficiency
EEM	Energy Efficiency Measure
EERS	Energy Efficiency Resource Standard
EIA	Energy Information Administration
EISA	Energy Independence and Security Act
EPA	Environmental Protection Agency
EPACT	Energy Policy Act
GHG	Greenhouse Gas
HPWH	Heat Pump Water Heater
HVAC	Heating, Ventilation, and Air Conditioning
kW	Kilowatt
kWh	Kilowatt-hour
LEED	Leadership in Energy and Environmental Design
MEF	Marginal Emissions Factor
MSA	Metropolitan Statistical Area
MWh	Megawatt-Hour
NO_x	Nitrogen oxides
NREL	National Renewable Energy Laboratory
PA	Pennsylvania
PAT	Parametric Analysis Tool
$PM_{2.5}$	Atmospheric Particulate Matter with a diameter of less than 2.5 micrometers
REAP	Residential Energy Assistance Program
SI	Supplementary Information
SO_2	Sulfur Dioxide
TMY3	Typical Meteorological Year (TMY3)
TWh	Terawatt-Hour
USGBC	U.S. Green Building Council
U.S.	United States'

1. Introduction

One of the most critical issues facing the world today is the risk of climate change. Human activities, especially through the burning of fossil fuels (i.e. coal, oil, and gas) as well as other contributions from agriculture, forestry, and other land-use activities have driven atmospheric greenhouse gas concentrations higher than any time in at least 800,000 years e.g. historic levels of global energy-related emissions were recorded in 2018[1], [2]. As a result, the Earth has warmed at very high rates over the past century, with average temperatures increased by 1.0^0C above pre-industrial levels, and likely to reach 1.5^0C between 2030 and 2052 if left unchecked[3]. As rising greenhouse gas (GHG) concentrations are expected to have a wide range of effects such as rising sea levels which affect populations living low-lying coastal areas due to increasing flooding, increase in prevalence of disasters such as hurricanes or typhoons as a result of changing weather patterns, increased pressure on water and food production, political instability as a result of food insecurity, as well as human health risks such as premature deaths due to air pollution, it is pertinent that significant changes are being made to limit these dangerous impacts that will come with climate change[4].

To combat climate change, different countries around the world have begun to work together to set goals to combat these reductions. For example, the Paris Climate Agreement which went into force in November of 2016 where world leaders representing 195 nations came to a consensus on an accord aimed at combating climate change. The United States, for example, which is the world's largest historical emitter and the second-biggest current emitter after China – committed to cutting overall greenhouse gas emissions by 26% to 28% below 2005 levels by 2025[5]. The roadmap to reducing these emissions in the U.S. have mostly fallen under three broad categories: cutting energy waste through energy efficiency improvements, electricity "decarbonization" through the implementation of low carbon technologies, and changing land use and management[1].

Energy efficiency, particularly building energy efficiency has long been touted as a significant way to reduce promote GHG reductions in the U.S. Buildings are the largest and second-largest contributor to energy consumption and carbon dioxide emissions at 40% and 36% of total energy consumption and emissions respectively[6], [7]. Although projections show that residential and commercial energy use will increase by 0.2% per year between 2018 and 2050 as a result of increase in the number of households and increased air conditioner use due to migration to warmer regions of the country, I find that these projected increases could have been magnified if not for potential contributions of energy efficiency and other distributed generation methods[8]. Through the use of different research and modeling approaches, various literature has identified the energy savings, emissions reduction potential, and costs associated with energy efficiency policies indicating the need for large investments in energy efficiency as they tend to be a cost-effective approach to achieving GHG reductions.

Not surprisingly, large investments in building efficiency have been recorded in recent years. In 2016, for example, building efficiency in the U.S. accounted for $68.8 billion in revenues at an 8% annual growth increase over the past five years[9]. These gains have been as a result of different factors, such as market forces as well as policy impacts[10]. For example, stricter building codes have been developed along with growing interest in greening buildings such as ENERGY STAR or Leadership in Energy and

Environmental (LEED) buildings. Utility energy efficiency programs are also growing in popularity especially as more states are implementing energy efficiency resource standard (EERS) which mandate that utilities or independent statewide program administrators must meet specific targets through customer energy efficiency programs. Similarly, appliance standards have improved dramatically through the combined effects of federal and state appliance standards, utility energy efficiency programs, and tax incentives that encourage manufacturers to develop more efficient products. As increased investments are being made in building energy efficiency, it is critical to ensure that programs and policies are indeed achieving their intended effects. While most energy efficiency policies are estimated to lead to energy savings, with some having cost per kWh estimates lower than private marginal electricity supply costs, recent academic literature is finding mixed results with ex-post evaluation indicating higher costs per kWh saved[11].

This thesis performs both a retrospective and prospective examination of different energy efficiency programs and policies with the aim of informing future decisions in the building sector. Specifically, it focuses on how future energy efficiency programs and policies should be evaluated to ensure that their intended goals are achieved. I also provide insight into future considerations that need to be evaluated when making the decision to implement energy efficiency programs.

In Chapter 2, I employ a panel data approach to examine the relationship between policies and growth in commercial green building retrofits. Specifically, I examine whether local and federal policies aimed at encouraging green building certifications are associated with increases in LEED certification in retrofitted commercial buildings in the U.S. Aggregating data at the Metropolitan Statistical Area (MSA) level, I find that local requirement and density bonuses are significant tools in driving commercial green retrofits. Although the effects are difficult to disentangle, I also observe the influence of federal policies and improvements to the rating system certification in driving commercial green building retrofit adoption. Our results suggest that governments (i.e. through local and federal policy) and private organizations (e.g. through streamlining the rating system process) can work in concert in driving green building adoption.

While Chapter 2 is based on the premise that green building certifications are associated with energy reductions, the proprietary nature of energy consumption data before and after the certification process makes it very difficult to measure in practice. In Chapter 3, I leverage the availability of energy consumption data to measure the associations of energy efficiency program implementation with reductions in energy usage. Specifically, I focus on biases that may occur when using data-driven approaches to examining energy efficiency program implementation, for example, the assumption that reductions would not occur without the implementation of the new technology. By examining concurrent electricity and gas reductions from residential buildings energy efficiency implementation using a panel data of month electricity and gas usage from 2010 to 2016 in the City of Palo Alto, I can examine the reductions in gas usage for electricity-only programs and vice versa. I find significant gas reductions from electricity-only programs indicating that data-driven approaches may also not be adequately estimating program impacts. I also highlight the importance of behavioral programs over financial incentive programs in promoting energy efficiency reductions in buildings.

Having examined the role of energy efficiency programs and policies in driving reductions in the commercial and residential building sector, I shift to investigating the considerations which are pertinent when choosing between competing energy efficiency measures. In a bid to promote reductions through energy efficiency, many states in the U.S. have developed EERS standards which mandate that utilities must meet specific targets through customer efficiency. However, when understanding the potential for energy efficiency in these states, most studies focus on just electricity reductions with little or no regard to public health, environmental and climate benefits. In Chapter 4, I quantify the energy reductions, greenhouse gas and other air emission reductions, as well as private and social benefits that result from the implementation of different energy efficiency measures (EEMs) using the residential single-family (SFD) housing stock in Pennsylvania as a case study. While I find significant health and climate change benefits through the implementation of these EEMs compared to the baseline, these reductions contribute to a very small percentage of total reductions needed if Pennsylvania will meet its set aggressive climate reduction goals. Furthermore, I find that many of these measures are cost-intensive and highlight the need for appropriate incentive and/or financing options.

Chapter 5 synthesizes the findings from these three studies and provides a discussion of the possible policy recommendations. As varied stakeholders e.g. consumers, government, utilities etc., make the decision on how energy efficiency is implemented, it is pertinent that the appropriate considerations are put in place. In this work, I provide insight as to how energy efficiency is presently implemented and provide recommendations on the way energy efficiency can be thought of in the future e.g. through incorporating other health and climate decisions into the decision and policy making process. I hope that with this project, the set goals of a more sustainable future can be more readily achieved.

2. Federal policy, local policy, and green building certifications in the U.S.

Abstract
Buildings account for a large proportion of total U.S. energy consumption, and as a result, greenhouse gas and criteria air pollutant emissions. Concerns about these emissions have led federal, state, and local governments to pass policies aimed at reducing energy use in buildings. In this paper, we examine whether policies aimed at encouraging green building certifications are associated with an increase in the square footage of Leadership in Energy and Environmental Design (LEED) certifications in retrofitted commercial buildings. Using a panel data approach, we find that metropolitan statistical areas (MSAs) with local policies, particularly requirement and density programs, are associated with significant increases in commercial LEED retrofits. Specifically, we find that the switch of an MSA from having no requirement policy to having a requirement policy is associated with an increase of 0.22 LEED sqft/capita in that MSA (a marginal increase of 37% of total per capita LEED square footage in 2016). We also find that federal policies and improvements to the LEED rating system are associated with increases in LEED certifications. While the impacts of federal policy and LEED rating system updates are difficult to separate, our work suggests that local policy, federal policy, and modifications to the LEED rating system can work in concert to drive green building adoption.

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2.1. Introduction

In the United States (U.S.), residential and commercial buildings account for around 40% of total energy consumption and over 70% of total electricity use, resulting in substantial CO_2 emissions[12], [13]. Commercial buildings alone account for approximately 18% of total U.S. energy consumption with projections indicating the growth in energy consumption in commercial buildings at 0.3% per year from 2017 to 2050[12], [14]. To lower CO_2 and air pollution-related emissions, a number of local, state, and federal policies have been implemented as a way to reduce energy use in buildings. One popular strategy has been to encourage existing buildings to attain green building certifications. Here, we focus on the U.S. Green Building Council's (USGBC) Leadership in Energy and Environmental Design (LEED) certification, which is a third-party green building certification program aimed at recognizing high-performance buildings with respect to a number of characteristics, including energy use. LEED is the most widely used green building certification system in the world and is the building benchmark of choice for many U.S. federal government buildings [15], [16].

By the end of 2015, 273 different regulatory policies had been enacted at the city, county, and state levels in the U.S. to induce LEED certifications of commercial buildings[17]. For example, On December 16, 2009, the City of Morgan Hill established a tiered requirement rating system for commercial building renovations and tenant improvements of different sizes (where buildings >1000sqft must achieve 16

LEED points, > 5000sqft must be certified LEED Silver, ≥ \$350,000 permit valuation must achieve 10 LEED points, ≥ \$500,000 permit valuation must be LEED Certified and ≥ \$1,500,000 must be certified LEED Silver)[18]. In a second example, on June 11, 2013, the State of Nevada offered a 25% - 35% reduction on property taxes for one year based on the level of LEED certification[19].
At the same time, federal policies have aimed to improve the energy profile of the U.S. more broadly, including the Energy Policy Act of 2005 (EPAct 2005), The Energy Independence and Security Act of 2007 (EISA 2007), and the American Recovery and Reinvestment Act of 2009 (ARRA 2009). EPACT's section 109 established energy efficiency goals for new federal buildings and provided tax deduction for commercial buildings that reduced energy and power use, then EISA furthered these goals by increasing the federal energy reduction goal from 2% per year (as stated in EPACT 2005) to 3% per year from 2008 to 2015, for an overall reduction goal of 30% relative to the baseline year of 2003[20]–[22]. EISA also established a "Zero Net Energy Commercial Building Initiative" intended to achieve zero net energy performance in all newly constructed commercial buildings by 2030, in 50% of the commercial building stock by 2040, and in all commercial buildings by 2050. ARRA was established in 2009 and through the Energy Efficiency Conservation Block Grant Program helped states, units of local government, and Native American tribes develop energy efficiency and conservation strategies, financial incentives for energy efficiency improvements (e.g. loan and rebate programs), and retrofits of municipal buildings and utility infrastructure.

Sweeping changes to the LEED rating system have coincided with some of these federal policies. The LEED Existing Building: Operation and Maintenance (EB) rating system, for example, was publicly launched in 2004 with major updates in 2008, minor updates in 2009 (LEEDv2009 formerly known as LEED v3) and version 4 LEED v4 launched in 2013[23]. LEED-EB over time has focused on improving performance requirements, reducing reporting burden as well as updating prerequisites and credits for certification[1]. LEED v4 provided more flexibility, such as tailoring certifications to different building types, more streamlined documentation processes, and improving credit categories and prerequisites[2].
Few studies to date have examined the relationship between policy implementation and commercial green building certification. Among the existing studies, a consistent finding is that a mandatory requirement to obtain LEED is an effective way to encourage the growth of commercial buildings[24]–[28]. In other studies, the mere presence of a local policy – regardless of policy type is associated with LEED adoption[29], [30]. Recent studies examine the impact of other factors other than policy in driving commercial green building adoption. York *et al.*, found that apart from policy, private organizations such as social movement organizations, market intermediaries, and environmental entrepreneurs play an important role in encouraging adoption[31]. However, these studies did not take federal policies and changes to the LEED rating system into account – with the exception of Sanderford *et. al*. who examined ARRA funding as a predictor of Energy Star adoptions in the U.S. single-family housing stock[32].

In this work, we examine the impact of local and federal policies while taking into account the simultaneous effect of USGBC LEED rating system improvements in encouraging green building

[1] Some articles have attributed the increase in LEED EBOM to be as a result of improvement of the LEED certification process: https://buildingefficiencyinitiative.org/articles/second-look-green-buildings-rise-certifications-around-world, https://continuingeducation.bnpmedia.com/article_print.php?L=5&C=465, https://www.greenbiz.com/news/2008/07/02/renovation-leed-eb

[2] https://www.usgbc.org/resources/leed-v4-user-guide

retrofits. We use existing buildings because green retrofitting is important for meeting national sustainability goals. For example, a recent study by Nadel shows that for the U.S. to achieve energy use reductions by 50% by 2050 through energy efficiency, 75% of existing commercial buildings would need to be retrofitted[33]. We use city, county, state, and federal level policies specifically aimed at encouraging LEED adoption in the U.S. from 2002 to 2016. We measure adoption as the added square footage of commercial LEED buildings in a Metropolitan Statistical Area (MSA) in each year during this time frame. Data on the square footage of retrofitted commercial LEED buildings comes from the U.S. Green Building Council's (USGBC) database[34],[35]. The information regarding the policies comes from the Database of State Incentives for Renewables and Efficiency (DSIRE) and the USGBC policy databases. Economic data (e.g. Population, GDP, Unemployment rates) comes from the various sources that report US Statistics (such as US Census, US Bureau of Economic Analysis, US Bureau of Labor Statistics) for each MSA[36]–[38]. Other controls that measure an area's demand for green products such as the non-residential solar PV installations (from the Lawrence Berkeley National Laboratory Tracking the Sun dataset) and the count of Electric Vehicle fuel stations in an MSA (from the US Department of Energy's Energy Efficiency and Renewable Energy Datasets) are also included. We leverage the availability of multiple years of data in each MSA to remove time-invariant confounding effects of endogenous policy choices. Specifically, we use location and year fixed effects to account for omitted variables that are constant for each MSA across time and for all MSAs in each year.

The work extends the existing literature in several novel ways. First, we use panel data from years 2002 to 2016 using the change in annual LEED square-footage as our unit of observation. Secondly, we account for not only local policies but also federal policies and changes to the LEED rating system. Finally, we examine policy effects separately for owners and tenants. The rest of this paper is organized as follows: first we explain our data and methods then we follow with our findings and a discussion of our results in the last section.

2.2. Data and Methods

2.2.1. LEED building and policy characteristics

LEED buildings and certifications: The added squared footage of LEED-certified buildings is our metric of interest. We use data on the number and type of retrofitted commercial buildings from the USGBC LEED projects database[39]. Between its inception in 2000 and October of 2018, the USGBC has certified over 137,000 U.S. buildings. However, a major portion of LEED buildings is certified as "confidential" (for example military-owned buildings) or residential buildings. Our study looks into 10,420 existing buildings that received LEED certification under *existing buildings: operations and maintenance (EB), commercial interiors (CI),* and *core and shell (CS) rating* system categories (See Appendix A.1.-A.2. for more details,). In Figure 2.1, we show buildings that registered and went on to pursue certification annually between 2002 and 2016 broken down by count and total added square

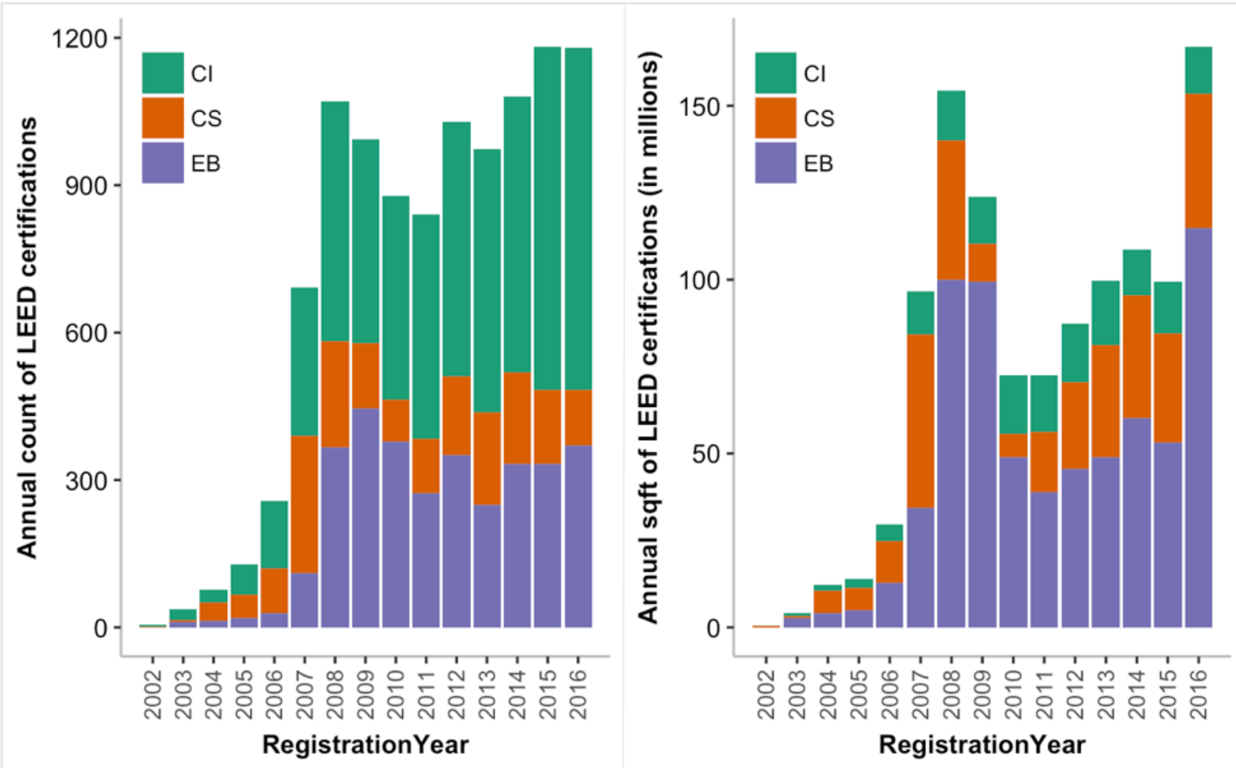

Figure 2.1 - Number of retrofitted commercial buildings added each year for the different rating systems by count (left) and total square footage (right) from January 2002 to December 2016. CI – Commercial Interiors, CS – Core and Shell, EB – Existing Buildings: Operations and Maintenance. Source: Produced by the authors using data from USGBC Policies database[39]

footage. While we have data through October 2018, we chose 2002 as the beginning year of our analysis when a pilot version of the LEED program began.

USGBC LEED Rating System Updates. We include dummy variables in our model for the launch dates of new USGBC LEED rating systems, coded as 1 during the years the LEED rating system version was in place and 0 otherwise. Some important events were the LEED-EB update in 2008 which as it was a major overhaul from the initial LEED version, as well as the LEED v4 program in 2013. While updates to the CI and CS program were made in 2009 through the LEED v2009 update, the dummy variable indicator would have been confounded with the ARRA-EECBG Federal program as discussed above so it was excluded from the analysis (See Appendix A.1. for more details,).

City, county and state level policies. We identify 273 relevant government policies enacted by the year-end 2015 specifically aimed at encouraging LEED certification among existing commercial buildings. Of these 273 policies, 224 are city-level programs, 34 are county-level programs, and 15 are state-level programs. Based on our literature review of related papers, we grouped these into 5 major categories: (1) requirements, (2) recommendations, (3) height/density bonuses, (4) financial incentives, and (5) non-financial incentives. In Appendix A.3., we provide a detailed description of the different policies under each of these categories as well as a breakdown of the policies by MSA. In Figure 2.2, we show the different categories of policies in the U.S. over time. The most common policy types are recommendation policies where buildings are encouraged to build LEED without any form of enforcement in place, for example, a LEED checklist program where a checklist is filled out to adhere to LEED standards but no formal certification is mandated. Financial incentives range from as little as a LEED certification fee reimbursement to substantial property tax reductions. Non-financial incentives, such as an expedited permitting process for LEED construction, and requirement programs, such as a mandatory requirement to obtain LEED in a city or county above specified square footages, are also relatively common. The majority of the policies were enacted between 2007 and 2009, particularly in 2009, during the ARRA implementation. Also, the incentives vary widely by state, with California and Florida implementing the highest number of policies.

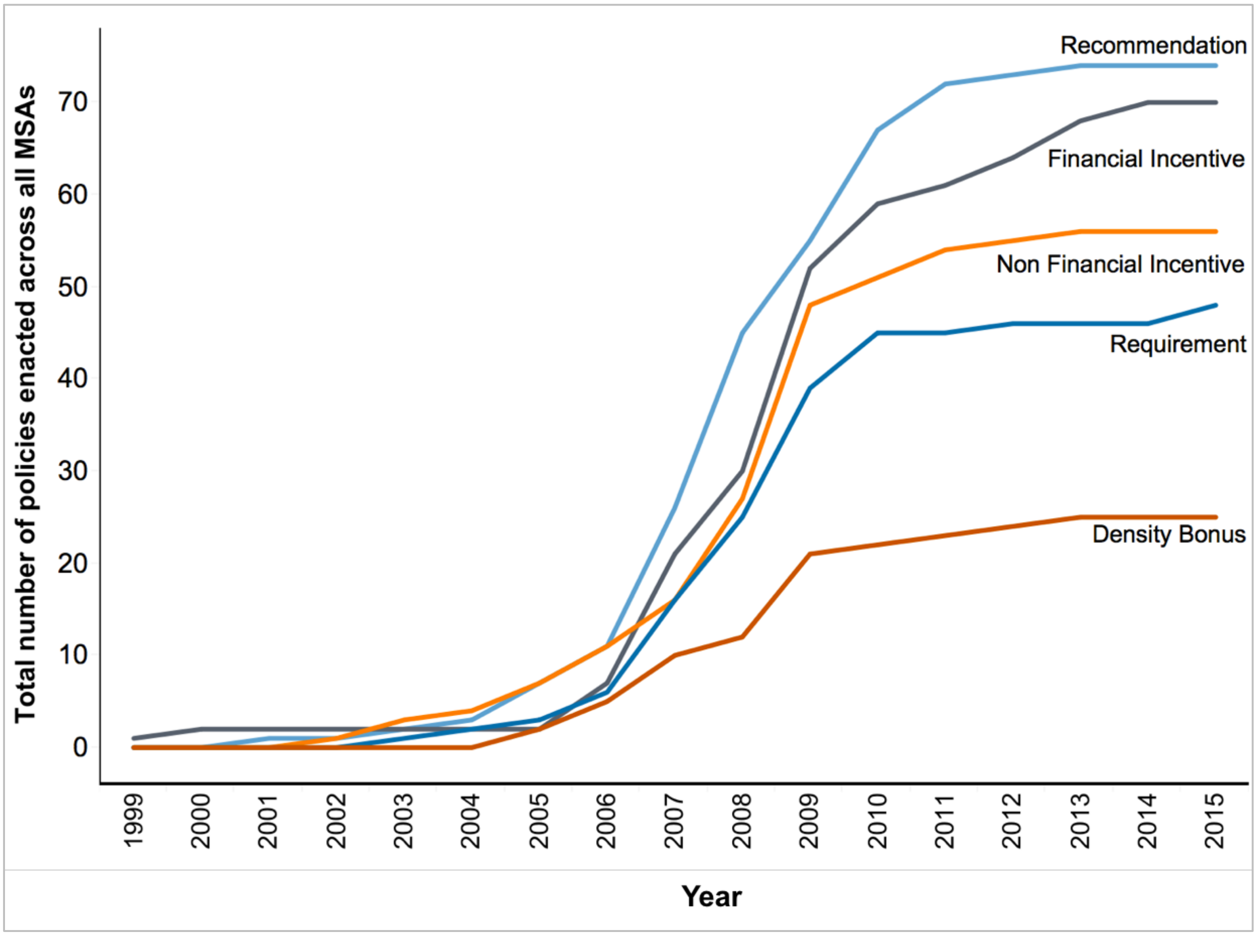

Figure 2.2 - Number of state, city and county policies in effect in each year from 1999 to 2015 related to existing commercial LEED building certifications. Source: figure produced by the authors using data from USGBC Policies database[17]

2.2 Model Approach

We deviate from our primary and preregistered analysis (presented in osf.io/e7qzk) because we observed very large lagged effects three years after policy implementation. Upon further examination, we realized that USGBC LEED updates as well as federal policy implementation needed to be explicitly included in the model (See Appendix A.10. for more details on the initial model as well as results preplanned for this study). In this section, however, we present the final model used to inform our results.

We use a panel approach at the level of the metropolitan statistical area (MSA). Specifically, some MSAs implement a policy (e.g. financial incentive) and we observe the change in the square footage of LEED certified building space per capita in that MSA over time. To understand our analysis, we discuss two topics in turn: 1) our method for determining the degree to which an MSA is treated by a policy, and 2) mathematical representation of our final model.

2.2.2. Method for determining the degree to which an MSA was treated by a policy

Because the policies were enacted at the city, county, or state level, but our level of analysis was the MSA, we look at the proportion of people potentially affected by the presence of a policy in the MSA as our treatment variable. For example, if San Mateo city, CA, enacts a density bonus in 2004, the fraction of San Francisco-Oakland-Hayward MSA that gets treated in 2004 is calculated by dividing San Mateo's city population by the total San Francisco-Oakland-Hayward MSA population. However, if San Francisco county (which contains San Mateo) gets treated by a density bonus in 2006, we calculate the density bonus treatment in 2006 as the fraction of the total county population divided by the total MSA population, ignoring San Mateo city. This method is implemented to avoid double counting, as cities are nested within counties, which are nested within MSAs. On the other hand, if a state-level density bonus is implemented in CA on the other hand, then the total MSA gets treated by the policy and the fraction of the MSA treated assumes a value of 1.

2.2.2 Mathematical representation of final models

We compare the change in square footage for MSAs that implemented a policy to the change in square footage for MSAs that don't implement a policy, adjusting for time-varying economic covariates (e.g., GDP in the MSA). We look at changes between MSAs treated by a policy and MSAs not treated to mitigate the effect of any time-invariant unobserved differences between MSAs that might affect both policy choice and LEED certifications. Our main model specification (with results presented Table 2.1) is:

$$Y_{i,t} = \alpha REQT_{i,t} + \beta RECOM_{i,t} + \gamma FINAN_{i,t} + \delta NOFINAN_{i,t} + \lambda DENSITY_{i,t} + \rho GDP + \mu UNEMPLOY_{i,t} + \varphi SOLARPV_{i,t} + \varphi EVCOUNT_{i,t} + \lambda_t + MSA_i \qquad (2.1)$$

where *i* represents an MSA and *t* represents the time period (2002 – 2016). $Y_{i,t}$represents the change in LEED square footage per capita in each MSA from one year to the next. $REQT_{i,t}$, $RECOM_{i,t}$, $FINAN_{i,t}$, $NONFINAN_{i,t}$, and $DENSITY_{i,t}$ range between 0 and 1 and represent the change in fraction of MSA population *i* affected by the presence of a requirement, recommendation, financial incentive, non-financial incentive, and density bonus policy from one year to the next. $GDP_{i,t}$, $UNEMPLOY_{i,t}$, $SOLARPV_{i,t}$, and $EVCOUNT_{i,t}$ represent the Gross Domestic Product (GDP) , Unemployment rates, total non-residential solar PV installations (excluding utility-scale solar), and total number of Electric Vehicle (EV) charging stations for an MSA in a year. MSA_i, λ_t, and $\varepsilon_{i,t}$ represent MSA dummy variables, time dummy variables and the error term, respectively.

Our control economic variables include the gross domestic product and unemployment rates across for MSA in a year. The real GDP by metropolitan area was sourced from the U.S. Bureau of Economic Analysis (BEA) and is an inflation-adjusted measure of the economic activity of each metropolitan area based on the national prices of the goods and services produced within that MSA. Because the GDP itself is computed using dimensions that are affected by LEED construction (which would be problematic in our regression model because of conditioning on an effect), such as construction GDP (i.e. contribution of the GDP to residential and commercial building structures), manufacturing GDP (includes wood products, fabricated metals and furniture), and real estate GDP (includes contributions to rentals and leasing) we removed those portions of the GDP in our analysis. The unemployment rate statistic is obtained from the U.S. Bureau of Labor Statistics (BLS). BLS provides annual estimates of the unemployment rates at the county level, which we averaged over MSAs.

We also include environmental control variables to account for areas who demand for more green products and services. We include non-residential solar PV installations and the total EV counts in an MSA in a given year. The Solar PV data was obtained from the Lawrence Berkeley National Laboratory (LBNL) Tracking the Sun Dataset which includes information on solar PV installations for different customer segments. We aggregated non-residential solar PV installations at the zip code and city levels to the MSA level for the purpose of our analysis. The total EV count data was obtained from the Office of Energy Efficiency and Renewable Energy (EERE) through the U.S. Department of Energy (See Appendix A.4 for more details on these controls).

We replicate equation (2.1) four times by changing the dependent variable to account for existing commercial buildings (1) irrespective of LEED rating system type, (2) under the LEED-EB rating system, (3) under the LEED-CI rating system, and (4) under the LEED-CS rating system. The results of these regressions are presented in Columns (1), (2), (3), and (4) of Table 2.1 respectively.
Alternative model specifications are presented in Appendix A.5. – A.8. Firstly, we attempted to include the impact of federal policies as well as the USGBC LEED rating system updates in our main model. However, the time dummy variables are confounded the federal policy and USGBC LEED rating system update indicators. We modify equation (1) by dropping the time dummy variables as follows:

$$Y_{i,t} = \alpha REQT_{i,t} + \beta RECOM_{i,t} + \gamma FINAN_{i,t} + \delta NOFINAN_{i,t} + \lambda DENSITY_{i,t} + \rho GDP_{i,t} + \mu UNEMPLOY_{i,t} + \varphi SOLARPV_{i,t} + \varphi EVCOUNT_{i,t} + \varrho AFTER_{EPACT_{i,t}} + \psi AFTER_{EISA_{i,t}} + \varsigma AFTER_{ARRA_{i,t}} + MSA_i + \varepsilon_{i,t} \qquad (2.2)$$

Equation (2.2) represents the base case situation where the dependent variable accounts for all existing commercial LEED buildings irrespective of the rating system type. $AFTER_{EPACT_{i,t}}$ and $AFTER_{EISA_{i,t}}$ and are policy indicators for EPACT and EISA that takes on a value of 1 and onwards for years 2005 and 2007 respectively for all MSAs and all years. $AFTER_{ARRA_{i,t}}$ takes on the value of 1 between the years 2009 and 2012 (to account for the disbursement of EECBG funds) and 0 otherwise. In Appendix A.6, we replicate Equation (2.3) to include LEED-EB update in 2008 as well as the LEED v4 update in 2013.

We also examine the effect of local policies on commercial green buildings using a first differences approach (with results presented in Appendix A.8) as follows:

$$
\begin{aligned}
Y_{i,t} - \ Y_{i(t-1)} \ = \alpha(REQT_{i,t} - \ REQT_{i(t-1)}) \ + \beta(RECOM_{i,t} - \ RECOM_{i,(t-1)}) + \gamma(FINAN_{i,t} \\
- \ FINAN_{i,(t-1)}) + \delta(NOFINAN_{i,t} - \ NOFINAN_{i,(t-1)}) + \lambda(DENSITY_{i,t} \\
- \ DENSITY_{i,(t-1)}) + \ \rho(GDP_{i,t} - \ GDP_{i,(t-1)}) \ + \mu(UNEMPLOY_{i,t} \\
- UNEMPLOY_{i,(t-1)}) \ + \ \varphi(SOLARPV_{i,t} - \ SOLARPV_{i,(t-1)}) + \ \varphi(EVCOUNT_{i,t} \\
- \ EVCOUNT_{i,(t-1)}) \ + \ \lambda_t + MSA_i + \varepsilon_{i,t} \qquad (2.3)
\end{aligned}
$$

Finally, we use the Anderson-Hsaio estimation model to examine violations to strict exogeneity as it is possible that LEED certifications in the previous year has an effect on LEED certifications in the present year. To implement Anderson-Hsaio, we firstly implement a first-differenced estimation as in Equation (2.3) then use a 2 year lagged dependent variable as an instrument variable in the model as there is no correlation of the errors and regressors with a 2 year lagged dependent variable. The Anderson-Hsaio model (presented in Appendix A.8) is implemented as:

$$
\begin{aligned}
Y_{i,t} - \ Y_{i(t-1)} \ = \partial(\widehat{Y_{i(t-2)}}) + \ \alpha(REQT_{i,t} - \ REQT_{i(t-1)}) \ \ + \beta(RECOM_{i,t} - \ RECOM_{i,(t-1)}) \\
+ \ \ \gamma(FINAN_{i,t} - \ FINAN_{i,(t-1)}) + \delta(NOFINAN_{i,t} - \ \ NOFINAN_{i,(t-1)}) \\
+ \ \lambda(DENSITY_{i,t} - \ DENSITY_{i,(t-1)}) + \ \rho(GDP_{i,t} - \ GDP_{i,(t-1)}) \\
+ \ \mu\big(UNEMPLOY_{i,t} - UNEMPLOY_{i,(t-1)}\big) + \ \varphi\big(SOLARPV_{i,t} - \ \ SOLARPV_{i,(t-1)}\big) \\
+ \ \varphi(EVCOUNT_{i,t} - \ EVCOUNT_{i,(t-1)}) + \ \lambda_t + MSA_i + \varepsilon_{i,t} \qquad (2.4)
\end{aligned}
$$

We settle on equation (2.1) as the correct model specification as it was the most reasonable given the trends seen in the exploratory analyses of the dataset made using plots such as those in Figures 2.1 and 2.2 of the main paper. Appendix A.8 also gives a more detailed explanation of the fixed effects (our model) versus the first differences model, providing more credibility to our model selection approach.

For all the models implemented, we estimate the standard errors using a clustered bootstrap approach, which allows for correlation between the errors in the same MSA.

2.3. Results

Table 2.1 presents the results of the effects of different local policy types on retrofitted LEED square footage accounting for year and MSA effects in 4 columns: Column (1) presents results in all commercial building projects – irrespective of LEED rating system type. Column (2) presents results for commercial projects certified under the LEED-EB rating system. Column (3) presents results for commercial projects certified under LEED-CI rating system, and Column (4) presents results for commercial projects certified under LEED-CS.

Table 2.1 - Model results examining the effects of different local policy types on retrofitted LEED square footage in commercial building projects 1) irrespective of rating system type 2) certified under the LEED-EB rating system, 3) certified under the LEED-CI rating system 4) certified under the LEED-CS rating system

Variable	***Coefficient and robust standard errors***			
	(1)	**(2)**	**(3)**	**(4)**
Requirement	**0.22** **(0.10)**	**0.07*** **(0.04)**	0.03 (0.02)	0.08 (0.08)
Density/Height bonus	0.03 (0.10)	**0.13** **(0.06)**	**0.04*** **(0.02)**	-0.11 (0.08)
Financial incentive	0.02 (0.03)	-0.01 (0.01)	-0.0004 (0.005)	0.03 (0.03)
Non-financial incentive	0.09 (0.08)	0.01 (0.06)	-0.004 (0.01)	0.09 (0.10)
Recommendation	0.003 (0.06)	0.02 (0.06)	0.02 (0.01)	-0.03 (0.03)
GDP (in billions of dollars)	**0.004***** **(0.001)**	**0.002**** **(0.0009)**	**0.0005***** **(0.0001)**	**0.0009**** **(0.0005)**
PV System Size (in GW)	-0.006 (0.02)	-0.005 (0.007)	0.001 (0.002)	-0.002 (0.01)
EV charging stations (Count)	-0.0005 (0.001)	0.0003 (0.0009)	**-0.0002*** **(0.0001)**	-0.0005 (0.0005)
Unemployment rate (%)	-0.004 (0.005)	0.003 (0.004)	-0.001 (0.0006)	**-0.006 ***** **(0.002)**
Intercept	**-0.24***** **(0.07)**	**-0.11***** **(0.04)**	**-0.03**** **(0.01)**	-0.08 (0.06)
MSA dummies	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included
Observations	5730	5730	5730	5730
Number of groups	382	382	382	382

Robust standard errors in parentheses.
***** p < 0.01, **p< 0.05, *p<0.1.**
Notes: Values in bold represent statistically significant coefficients (at least p < 0.10). GDP = Gross Domestic Product, EV = Electric Vehicle

In Column (1), when examining all commercial building retrofits, we find that only requirement policies have a significant effect in increasing retrofitted commercial LEED square footage, with an increase of 0.22 LEED sqft/capita. To put this in context, about 166M square feet of retrofitted commercial LEED space was added in 2016 with a total population of 270M – yielding an average of 0.6 sqft/capita, so if an MSA switches from having no requirement policy to having a requirement policy, there is a marginal increase of as high as 37% of LEED sqft/capita in *that* MSA. We also find that an increase in GDP by 1 billion dollars is associated with a smaller 0.004sqft/capita increase of retrofitted commercial LEED sqft/capita. We find smaller non-significant effects of other local policies with non-financial incentives, density bonuses, financial incentives, and non-financial incentives associated with increases of 0.09sqft/capita (95%CI: -0.07 to 0.25), 0.03sqft/capita (95% CI: -0.17 to 0.23), 0.02sqft/capita (95% CI: -0.04 to 0.08), and 0.003sqft/capita (95%CI: -0.11 to 0.12) respectively. Other covariates which measure an MSA's economic and environmental appear to have little effect on commercial green building retrofits. There are almost zero effects with increases in non-residential solar PV installations, count of EV charging stations, and unemployment rates.

From Column (2), requirement policies, density bonuses, and GDP are associated with significant increases in LEED sqft/capita for commercial building retrofits certified under LEED EB. There are increases of 0.07sqft/capita, 0.13sqft/capita, and 0.002sqft/capita respectively. While we lumped LEED policies and LEED program types in Column (1), we are cognizant that the motivation to retrofit as green may vary widely depending on project type. For LEED-EB, it appears that density bonuses also are important in driving commercial LEED retrofits. Just like Column (1), GDP and requirement policies have a significant effect of LEED sqft/capita increases.

Column (3) which examines the effect of local policies on LEED sqft/capita in the CI space show significant effects with the implementation of density bonus policies only. These effects are much smaller than Column (1) and Column (2) effects as explained in the data section above, LEED-CI mostly targets interior spaces as opposed to whole building projects resulting in smaller added LEED sqft/capita. Just like Columns (1) and (2), GDP has a significant effect on commercial building retrofits in the CI space as well.

In Column (4), none of the local policies have a significant effect on encouraging commercial LEED-CS retrofits. While average estimates of requirements and non-financial incentives are large at 0.08sqft/capita and 0.09sqft/capita respectively, there is a large variation in the standard errors. We hypothesize that this may be due to low variation in the number of projects who get the LEED-CS certification compared to other LEED rating system types.

Figure 2.3 shows a plot of the year-over-year estimates of Column (1) of our main regression results to tease out the effect of federal policies as well as USGBC LEED rating system updates with the year 2002 being the base year. We do not find a significant effect on added LEED sqft/capita until 2007. We hypothesize that this is partially due to the implementation of federal policies such as EISA and ARRA which began in 2007 and 2009 respectively. However, federal policy implementation also coincides with LEED rating system updates as seen in Figure 2.3. For example, the highest year effect occurred in 2008 which may be due to the launch of LEED-EB v2 as it was majorly overhauled from the pilot version to streamline the certification process and reduced overlap with the LEED new construction rating system. In 2012 and 2013, there is a slight drop-off of the year effects which indicate the end of ARRA funding and the beginning of LEED v4 respectively. Therefore, we hypothesize that some of these year effects are driven by federal policies as well as LEED rating system updates. We also find similar results when examining year-over-year effects for individual LEED rating system types (with results presented in Appendix A.5).

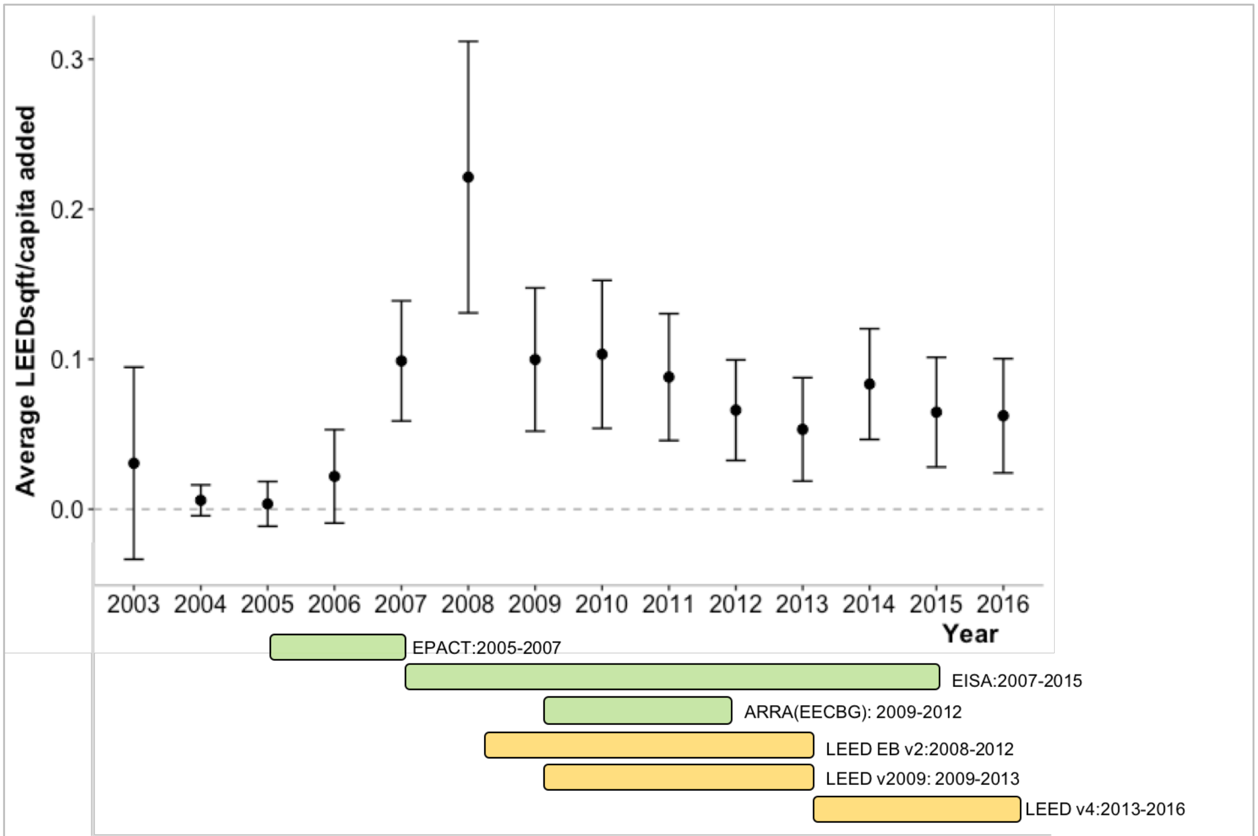

Figure 2.3 - Year-over-year estimates showing the effects of federal and USGBC LEED rating system updates between 2003 and 2016 using 2002 as the base year. Blocks in green represent federal polices while blocks in yellow represent internal USGBC rating system updates.

Overall, our results show greater rates of commercial green building certifications among MSAs that implement requirement and density bonus policies. We also find that increased economic health in an area (i.e. GDP) is associated with increases in LEED certifications on the average as areas that are more financially buoyant may be willing to invest in more green infrastructure as compared to areas that as not as wealthy. Additionally, federal policies and USGBC LEED rating system updates play a large role in motivating building owners and tenants in certifying green. However, the impacts of federal policies are hard to separate from LEED rating system updates.

2.4. Discussion and Policy Recommendation

In this work, we examine the relationship between local policies, federal policies, and growth in commercial green building retrofits. By using a panel data model with location and year effects, we find that overall, requirement policies are the most effective in driving commercial green building retrofits. More specifically, requirement and density bonuses are most-effective in driving the LEED-EB rating system type while density bonus policies are the most significant in driving projects certified under LEED-CI. However, none of the local policies have a significant effect on driving projects certified under the LEED-CS rating system type. We also find that federal policies and USGBC LEED rating system improvements also play a major role in green building certifications. The extent of this effect is more difficult to quantify compared to the role of local policies because federal policies occur simultaneously with changes to the LEED rating system.

Our results are consistent with earlier work that finds that requirement policies are significant tools for promoting green building development. While other papers have mostly focused on policies in relation to new construction growth, our work shows that requirement policies are also successful with regards to existing building retrofits. Requirement policies may be successful in part due to the penalization of buildings that fail to implement mandatory LEED standards set by the city. Cites in the U.S. such as Portland and Washington (D.C.) implemented "feebates" and performance bond programs, respectively, that penalize commercial buildings that fail to meet the LEED regulatory requirement in their respective cities. In 2013, for example, 78% of projects certified in Washington DC was certified under LEED-EB[3]. Our analysis also shows that a requirement policy could account for as much as a 37% increase in retrofitted commercial floor space thereby indicating the significance of the policy type in driving commercial green buildings.

Density bonuses are significant in promoting certifications under the LEED-EB rating system where we find an average increase of 0.11sqft/capita with the implementation of a density bonus policy. As the LEED-EB rating applies to the entire building, building owners may be incentivized to retrofit as green to take advantage of the extra floor to area bonuses that is conferred if a building is certified as LEED. These may lead to increased monetary benefits for the building owner especially in areas with a dense population as commercial space is highly sought after and even more so when the commercial space is certified as green[4].

The impact of local policies on LEED-CI certification is similar where we find smaller significant effects of density bonuses. The LEED-CI rating system applies to projects which are a complete interior fit-out, therefore, renovations or additions to an existing building may qualify to be certified under this category. Because LEED-CI does not apply to a whole building, the amount of space added under LEED-CI is much smaller than that of LEED-EB, lending credibility to our results. From our dataset, there is a four-fold increase in LEED-EB space certified compared to LEED-CI space certified in the time frame of analysis although the count of CI spaces certified is almost double that of EB. This highlights the importance of taking into account the types of building spaces that are being certified, which could range from small spaces such as a restaurant that is a few thousand square feet, to large offices that account for hundreds of thousands of square feet.

For LEED-CS, we find no significant effects of local policies on commercial green building certifications. We hypothesize that this is due in part to less significant variation in the number of buildings certified under the LEED-CS space, as only 1802 out of around 10420 spaces were certified as LEED-CS. If we examine estimates of local policies as in Column (4) of Table 2.1, we find that requirements and non-financial incentives have the highest effect on added LEED-CS space. LEED-CS is mostly used when the developers control the building's design and construction of the mechanical, plumbing, and fire protection

[3] https://www.usgbc.org/articles/taking-sustainability-seriously-washington-dc
[4] https://www.usgbc.org/articles/business-case-green-building

system but not the design and construction of the interior fit-out[5]. As the review and permitting processes for different jurisdiction varies widely from one to the next, in some cases taking as long as one and half years, expedited permitting may indeed yield significant cost savings to the developer. Overall, with LEED-CS, requirements and expedited permitting policies seem to be the most promising[6].

Surprisingly, we do not find large or significant effects of financial incentives and recommendation policies for the different rating system categories. Recommendation policies are only put in place to encourage LEED certification, but there is no enforcement, therefore we might find an effect on the number of LEED registered buildings who do not actually go on to certify their projects. The results of financial incentives being a predictor of LEED certifications are consistent with previous studies that have not found an effect in financial incentives in promoting green construction[24], [40]. We attempted to code the financial value of city-level financial incentives for achieving LEED Gold Status and estimated about $0.01 per sqft in Chattanooga, TN to $6.3 per sqft in Onondaga County, NY (See Appendix A.9 for more details). However, due to difficulties in building specification as most incentives are estimated on a case-by-case basis, we were unable to estimate the financial range for all financial incentive programs in our dataset.

Federal policies, as well as USGBC LEED updates also play a significant role in encouraging commercial green building retrofits. We attempt to quantify the size of these effects by conducting linear regressions including dummy variables for federal and internal LEED policies, however, these results are confounded with the year dummies (See Appendix A.6 for more details). Therefore, examining year-on-year effects show a clearer picture of the federal policies as well as internal LEED updates (as presented in Figure 2.3 in the main paper and in Appendix A.5 for individual LEED rating systems). For all rating systems, we find a generally increasing trend following EISA and ARRA. However, not only federal policies but also LEED rating system updates are associated with green retrofits. For LEED-EB for example, we find a significant increase during its first major LEED update. LEED-CI and LEED-CS largest effects are observed around 2009 which coincides with the LEED-CI and LEED-CS update to LEED v2009 as well as ARRA implementation. We also find small increases after LEED v4 update in 2013 indicating that some increases in LEED certifications may also be due to improvements in LEED rating systems as LEED has been focused on improving prerequisites, credits, as well as overall user experience through the LEED process[7]. USGBC also started the LEED Volume project in 2011 which streamlines the LEED certification process for buildings of similar types[8]. Companies such as Starbucks, PNC, Wells Fargo have taken advantage of the LEED Volume program which has also made the certification process a lot easier especially in the case of companies with a large portfolio. We attempted to capture the effects of LEED Volume by examining an alternative specification model using the counts of LEED buildings certified under the different rating systems as opposed to the added LEED sqft/capita added (See Appendix A.7 for more details) and found that LEED Volume is also a significant player in driving LEED certification. Further research into these companies also shows that companies who took advantage of the

[5] https://www.usgbc.org/discoverleed/certification/bd-c-core-and-shell/
[6] https://www.usgbc.org/articles/good-know-green-building-incentive-strategies-0
[7] https://www.usgbc.org/resources/summary-changes-leed-2009-v4-om
[8] https://www.usgbc.org/articles/leed-volume-program-myth-vs-fact

LEED Volume program also have sustainability commitments in place[9]. While we were not able to examine each of the companies in the LEED projects database sustainability portfolios, we have some evidence that the LEED Volume program has provided an easier means of achieving a company's sustainability goals.

Our analysis is subject to several limitations that highlight opportunities for additional research. Our data was focused on existing buildings as opposed to new construction because the base rate of new construction in each MSA was not known. Future analysis could expand these analyses by examining these effects (especially the federal policies and USGBC LEED updates) on new construction (NC) as opposed to existing buildings. Significant challenges were also faced when categorizing policies as existing building policies as opposed to new construction policies as the language used in the policy documents could be confusing. Similarly, the LEED project directory did not specifically state if buildings certified under LEED-CI or LEED-CS program was in a new or an existing building. Through conversations with USGBC officials, we characterized the buildings and policies as we thought appropriate. However, our results may be more significant if those distinctions between NC and EB are specifically delineated. We had difficulties estimating the actual value of the financial incentives in our dataset as in many cases, significant documentation of building is needed. Therefore, future research could focus on estimating the financial value of the financial programs to better capture its effects. Additionally, we also do not have energy consumption information on these certified buildings before and after the certification process as this information is proprietary making it more difficult to measure the real impacts of greening a retrofitted building. Studies have shown varied effectiveness of LEED certification with some earlier research indicating that LEED may not be achieving the savings it claimed. However more recent research has indicated significant energy savings therefore as standards are getting more stringent, LEED certifications appear to be achieving energy reduction goals[41]–[46]. Therefore, future research could focus on also specifically quantifying the amount of energy and carbon savings from implementing local and federal policies. Finally, while we were able to look at different LEED rating system types, the motivation for various project types may be different – office spaces motivation to certify as green could be separate from that of a warehouse. Future work could look further drill down and examine different project types so policies could be specifically tailored to meet the needs of various building categories.

Policies that promote the certification of green buildings, such as LEED, have the potential to meet energy efficiency and carbon reduction goals. The effectiveness of these policies depends on their nature (the type of policy) and the background federal policy context. We find that requirements and density bonuses are a useful tool in promoting green building retrofits. Similarly, the implementation of federal policies and funding such as EISA and ARRA are associated with increases in commercial green building retrofits. Also, as the LEED process gets better tailored to different building types and allows for a better focus on user experience, building certification becomes less intimidating and more achievable. While we

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[9] Sustainability commitments for: Starbucks: https://www.starbucks.com/responsibility/environment/leed-certified-stores;

Kohls: https://corporate.kohls.com/news/archive-/2018/october/kohl-s-recognized-for-industry-leading-sustainability-practices;

Wells Fargo: https://newsroom.wf.com/press-release/community/wells-fargo-ranks-no-1-leed-projects-financial-industry have only begun to examine the extent to which different stakeholders help in promoting green buildings, this study highlights the importance of the different roles of public policy and private actions in encouraging green building certifications.

3. Do LED lightbulbs save natural gas? Detecting unexpected program impacts using electricity and natural gas billing data

Abstract
Energy efficiency programs have been implemented at the local and state levels to promote reductions in residential energy use. Ex-post evaluation using data-driven approaches is commonly used to complement ex-ante engineering estimates in determining the extent to which these programs are associated with energy reductions. A critical assumption made during these evaluations is that these reductions would not occur without the implementation of the new technology. This assumption is difficult to test, especially if other technologies being implemented are not simultaneously being observed. We provide a means of detecting unexpected impacts on program estimates by examining concurrent electricity and gas reductions from energy efficiency implementation using a panel data of monthly electricity and gas usage from 2010 to 2016 in the City of Palo Alto, California. Using difference-in-differences and event history approaches, we find evidence of significant gas reductions estimated for electricity-only programs, indicating that using only data-driven approaches may not adequately estimate program impacts and the value of simultaneous electricity and natural gas measurements for detecting unexpected effects. Lastly, we present evidence that energy savings from behavioral interventions can exceed those which offer financial rewards for energy efficiency.

A version of this chapter is currently under review in the Environmental Research Letters Journal as:
Adekanye O.G., Davis A. & Azevedo I.L. "Do LED lightbulbs save natural gas? Detecting unexpected program impacts using electricity and natural gas billing data"

3.1. Introduction

Energy efficiency is a cost-effective way of reducing energy use, with billions of dollars invested annually in reducing energy use [47]–[49]. With buildings responsible for about 41% of total U.S. energy consumption and around one-third of CO_2 emissions, there is the potential of using building energy efficiency as a tool in long term energy and carbon reduction goals[1], [6], [50]–[59]. While different local and state government bodies across the U.S. have implemented many financial incentives and technical support programs in a bid to promote building energy efficiency, the question remains on how much is ultimately delivered by a program or technology.

In quantifying the savings of new energy efficient technologies, most studies use a deemed-savings approach. For example, a new light emitting diode (LED) lightbulb should reduce energy use in a building depending on the number of hours it is used multiplied by the difference in energy use per hour compared to a prior technology (such as a CFL or incandescent bulb). Such analyses will be accurate to the degree that their assumptions are met in the real world, and will be inaccurate when those assumptions are wrong, for example, if LEDs are used more frequently than CFLs. Many studies have compared engineering analyses to actual consumption data, finding lower savings in practice than estimates[60]–[69].

Complementing engineering analyses are data-driven approaches, that provide empirical estimates of the energy savings of new technology in specific contexts, such as residential households. With the use of the appropriate statistical models, it is possible to empirically determine the impact of these new technologies on energy use. One of the most fundamental, and difficult to test, is the assumption that the adoption of new technology occurs in the absence of other changes to a building's energy profile. For example, estimating the energy savings of installing a few LED lightbulbs requires an assumption that other energy-saving approaches are not installed simultaneously, otherwise, some of the energy savings from those alternative approaches will be attributed to LED lightbulbs if those alternatives are not included in the model. Without observing technologies that are implemented simultaneously with technologies of interest, it is impossible to remove that bias from estimates, or even detect whether such a bias is present.

In this study, we provide a means of detecting unexpected program impacts by examining monthly electricity and gas billing data from approximately 27,000 households in the City of Palo Alto, California (CPA) from 2010 to 2016. While studies have shown that the substitution to higher efficiency lightbulbs may lead to additional heating and reduced cooling needs due to change in change in total heating, ventilation, and air conditioning (HVAC) use, the California Public Utilities Commission show that the additional HVAC electricity and reduced gas savings for the City of Palo Alto's climate zone is only around 4% and 2% respectively[70]–[72]. Therefore, significant impacts of an LED lightbulb program on gas usage is a first-level indication of unexpected program impacts.

3.2. Methods

The primary data for this study is panel data of approximately 27,000 household level (i.e. residential single-family homes) monthly electricity and gas consumption billing records from 2010 to 2016 from the CPA. Table 3.1 provides more detailed information on the different energy efficiency programs available during the timeframe of observation.

Energy program characteristics: We divide the dataset for our analysis into 3 parts: exploratory (20%), training (60%), and test (20%) to avoid problems with overfitting. We use 20% of the dataset for exploratory analysis to generate models that reasonably fit the data. We preregistered the models using the Open Science Framework (https://osf.io/jtnqf/), then used cross-validation to test these models against each other on the training 60% of the data. We choose the model with the lowest cross-validation error to predict the last 20% of the data (test set). Statistical inference for the candidate models (standard errors, confidence intervals) is calculated using the last 80% of the data. We focus on 80% of the dataset (excluding exploratory data) for the rest of this paper.

Figure 3.1 shows the average electricity consumption (in kWh/day) and gas consumption (in therms/day) for the middle 60% of the data (approximately 16,000 households). We observe seasonal trends both for electricity and gas consumption, with the seasonal trends more apparent for gas consumption compared to electricity consumption, where consumption is higher on average for both electricity and gas during the winter months. We use a log-transformation for both electricity and gas consumption as there are heavy right tails in their distributions. Figure 3.2 shows the average electricity and gas consumption information for the year 2016 with and without the log transformation respectively where the log transformation yields a more normal distribution pattern. The patterns of heavy right tails in the base case and normal distribution in the log transformation case are also seen for all years (see Appendix B.1. for more details).

Table 3.1 - Energy Efficiency program description in the CPA between 2010 and 2016[73]

From the sample of 16,000 households, 3480 households applied for at least one energy efficiency program between 2008 and 2015. Figure 3.3 shows the distribution of the energy efficiency programs applications over the time frame of our analysis and quarters over which these energy efficiency programs were received. The highest number of energy efficiency programs were received in the second quarter of 2010 when the LED 2/$8 program was rolled out. However, this program was rolled out in

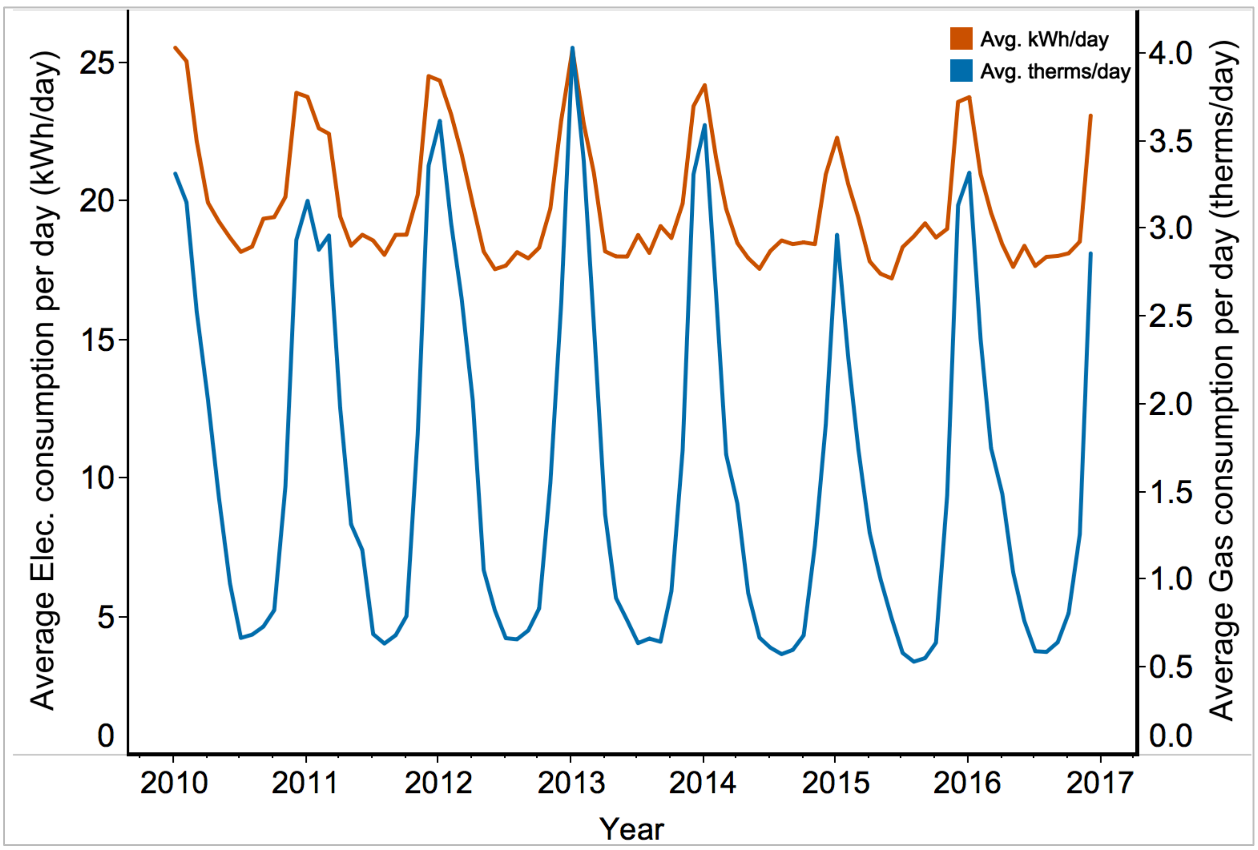

Figure 3.1 - Average electricity consumption (in kWh/day) and gas consumption (in therms/day) for our sample in the City of Palo Alto from January 2010 to December 2016

2010 and ended in 2011. Similar patterns are seen for the Home Energy Kit and CFL programs which were implemented over a one to two-year time frame. This yields significant implications for the purpose of our analysis as the lack of enough pre-treatment observations may affect the interpretation of the results. Other programs like the Smart Energy and LED Holiday lights program are relatively stable over the timeframe of our analysis. Collectively these two programs make up the largest percentage of energy efficiency programs received (about 86% of the total program enrollment) over the timeframe of consideration. Overall, the appliance rebate programs (i.e. Smart Energy program) and lighting programs

(LED Holiday Light, LED 2/$8) account for the highest percentage of energy efficiency programs received. Refrigerator Recycling accounts for a much smaller percentage - 8% of total energy efficiency programs while Green@home Acterra (i.e. education of residents on green at home practices) accounts for only approximately 6% of total energy efficiency programs received (Appendix B.1. contain more details).

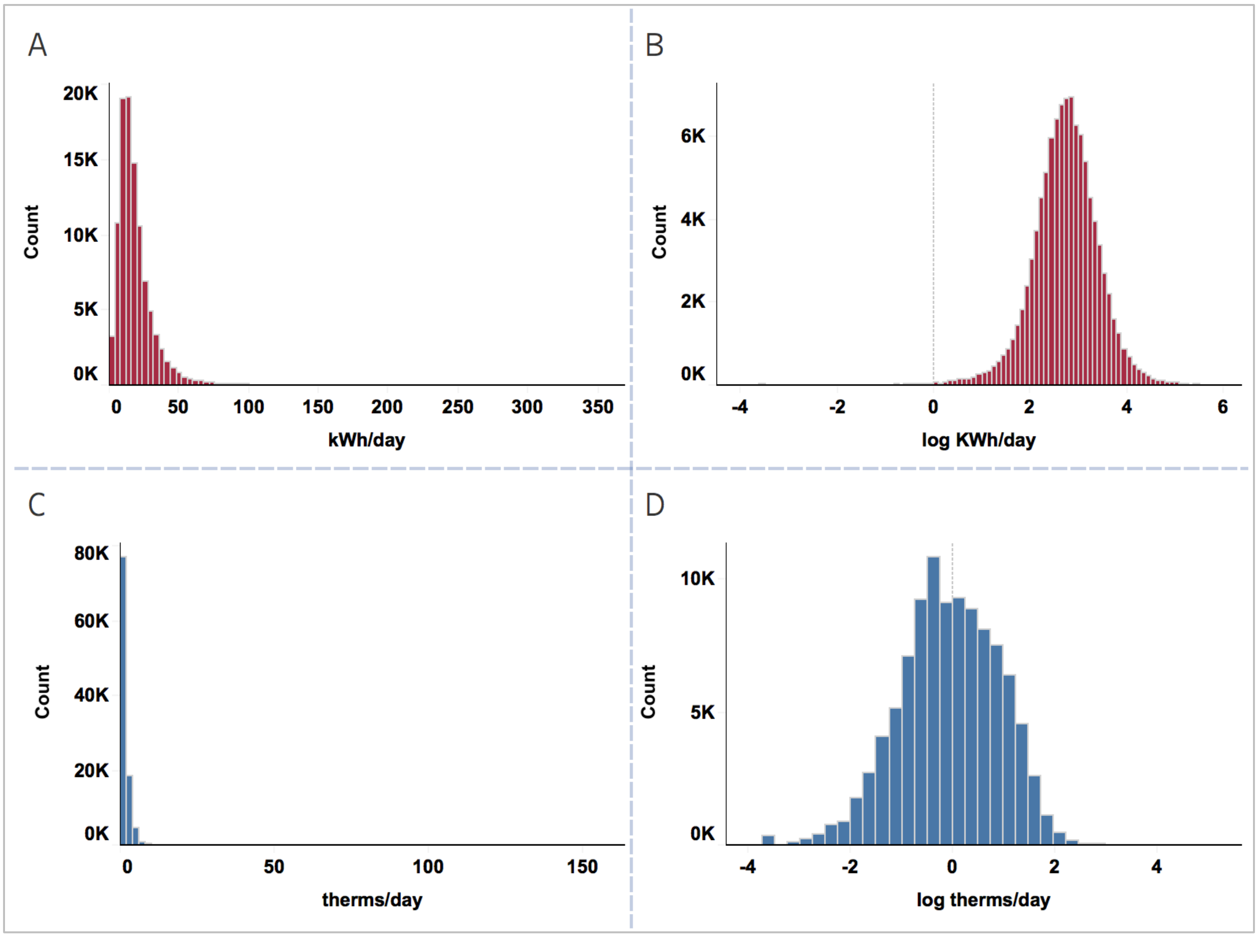

Figure 3.2 - A) Histogram of average electricity consumption per day in 2016. B) Histogram of logged average electricity consumption per day in 2016. C) Histogram of average gas consumption per day in 2016 D) Histogram of logged average gas consumption per day in 2016.

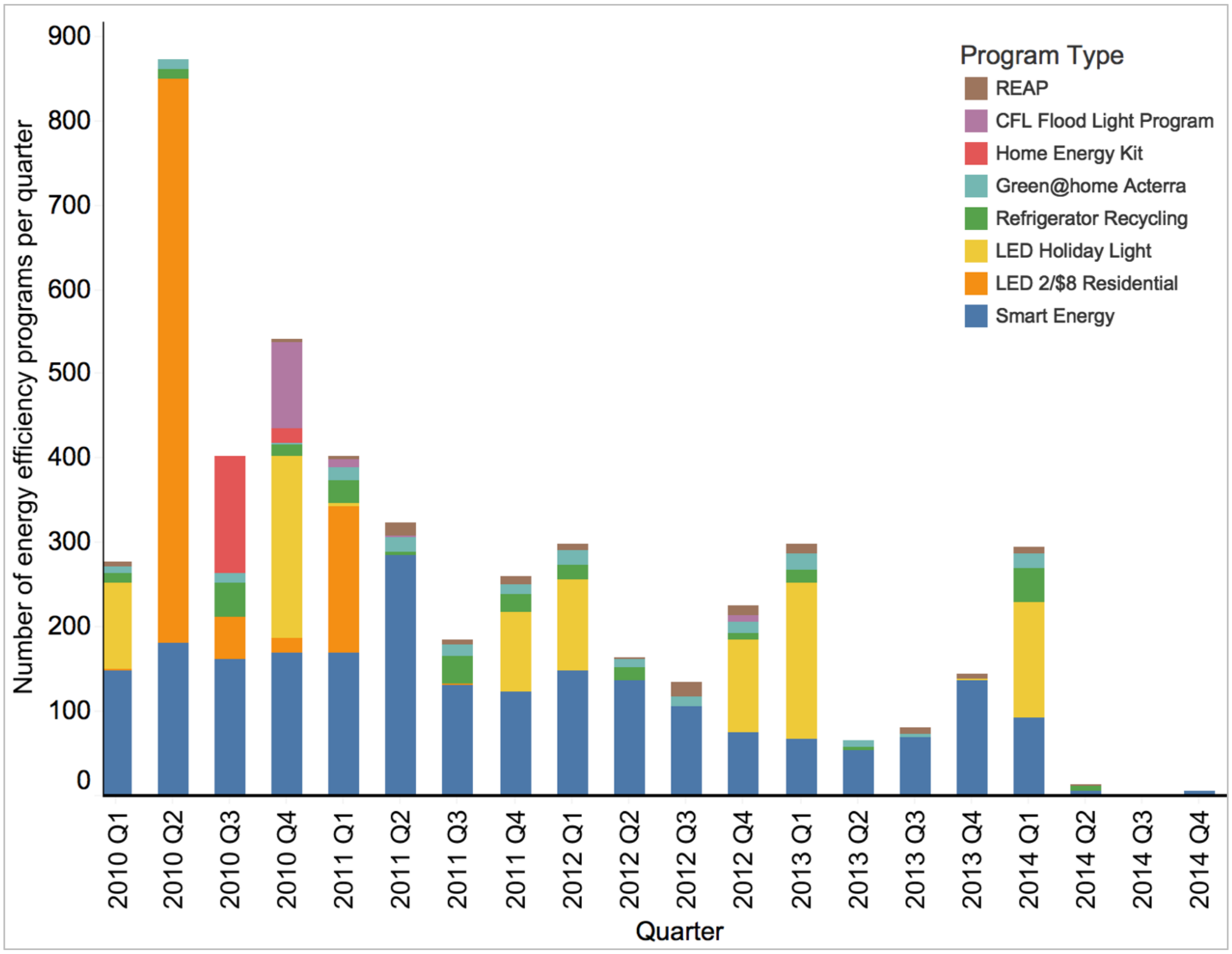

Figure 3.3 - Energy Efficiency programs implemented by the City of Palo Alto between 2010 and 2015

Modeling Strategy: The decision to participate in an energy efficiency program is voluntary, which raises concerns about issues such as selection bias. Selection bias occurs where participants of a study may share a characteristic which makes them different from non-participants thereby biasing the study estimates. Households, for example, may be more concerned about environmental issues – a study in 2017, indicates that more than six in ten adults favor California making its own policies to address global warming[74]. For example, households may be more conscious about environmental issues and therefore have a different trajectory of energy use before the implementation of the energy efficiency program.

To account for these issues, we use a combination of difference-in-differences and an event history approach to address the issues of selection bias, following the approach used by earlier studies as Ito, Fowlie *et al.,* Boomhower and Davis, Novan and Smith, and Zivin and Novan[62], [63], [75]–[77]. Firstly, we implement the difference-in-differences approach by comparing the change in electricity and gas consumption for households that received an energy efficiency program to those that did not receive an energy efficiency program adjusting for time-varying covariates (such as weather). Using a fixed effects approach, we examine these changes to reduce the effect of time-invariant unobserved differences between households that may affect both energy efficiency program applications and electricity or gas usage. We start with a simple difference-in-differences model:

$$ln\left(kWh_{pt}\right) = \alpha + \beta(House_p) + \gamma(MonthNumber_t) + \theta_r\left(EE_{pt}\right)_r + \varepsilon_{pt} \qquad (3.1)$$

$$ln\left(therms_{pt}\right) = \alpha + \beta\left(House_p\right) + \gamma(MonthNumber_t) + \theta_r\left(EE_{pt}\right)_r + \varepsilon_{pt} \qquad (3.2)$$

In Equation (3.1), kWh represents the electricity consumption per day of household p in month *t* where t ranges from month 1 to month 84 (as we have data over a 7-year time frame). $House_p$ and $MonthNumber_t$ represent the household and month-in-timeframe fixed effects to account for time-invariant household and month effects. As weather patterns are observed monthly do not vary by region as all data are obtained from the same area, we capture weather patterns by including the MonthNumber variable. EE_{pt} represents the different energy efficiency programs as described in Table 3.1 in the main paper and is an indicator variable which takes on a value of 1 onwards after an energy efficiency program is implemented and 0 otherwise. ε_{pt} represents the error term. Equation (3.2) notation is the same as that of Equation (1) with the exception of looking into gas consumption in *therms* instead of electricity consumption in kWh.

A key assumption when implementing the difference-in-differences model is the assumption that the treatment groups have similar trends to the control groups in the absence of the treatment. In our case, we assume that those who receive an energy efficiency program would follow a similar trend to the control group if they had not received the program – known as the parallel trends assumption. The difference-in-differences approach also assumes that the electricity and gas reductions roughly follow a step function (evidenced by the pre-post treatment indicators).

Because we have seven-years' worth of data, we are able to examine the pre and post-treatment trend patterns to ensure that the treatment and control groups do not violate the parallel trends assumption. As different households receive the energy efficiency program at different times, we standardize the modeling framework by implementing an alternate event history modeling framework to account for a time 0 for the month a household receives an energy efficiency program as well as 1-12 month windows before and after energy efficiency program implementation for the different programs. Months after the 12-month window is coded as 12+ while months before the 12-month window coded as -12+. We modify equations (3.1) and (3.2) for electricity and gas consumption as:

$$ln\left(kWh_{pt}\right) = \alpha + \beta\left(House_p\right) + \gamma(MonthNumber_t) + \theta_r\left(\sum_{j=m}^{1} \pi_j T_{pj}\right) + \theta_r\left(\sum_{j=1}^{g} \varphi_j K_{pj}\right) + \varepsilon_{pt} \qquad (3.3)$$

$$ln\left(therms_{pt}\right) = \alpha + \beta\left(House_p\right) + \gamma(MonthNumber_t) + \theta_r\left(\sum_{j=m}^{1} \pi_j T_{pj}\right) + \theta_r\left(\sum_{j=1}^{g} \varphi_j K_{pj}\right) + \varepsilon_{pt} \qquad (3.4)$$

where $j = (m, \dots, 3, 2, 1, 0, 1, 2,3, \dots, g)$ and T_{ij} are interactions of the energy efficiency program indicator (which equals 1 if household p ever adopted the specific energy efficiency program and time dummies for all periods before time 0. Likewise, K_{ij} is the treatment indicator interacted with time dummies for all time periods after time 0.

For all models in this study, we include the month number over the entire timeframe of observation to capture monthly changes that can impact building energy consumption (such as weather). We also cluster the standard errors at the household level to account for autocorrelation between errors of the households over different months.

Robustness checks: We conduct several robustness checks to ensure the accuracy of our program estimates by using the difference-in-differences modeling framework to implement alternative model specifications. Specifically, we compare models (3.1) and (3.2) in the previous section with the results of all our robustness checks. Firstly, we examine the sensitivity of the model estimates to account for seasonality effects as energy efficiency program impacts may be stronger in the winter, for example, compared to the summer. As some of the household-level data contain missing information for some months in our timeframe, we examine the electricity and gas reductions with a subset of households with more consistent data over the program timeframe. Specifically, we implement a long and short-run approach by taking into account shorter (12-month time window before and after program implementation) and longer (entire program timeframe) time windows to ensure that our results are not driven by outliers from households with inconsistent energy information. We also implement this approach to ensure that the reductions captured are indeed as a result of the energy efficiency program implementation and not of other factors implemented too in the future. Appendix B.2. provides more details of this approach.

We also perform a “shuffle test” where we redistribute information on control and treatment households to inspect if we get a non-significance of our model estimates. Due to publicly available reports in accordance with the SB 1037 bill implemented by the State of California, we also have access to the annual reports documented by the CPA for specific energy efficiency programs [34]. As a result, we are able to compare the savings from our data-driven approach with savings from the evaluation, measurement and verification process (EM&V) presented by the CPA for some energy programs available during the timeframe of our analysis. Finally, we compare the difference-in-differences and event history model using the remaining 20% of the data i.e. the test data. We make predictions about the test data comparing both model approaches and calculate the residuals to get the root-mean square error (rMSE) (See Appendix B.3-5 for more detailed approach and results).

3.3. Results

Energy savings of energy efficiency programs: Figure 3.4a, b shows the regression results on electricity and gas consumption respectively using Models (3.1) and (3.2) in the Methods Section (see Appendix B.2. for full model results).

From Figure 3.4a, b, we find varied effectiveness of the energy efficiency programs. Of all the programs, the Green@Home Acterra program is associated with the highest significant reductions in both electricity and gas usage at 6% (95%CI: 2% to 11%) and 6% (95%CI: 2% to 10%) respectively.

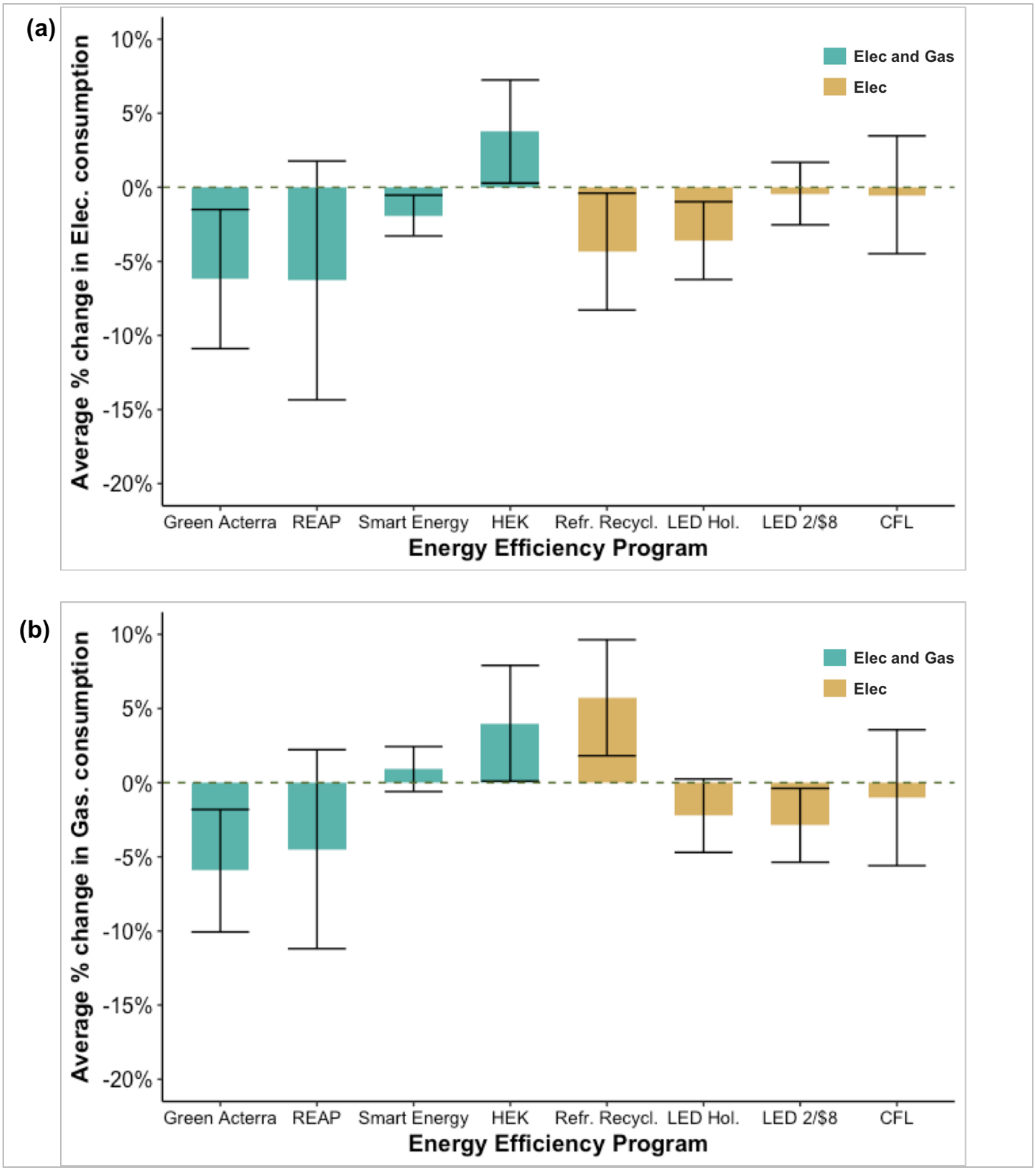

Figure 3.4 - Regression estimates of energy efficiency program impacts on (a) log electricity consumption (kWh/day) and (b) log gas consumption (therms/day) using the difference-in-differences model. Energy efficiency programs in green target electricity and gas reductions while programs in gold target only electricity reductions. (Green Acterra = Green@ Home Acterra, HEK = Home Energy Kit, Refr. Recycl. = Refrigerator Recycling, LED Hol. = LED Holiday Light, CFL = CFL Bulb). Error bars represent 95% confidence intervals clustered at the household level.

We find significant reductions for electricity but not gas usage at 2% (95%CI: 1% to 3%) and 1% (95%CI: -1% to 2%) respectively for the Smart Energy program while the REAP low-income program does not show significant reductions in either electricity or gas use. From the program description, a lot of appliances qualify for the Smart Energy rebate program and a significant number of appliances can be upgraded in households which qualify for the REAP program indicating that savings can vary widely from household to household. As a result, the wide ranges estimated for the REAP and Smart Energy program may be as a result of the grouping of a large number of appliances which have varied energy savings. Surprisingly, we find increases rather than decreases for the Home Energy Kit program. As the Home Energy Kit program was implemented and ended in 2010, the first year of the time frame for our dataset, there may be a lack of pre-treatment observations to appropriately estimate its effect. We also find that the Refrigerator Recycling program is associated with significant reductions in electricity usage, however, shows significant increases in gas use. It is unclear why this would be the case as we expect significant reductions in electricity use but non-significance with respect to gas use. We implement robustness checks in the section below to examine why this might be the case.

We find unexpected effects of some electricity-only programs on natural gas usage. The LED 2/$8 program shows no significant reductions with respect to electricity use but a small reduction effect with gas usage of 3% (95%CI: -0.4% to 5%). The LED Holiday light program shows both significant electricity and gas reductions of 4% (95%CI: 1% to 6%) and 2% (95%CI: 0.2% to 5%) respectively. Our results indicate that households that receive the LED lighting programs may also be undergoing other changes in their households which may be associated with both electricity and gas reductions.

Exploratory investigation of unexpected effects: From the previous section, we find unexpected effects of the LED 2/$8 and LED Holiday Light programs on natural gas usage. We hypothesize two of the reasons for this effect that might be artifacts of our estimation approach: 1) differences in the number of observations for each month over the timeframe of observation and 2) long and short-run effects. The observed electricity and gas data for most households in our dataset contain missing data for some months. Although these electricity and gas reductions are averaged when estimating different energy efficiency program impacts, there is the possibility that these reductions are unusually higher in some months compared to others thereby misattributing program impacts. To test this hypothesis, we subset our dataset to households who have at least 12 months out of 18 months of pre and post-treatment information. We implement this method of subsetting to ensure that we are capturing households with at least one full year of data before and after energy efficiency program implementation[10].

We also assume that significant effects may be estimated as a result of long-run effects as we may be capturing other effects too far into the future that may not be as a result of the implementation of the energy efficiency program. To compare the long-term impacts with the short term, we subset households with at least a full year of pre and post data to capture only the 12-month window pre and post-program

[10] Programs such as the Home Energy Kit, CFL Bulb, and LED 2/$8 do not have enough pre-treatment information so we subset households with 6 months, 9 months, and 6 months of pre-treatment information respectively (See Appendix B.2. for more detailed results).

implementation. (Appendix B.2. provides more detailed results). Figure 3.5a, b compares the results of the base case (as evidenced in Figure 3.4a, b), long and short-run effects of those with a full year of pre and post-treatment information.

As the number of households who qualify for these programs reduces as a result of the constraints on the long and short term effects, we examine not only the statistical significance of the programs but also the variation in estimates. From Figures 3.5a, b, we find that the majority of the program estimates do not significantly vary as a function of the model specification – the Green@Home Acterra program, for example, still is the most significant when examining electricity and gas reductions with estimate ranges only varying about 1% for electricity and 3% for gas (For electricity reductions – base: 6% (95%CI: 2% to 11%), long-run: 6%(95%CI: 1% to 10%), short-run: 7%(3% to 11%) ; For gas reductions - base: 6%(95%CI: 2% to 10%), long-run: 9% (95%CI: 4% to 14%), short-run: 7%(2% to 11%). Concerns such as increases in consumption for the Home Energy Kit and Refrigerator Recycling program, however, reduces significantly when examining the long-run and short-run effects indicating that the large number of post-treatment data and outliers may indeed impact program estimates. The Home Energy Kit electricity estimates, for example, reduces from a -4% (95%CI: -0.3% to -7%) slightly significant decrease in the base case to a -1% (95%CI: 4% to -3%) and 2% (95%CI: 2% to -4%) non-significant decrease in the long and short-run estimates.

As the detection of unexpected program impacts is a major concern, we examine the LED Lights program estimates. The LED 2/$8 program is highly sensitive with respect to the choice of model specification. From Figure 3.5b, we find that the short-run estimates are significantly smaller than the base and long-run estimates. The LED 2/$8 program gas estimates go from a 3% (95%CI: 0.4% to 5%) and 3% (95%CI: 0.04% to 6%) reduction in the base and long-run estimates to a 1% (95%CI: -1% to 4%) non-significant reduction in short term estimates. Just like the Home Energy Kit program, the LED 2/$8 program was implemented in 2010 and 2011, therefore, we hypothesize that we may be capturing other effects in the long-term which may be associated with significant gas reductions. The LED Holiday light program, however, show more consistent estimates irrespective of the model choice specification and still shows somewhat significant reductions in the short term. We find a 2% (95%CI: -0.2% to 5%) and 5% (95%CI: 2% to 7%) reduction in the LED holiday light gas estimates in the base and long-run case while the short term also shows a 2% (95%CI: 5% to -0.2%) reduction.

Event history model approach: We implement the alternative event history model specification to examine individual monthly trends before and after program implementation. We find that generally, the event history models for each of the energy efficiency programs roughly approximate a step function indicating that the difference-in-differences approach may be appropriate for our analyses (Appendix B.2. shows the event history plots).

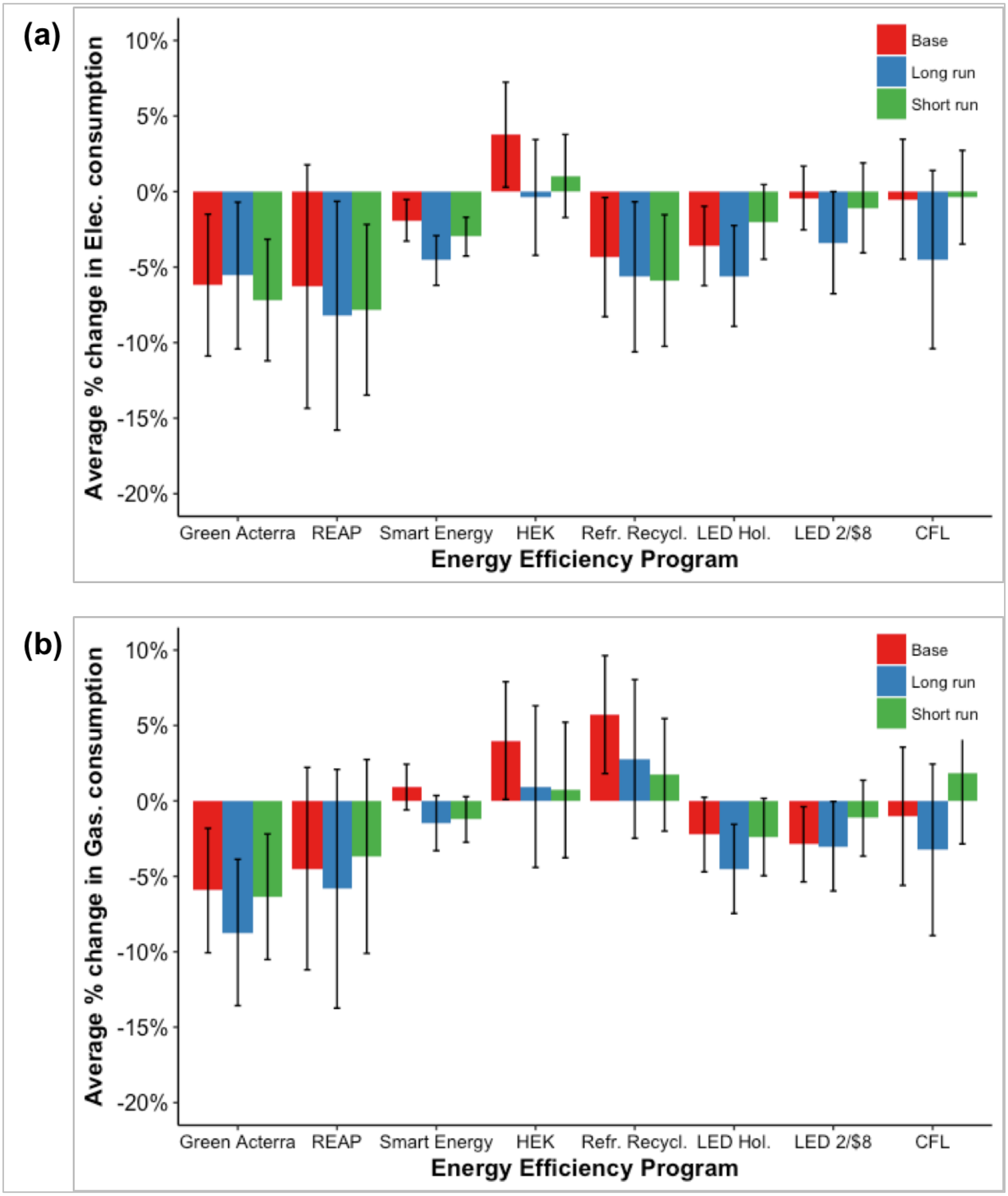

Figure 3.5 - Regression estimates comparing base case, long-run, and short-run estimates of different energy efficiency programs impacts on (a) electricity consumption and (b) gas consumption using the difference-in-differences model. (Green Acterra = Green@ Home Acterra, HEK = Home Energy Kit, Refr. Recycl. = Refrigerator Recycling, LED Hol. = LED Holiday Light, CFL = CFL Bulb). Error bars represent 95% confidence intervals clustered at the household level

3.4. Discussion

In this study, we find evidence of unexpected effects where we observe significant gas reductions for electricity-only programs. While ex-ante engineering estimates are being used to estimate the savings from the implementation of new technologies, a lot of academic research has begun to use data to examine the predicted versus actual savings, with a majority realizing that actual savings are significantly lower compared to estimates[62], [77]–[80]. Although varied statistical approaches are used to examine the actual impacts of these programs, we find that data-driven approaches need to also be appropriately examined as its results may also be biased. Earlier research has mostly used electricity savings (in kWh) or energy (KBtu) to examine program impacts, as it is expected, for example, that an electricity-only program should ideally only show significant kWh reductions. As randomized control approaches are very difficult to design for energy efficiency intervention programs as households decide to opt into a program, it is very difficult to tease out if reductions are indeed a function of program implementation of other factors [81]–[83]. This is not to say these programs are not effective, as they are meant to serve as an introduction to a new energy-efficiency measure. However, households who opt into this program may have reduced energy use regardless of whether they got this new energy efficiency measure. Without further surveys, the exact reasons for these reductions are unknown, but by using natural gas measurements, we are able to provide a first-level indication of unexpected program impacts. We note here that we are able to examine unexpected effects because we have access to both electricity and gas use data which may not be available for other studies. However, other proxies such as water use can also be used in situations where gas use data is not available. We recommend that future work using ex-post approaches implement this method of program impacts detection to ensure that savings using actual data is indeed accurate.

Our results also contribute to the existing literature on the importance of behavioral programs in energy efficiency interventions. We find the highest reductions in electricity and gas usage from the Green@Home Acterra program which performs a walk-in energy audit and trains residents on energy consumption reduction methods. Here, we find average reductions of 6% on the average of those who engaged in the energy audit program offered by the CPA. Our results are in line with earlier research that has found reductions in electricity consumption through the use of behavioral approaches[77], [84]–[86]. Although it is impossible to detect, by using energy consumption data, if households simply changed their behavioral patterns or replaced old equipment to newer more-efficient equipment, we add to the body of existing literature which highlights the importance of information provision versus financial incentives to reducing energy use.

Our results are subject to some limitations which yield opportunities for future research. While we have attempted to disentangle the effects of the program using quasi-experimental approaches, our work would be subsequently improved with access to customer demographic and behavioral information which may characterize the types of customers and situations surrounding the reasons for opting into a program. While this may be cost-intensive, it provides a way of better tailoring programs to the needs of customers and helps reduce unexpected program impacts which are measured when examining program effectiveness.

Energy efficiency programs have the potential to significantly reduce electricity and gas use in buildings. However, the ex-post evaluation of these programs need to be appropriately measured to ensure that these reductions are indeed associated with policy implementation as significant amounts of money and time is invested in the implementation of these programs. Our work, in addition to corroborating existing research on energy efficiency program effectiveness, provides a simple approach of detecting unexpected program impacts, which can be difficult to identify.

4. Using time-varying load profiles to quantify the health and climate benefits of energy efficiency: Application to residential buildings in Pennsylvania

Abstract
One of the well-established ways of reducing energy consumption and pollutant emissions is through energy efficiency. In considering the energy efficiency reduction potential for buildings, most studies focus on electricity reductions while impacts on public health, environmental, and climate change are often neglected. In this work, we quantify the energy reductions, greenhouse gas and other air emission reductions, as well as private net costs and social benefits that would result from implementing energy efficiency measures (EEMs) in the residential single-family detached (SFD) housing stock in Pennsylvania. We estimate reductions of 36%, 44%, 19%, and 43% of electricity, gas, propane, and fuel oil consumption compared to 2017 baseline levels. These EEMs are also associated with total avoided emission reductions of 14M metric tons of CO_2, 16K metric tons of SO_2, 1.4K metric tons of $PM_{2.5}$, and 6K metric tons of NO_x per year with total health, environmental, and climate change benefits of $2.4billion per year (assuming a 7% discount rate). While these EEMs could reduce the SFD carbon footprint by 34% compared to 2017 baseline levels, it only meets 6.3% of the total carbon reduction goal that has been set by Pennsylvania in 2050 compared to 2005 levels. As many of these measures are cost-intensive, we recommend that Pennsylvania focus on providing appropriate financing and/or incentive options for drill-and-fill insulation, ductless heat pumps (DHPs), LED lighting, and air sealing upgrades as these four EEM technologies provide the best balance of private and social benefits for the state.

The contents of this chapter is currently a draft working paper.

4.1. Introduction

In the United States (U.S.), decreasing energy consumption through energy efficiency has become a major focus for policymakers at all levels of the government. In 2017, for example, U.S. states spent approximately $7.9 billion on utility sponsored energy-efficiency programs with total estimated savings of approximately 27.3 million megawatt-hours (MWh) – accounting for 0.72% of total electricity sales [87], [88]. Residential building energy efficiency has been identified as one of the most cost-effective approaches for not only energy but also emission reductions because residential buildings are responsible for about 37% of total electricity sales in the U.S.[89], [90]. Various studies have identified the potential for different residential energy efficiency measures such as improved attic insulation, ENERGY STAR appliances, lighting upgrades, and other weatherization programs---in reducing not only private energy expenditures but also public energy use externalities[54], [56], [91].

In quantifying the benefits from energy efficiency, many studies focus on the economic value of annual energy reductions without regards to the time-of-day of these reductions. For example, a study by Boomhower and Davis notes that the U.S. Department of Energy (DOE) has historically only considered annual energy savings when examining new appliance energy efficiency standards and building codes[75]. Similarly, when states commission analyses to identify potential savings within their jurisdictions, they typically focus on total energy savings[92]–[95]. Using the Commonwealth of Pennsylvania as an example, analysis was done in 2015 to evaluate the electric energy efficiency potential savings for its 7 largest Electric Distribution Companies (EDC). The analysis focused on the independent effects of season (summer and winter) and time-of-day (on-peak and on-peak hours, ignoring the time-of-day variation within each season. Many other studies also examine the economic potential for energy efficiency in Pennsylvania but do not include time-of-day effects[94], [96], [97]. When generation, demand, and price for electricity vary throughout the day, the timing of demand—and demand reductions--becomes more important[98]. Although states like California are beginning to incorporate the use of hourly electricity load profiles in utility-sponsored energy-efficiency programs, end-use load profiles are very limited across energy-saving measures as well as geographically [99].

Environmental costs associated with electricity consumption vary by time-of-day, season, and location. As electricity generation is a major source of air pollution--including criteria pollutants (e.g. $PM_{2.5}$, SO_2, and NO_x) and greenhouse gas emissions (e.g. CO_2), significant health and environmental benefits can be achieved by energy efficiency. However, few energy efficiency potential studies consider these emission reductions, let alone how they vary with time-of-day. Some studies use an "average emissions factor" (AEF) approach which divides total annual electricity production by the total annual emissions[100]–[105]. By using the AEF approach, these studies assume that decreased energy use has the same impact on emission reductions at any time of day. Alternatively, the "marginal emissions factor" (MEF) approach is a significant improvement to the traditional AEF method as it accounts for varying generation that is on the margin (e.g. coal vs wind) hour by hour [106]–[108]. Studies that have used the MEF approach to estimating energy reductions focus only on a few energy efficiency measures at a national scale--e.g. residential insulation[109], [110], air conditioners and lighting[111]. Others assume that the success of national or regional demand-side management programs will have large effects on reducing peak load[103], [112].

While the potential benefits of building energy efficiency with regards to electricity reductions, air quality, and health impacts are generally understood, the lack of granular data--e.g. local (sub)hourly load profiles--hinders the accurate quantification of these benefits. We find that most studies either do not have access to more detailed energy data or quantify the benefits in a way that may be misleading--e.g. the use of AEF vs MEF when quantifying social benefits. In this study, we improve upon these existing approaches by using publicly available hourly energy and emissions level data to measure the energy reductions and associated health and environmental impacts in residential single-family detached (SFD) homes using Pennsylvania as a case study. Specifically, we focus on understanding the best energy efficiency measures (EEMs) which balance both private and social benefits and the extent to which Pennsylvania should encourage SFD homes to invest in these measures. We estimate that Pennsylvania could reduce its CO_2 emissions by 34% and its annual environmental health damages by $2.4billion compared to the 2017 baseline levels through residential EEMs in its building stock. However, many of these EEMs are cost-intensive, therefore we recommend that PA support these EEMs through equity-oriented programs. While our results are specific to Pennsylvania, the method can be applied to other states or cities in the United States and can help identify the most cost-effective EEM investments for meeting broader public environmental goals.

The rest of this paper is organized as follows. First, we explain our data and methods. Next, we present our results, which includes the energy savings, emission reductions, private net costs, and social benefits of 14 different energy efficiency improvements. We then analyze the impacts of discount rates on energy reductions. Finally, we discuss the implications and limitations of our results.

4.2. Data and methods

We estimate the energy reductions, CO_2, SO_2, $PM_{2.5}$, and NO_x emission reductions, private net costs, and social benefits of 14 different EEMs to PA's SFD baseline stock. Table 4.1 provides a description of the different upgrades considered as well as the baseline--or reference scenario--for the different upgrades. See Appendix C.1. for more detail. As the different upgrades have different lifetimes, we present all results in annualized values. We assume that all upgrades are available for implementation immediately with a baseline discount rate of 7%, which is the average discount rate used presently in Pennsylvania in determining the cost-effectiveness threshold utilities must meet[113]. However, we conduct a sensitivity analysis varying the discount rates at 3% and 15%. Our analysis approach is shown in Figure 4.1 and summarized as follows: (1) we use NREL's ResStock methodology via the Open Studio Parametric Analysis tool (PAT) to characterize PA's baseline housing stock, baseline energy consumption as well as upgrade energy consumption scenarios for each EEM considered, (2) we estimate the energy savings for each EEM by subtracting the baseline/reference case from upgrade scenarios, (3) we estimate the emission reductions for the different EEMs, (4) we quantify the private net cost of each upgrade by subtracting the incremental cost of the EEM from the cost of energy savings, and (5) we monetize the avoided emissions by estimating the avoided damages associated with reduced emissions using a reduced form air quality model. In Table 4.2, we summarize the different data sources used in this analysis. We describe each of the model components in the sections that follow, with more information about the modeling assumption in Appendix C.1.

Table 4.1 - Description of the different energy efficiency upgrades considered in this paper

Upgrade Category	Upgrade Name	Upgrade Description	Reference**
Enclosure	Air Sealing	25% reduction in building enclosure filtration	Baseline (do nothing)
Enclosure	Drill-and-fill wall insulation	Add fiberglass cavity insulation to uninsulated wood frame walls	Baseline (do nothing)
Enclosure	Duct Sealing	Seal and insulate ducts in unconditioned spaces	Baseline (do nothing)
Enclosure	Low-E Storm Windows	Install low-E Storm windows on single and double pane windows (DIY)	Baseline (do nothing)
Enclosure	R-10 Finished Basement		Baseline (do nothing)

		Add R-10 interior XPS to walls and rim joists of unfinished basements	
Enclosure	R-10 Unfinished Basement	Add R-10 interior XPS to walls and rim joists of finished basements	Baseline (do nothing)
Enclosure	R-49 Attic Insulation	Add R-49 blown-in insulation to attic floor	Baseline (do nothing)
HVAC*	Ductless Heat Pumps (DHP) -(displaces electric baseboard)	Displace electric baseboard with DHP (SEER 19.3, HSPF 14)	Baseline (do nothing)
HVAC*	Heat Pump Water Heater (HPWH)	Upgrade electric water heater (≤55 gal) to HPWH (50 gal) at wear out	Federal minimum standard (EF 0.95)
HVAC*	Central Air Source Heat Pumps(ASHP)	Upgrade conventional heat pump to variable speed heat pump (SEER 22 HSPF 10)	Federal minimum standard (SEER 14 HSPF 7.7)
Appliance	AC,SEER 18	Upgrade central air conditioner to SEER 18 at wear out	Federal minimum standard (SEER 13)
Appliance	ENERGY STAR Clothes washer	Upgrade clothes washer to ENERGY STAR at wear out (123kWh/yr)	Federal minimum standard (387 kWh/year)
Appliance	ENERGY STAR Refrigerator	Upgrade refrigerator to ENERGY STAR at wear out (EF 19.9)	Federal minimum standard (EF 17.6)
Lighting	LED Lighting	Replace lamps with LED (80 lumens/watt)	Baseline (do nothing)

* HVAC = Heating, Ventilation, and Air Conditioning,
** Reference scenario represents the business-as-usual point of comparison for upgrade scenarios. For some upgrades, such as insulation upgrades, the reference is the existing condition. For other upgrades, such as equipment upgraded at wear out, the reference is the current federal standard.

4.2.1. Characterizing Pennsylvania's baseline housing stock and energy consumption of baseline and upgrade scenarios

We use NREL's ResStock tool to characterize the baseline housing stock and baseline/upgrade energy consumption for SFD homes in Pennsylvania. ResStock is an energy simulation tool that uses probability distributions of SFD homes across the country to simulate representative samples of the housing stock across different locations in the U.S. We choose ResStock because it provides a detailed level of granularity mostly unavailable in other energy efficiency potential studies. To characterize the baseline building housing stock in the U.S., NREL uses building characteristics curated from multiple data sources such as national residential consumption surveys and other data from field studies to develop a data model needed to represent the energy-related characteristics of the U.S. SFD housing stock. Next, they use a modified Latin Hypercube sampling approach to select representative homes defined by the housing stock data model. With a sampling approach, they identify 350,000 homes as the number of building/location models needed to represent the current U.S. housing stock. Weighting factors used to scale 350,000 to the 80 million SFD homes are included in the analysis. Next, they leverage the capabilities of EnergyPlus, the Department of Energy's flagship energy simulation energy to determine the subhourly annual (i.e. electricity, natural gas, fuel oil, and propane) usage using the building characteristics defined. This housing stock model was also validated by comparing modeled consumption against the U.S. EIA's Residential Energy Consumption Survey 2009 with iterative changes made to bring modeled consumption closer to the reference consumption[114]. In Appendix C.2, we provide a more detailed explanation of their modeling procedure, and for more details, the reader can refer to Wilson et. al[57]. Apart from the advantage of the detailed level of granularity, the tool allows for the ability to analyze different scenarios of interest even for a specific utility or service territory by selecting different input combinations.

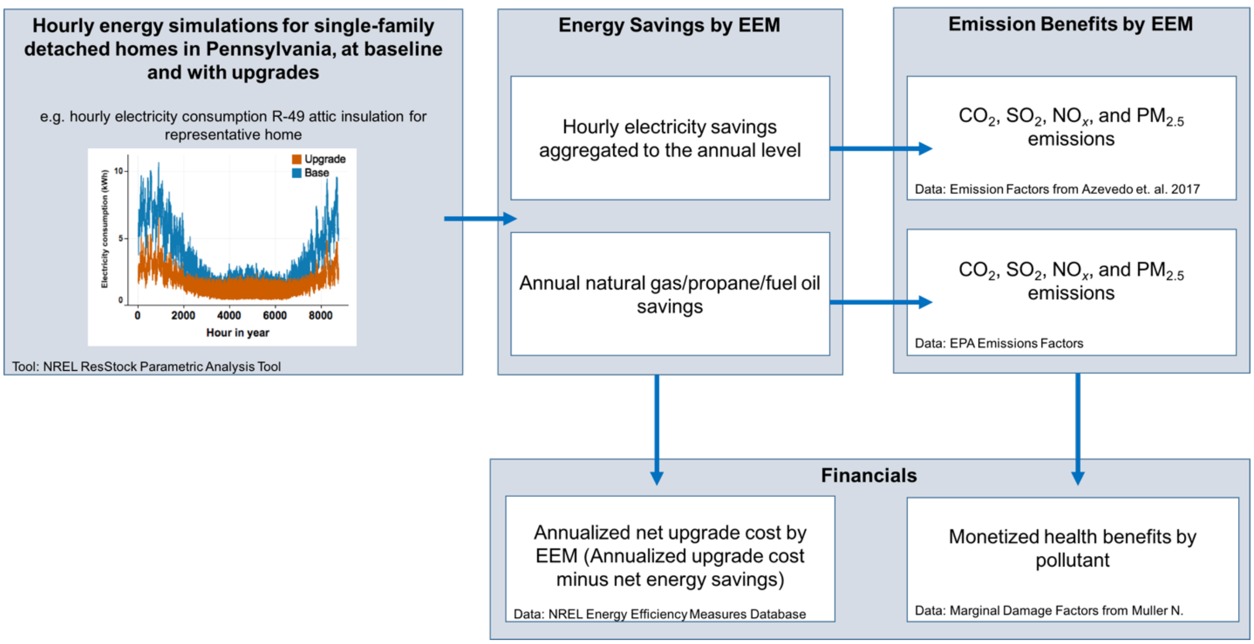

Figure 4.1 - Flow diagram depicting all components in our simulation approach

We characterize Pennsylvania's baseline housing stock and energy consumption using the ResStock tool as follows. First, we select 8 out of the 216 TMY3 regions presented in the tool which capture the Pennsylvania area. With the capabilities of Energy Plus, the tool outputs the hourly energy consumption of the representative baseline homes (16,168 homes in Pennsylvania's region). These hourly resolution outputs are then combined and scaled up to represent the 2.9 million residential SFD homes in Pennsylvania. Next, we re-simulate the baseline housing stock using the tool with the assumption that the baseline homes have been "replaced" with the new EEM. With these simulations, we are able to compare the baseline energy consumption with that of the energy efficient case for the different EEMs.

Table 4.2 – Inputs and Data Sources used in the analysis

Variable	Source	Reference
Building load profile	Simulations run using NREL ResStock tool	[57]
Utility rates (Electricity, Natural Gas, Propane, and Fuel Oil)	EIA 2017 Residential Rates for PA	[115]–[117]
Equipment Upgrade Cost	NREL Energy Efficiency Measures Database	[118]
Emissions Factors from Electricity Generation	Center for Climate and Decision Making Electricity Marginal Factor Estimates	[119]
Emission factors from Natural Gas/Propane/Fuel Oil Combustion	U.S. Environmental Protection Agency (EPA) Emission Factors	[120]
Health and Environmental Damage Factors	EPA Social cost of Carbon, AP3 Model	[121], [122]

4.2.2. Energy savings for EEMs

We estimate the total annual electricity savings for the different EEMs by subtracting the hourly electricity demand of the baseline from that of the upgrade case for the subset of the housing stock which qualify for that upgrade. Using the R-49 Unfinished Attic Insulation as an example, we know that 30% of homes in Pennsylvania have Attic insulation levels of R-49 and the remaining 70% have insulation levels of R0 (Uninsulated) to R-38 levels. Therefore, to determine the total electricity savings for the R-49 upgrade, we calculate the following:

$$Tot.Elec.Savings_{attic}\left(\frac{kWh}{yr}\right) = \left(\sum_{house=1}^{house=11317}\sum_{h=1}^{h=8760}\left(Elec_{base}(h) - Elec_{upg,attic}(h)\right)\left[\frac{MWh}{hr}\right]\right) \times \left(\frac{2.9M}{16168}\right) \quad (4.1)$$

Since 70% of homes qualify for the R-49 attic insulation upgrade (11317 = 70% × 16168 baseline homes in Pennsylvania) , we subtract the individual baseline electricity savings for those homes from the upgrade scenario (i.e. $Elec_{base} - Elec_{upg}$), sum them up on the hourly level and then scale up by (2.9M/16168 ~= 180) to determine the total electricity savings for R-49 unfinished attic upgrades in the Pennsylvania's housing stock. For natural gas, propane, and fuel oil savings, we use yearly consumption estimates before and after the implementation of the upgrade to determine the total savings for the subset of homes which qualify for the upgrade. We aggregate on a yearly level as we are not concerned about the timing of the savings for these energy use types.

4.2.3. Avoided Health, Environmental, and Climate Change Emissions

To determine the total avoided emissions from reducing pollutants of CO_2, SO_2, $PM_{2.5}$, and NO_x for the different EEMs, we perform two analyses: first, we estimate the avoided emissions from pollutant reductions through electricity reductions, then we estimate the emission reductions from the residential combustion of natural gas, propane, and fuel oil savings.

To determine the avoided emissions from electricity reductions, we use the Marginal Emissions Factor (MEF) approach. We estimate the avoided marginal emissions by using MEF estimates from the Center of Climate and Energy Decision Making (CEDM) "Electricity Factors Emissions" website by Azevedo et. al.[119].These estimates, similar to that used in the Siler-Evans et. al. paper uses a regression model approach which uses the Continuous Emissions Monitoring System (CEMS) Environmental Protection Agency's data for 8 NERC regions in the U.S. to calculate the change in fossil generation and emissions by hour of day and by season[123]. We use 2017 Marginal Emission factor estimates for the Reliability First Corporation Region (RFC) region (in kg of pollutant per MWh) to determine the avoided emissions per hour. Therefore, total emission reductions of pollutant per EEM from electricity reductions can be presented mathematically as:

$$Avoided\ Marginal\ Emissions\ Elec_{pol,EEM}(kg/yr_{pol}) = \sum_{EEM} \sum_{h=1}^{h=8760} Elec.savings_{EEM}\ (h) \left[\frac{MWh}{hr}\right] \times\ MEF_{pol}(h) \left[\frac{kg}{MWh}\right] \quad (4.2)$$

where pol is the pollutant type and MEF is the marginal emissions factor for the different pollutants. Next, we estimate the emission reductions from the residential combustion of natural gas, propane, and fuel oil using the EPA's National Emissions Inventory database which includes emission factor estimates of CO_2, SO_2, $PM_{2.5}$, and NO_x. Reductions from the residential energy combustion are presented mathematically as:

$$Avoided\ Marginal\ Emission\ ResCombust_{ft,EEM}\ \left(kg/yr_{ft}\right) = Ann.Savings_{ft} \left[\frac{kBTu}{yr}\right] \times EF \left[\frac{kg}{kBTu}\right] \quad (4.3)$$

where ft is the fuel type and $Savings_{ft}$ is the annual energy savings of the fuel type (i.e. annual natural gas, fuel oil, or propane savings) while EF is the emission factor value for the fuel type. Total avoided emission reductions are then estimated by summing up emissions reductions from electricity reductions and that from residential energy combustion.

4.2.4. Private net-cost of energy efficiency upgrades

The private net cost of an EEM equals the upgrade cost minus the energy savings. We estimate the upgrade cost as the cost of improving the baseline stock to the more energy-efficient equipment. Using the R-49 attic insulation example, we estimate the total cost of upgrading to R-49 insulation by summing up the individual upgrade costs of Uninsulated, R-13, R-19, R-30, R-38 to R-49 insulation from the baseline/reference scenarios for the appropriate subset of the baseline housing stock. As explained above, these results are scaled up to capture the total costs for the subset of homes which qualify for the attic insulation upgrade. We consider only installation costs for this analysis (maintenance costs are excluded) and annualize the cost results as the lifetime for upgrades vary by equipment. We obtain measure cost and lifetime data for each of the equipment upgrades from the NREL Residential Energy Efficiency Measures database and use a baseline discount rate of 7% with alternative rates of 3% and 15% (we assume 3% is the social discount rate and 15% represents a discount rate closer to EPA's participant's discount rate)[57], [113], [124], [125]. We estimate the annual energy cost (in $) by multiplying the total energy (i.e. electricity, natural gas, propane, and fuel oil savings) by the average electricity, natural gas, propane, and fuel oil price respectively in the Pennsylvania's region for the year 2017 as provided by the Energy Information Administration (EIA)[115]–[117].

The private net costs can be presented mathematically as:

$$Net\ Upgrade\ Cost_{EEM}[\frac{\$}{yr}] = Ann.Upgrade\ Cost_{EEM}[\frac{\$}{yr}] - Ann.Energy\ Savings_{EEM}[\frac{\$}{yr}] \quad (4.4)$$

where $Ann.Upgrade\ Cost_{EEM}$ and $Ann.Energy\ Savings_{EEM}$ is the annualized upgrade cost and annualized energy savings of the EEM.

4.2.5. Avoided Health, Environmental, and Climate Change Emissions and Monetized Damages

To determine the monetized benefits from reducing pollutants of CO_2, SO_2, $PM_{2.5}$, and NO_x for the different EEMs, we perform two analyses: first, we estimate the benefits from pollutant reductions through electricity reductions, then we estimate the monetized benefits from the residential combustion of natural gas, propane, and fuel oil savings.

To obtain the monetized benefits from reduced pollutant emissions from electricity generation, we use the marginal damage factor values expressed in dollars per ton of emissions of SO_2, $PM_{2.5}$, and NO_x for the year 2017. We obtain the location-based marginal damage factors from the AP3 model - the updated version of the Air Pollution Emissions Experimental and Policy analysis model (APEEP) as described in the paper by Muller N.[121] This model estimates the dispersion of pollutants and the resulting concentration at different resolutions – from block groups up to the national level, and relies on the dose-response function to estimate physical impacts. This model then monetizes the impacts by using inputs such as the values of statistical life (which is assumed to be $9.8M in 2017 USD) for SO_2, $PM_{2.5}$, and NO_x .We assume that marginal damages for CO_2 are $40 per ton following EPA's Social Cost of Carbon for Regulatory Impact analysis[122]. Next, we multiply the location-based marginal damage factor values obtained on the state level and the time of day marginal emission factor estimates explained in 4.2.3 above to obtain a $ per kWh value – which is then multiplied by the avoided hourly electricity consumption for the different EEMs for each hour in the year. The hourly estimates are then combined to obtain yearly value estimated of monetized benefits. This can be expressed mathematically as:

$$Avoided\ Monetized\ Damages\ Elec_{pol,EEM}(\$/yr_{pol}) = \sum_{EEM} \sum_{h=1}^{h=8760} Elec.savings_{EEM}(h)[\frac{kg}{MWh}] * MarginalDamages_{pol}(h)[\frac{\$}{MWh}] \quad (4.5)$$

We then estimate the avoided damages from the residential combustion of propane, fuel oil, and natural gas for the different pollutants by multiplying the marginal damage factor values from the AP3 model by the avoided marginal emission estimates obtained in equation (4.3) above. This can be expressed mathematically as:

$$Avoided\ Monetized\ Damages\ ResCombust_{ft}\left(\frac{\$}{yr_{ft}}\right) = Avoided\ Marginal\ Emissions\ ResCombust_{ft}\left[\frac{kg}{yr}\right] \times MD_{ft}\left[\frac{\$}{ton}\right] \quad (4.6)$$

where MD_{ft} is the marginal damage value of the fuel type. The avoided damages from electricity generation and residential energy combustion are then summed up to get total avoided monetized estimates from reduced pollutant emissions.

4.3. Results

4.3.1. Total electricity potential and avoided emissions for different energy efficiency measures

In Table 4.3, we show our baseline consumption and total reduction potential of implementing the different EEMs for residential SFD homes in Pennsylvania. We estimate a baseline consumption of 39TWh of electricity, 1.3 billion therms (130MMBTu) of natural gas, 36MMBTu of propane, and 74MMBTu of fuel oil accounting for a total of 373.4MMBTu site energy consumption in the residential SFD housing stock in Pennsylvania. Comparing our estimates 2017 EIA estimates for residential homes in Pennsylvania, with the assumption that 58% of total consumption is from residential SFD homes[11], electricity and natural gas consumption are 32TWh of electricity and 132MMBTu of natural gas respectively. These EEMs also result in about \$3.4 billion per year in energy bill savings. The total avoided marginal emissions associated with these EEMs amount to approximately 14M metric tons of CO_2, 16K metric tons of SO_2, 1.4K metric tons of $PM_{2.5}$, and 6K metric tons of NO_x per year. Putting this number in context, Pennsylvania established its first statewide goal in 2019 of reducing total greenhouse gas emissions by 80% in 2050 compared to 2005 levels[12]. While this paper estimates that EEMs could reduce Pennsylvania CO_2 emissions by 34% compared to 2017 baseline levels in the residential sector, it would reduce the total Pennsylvania CO_2 emissions—including all end-use sectors-- by just 6.3% in 2050 compared to 2005 levels, while accounting for 21% of total emissions in just the residential sector.

[11] 2018 baseline study for Pennsylvania indicates that 58% of total residential consumption comes from SFD homes: http://www.puc.pa.gov/Electric/pdf/Act129/SWE-Phase3_Res_Baseline_Study_Rpt021219.pdf

[12] https://www.governor.pa.gov/governor-wolf-establishes-first-statewide-goal-reduce-carbon-pollution-pennsylvania/

Table 4.3 - Baseline consumption and reductions through energy efficiency measures in the residential SFD stock in Pennsylvania

Source	Baseline consumption	Reductions through EEMs (% reduction)
Electricity	39TWh	14TWh (36%)
Natural gas	130MMBTu	57MMBtu (44%)
Propane	36MMBtu	7MMBtu (19%)
Fuel Oil	74MMBTu	31.5MMBtu (43%)

4.3.2. Mitigation supply curves for CO_2, SO_2, $PM_{2.5}$, and NO_x

In Figure 4.2, we provide mitigation supply curves from the implementation of the different EEMs where we compare the private cost per ton of pollutant avoided to the total magnitude of CO_2, SO_2, $PM_{2.5}$, and NO_x saved. The width of each block is the net cost of avoided emissions (i.e. cost of upgrade minus utility savings from the upgrade) and the height of the block is the total metric tons of pollutant saved from the implementation of the upgrade. Therefore, tall blocks have very good economics and wide blocks have large potential savings.

From Figure 4.2, we find that at a 7% discount rate, not all EEMs considered are cost-effective (e.g. low-storm windows, duct sealing, and R-10 basement insulation upgrades are not cost-effective). Also, we find that EEMs which make the most economic sense do not necessarily save the largest amount of emissions. Drill-and-fill insulation and high-efficiency ductless heat pumps (DHPs), for example, save the largest amount of pollutants among all the EEMs considered though they are relatively expensive. More interestingly, we find that the choice of an EEM is dependent on the type of pollutant reduction that is being considered. For example, LED lighting is more cost-effective than drill-and-fill wall insulation when considering CO_2 and SO_2 emission reductions, while the reverse is the case when considering NO_x and $PM_{2.5}$ emission reductions. As pollutant emissions vary to different degrees by hour and time of year e.g. NOx emissions are highest in non-summer months, therefore EEMs which result in significant heating savings (e.g. drill-and-fill insulation) may save higher NOx pollutants

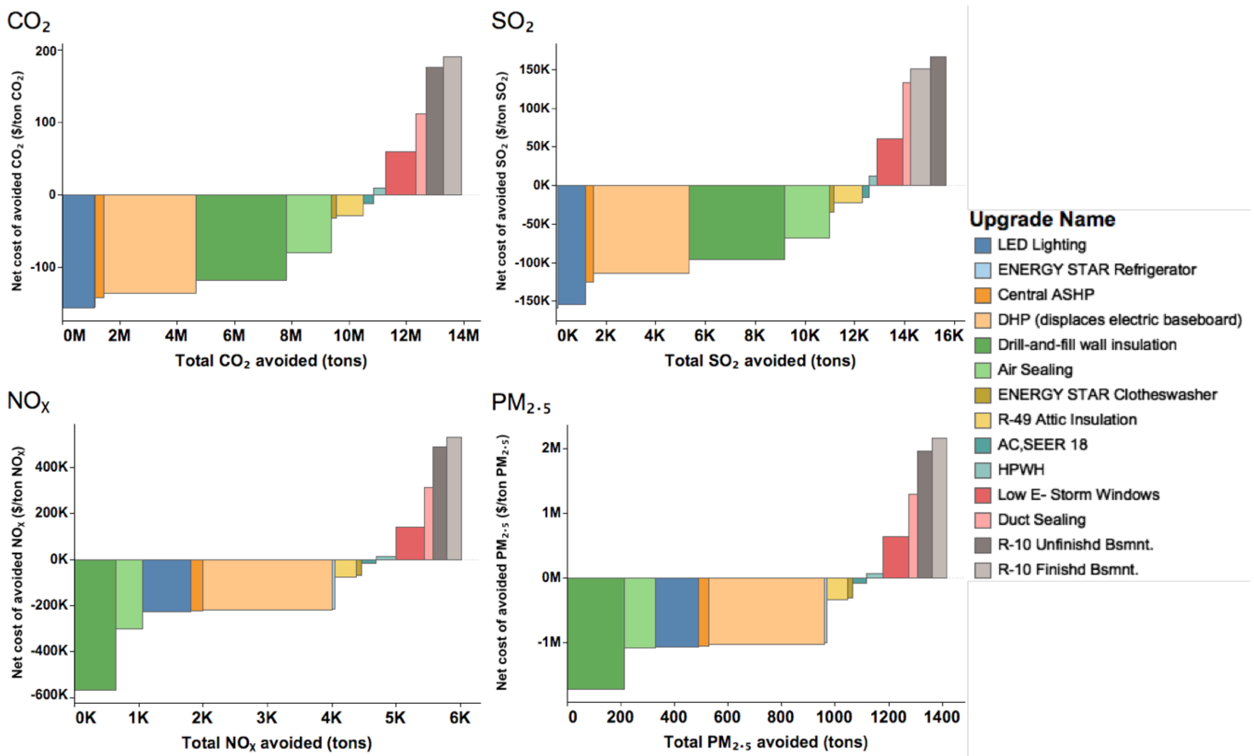

Figure 4.2 - Mitigation supply curves comparing the private net-cost of different EE upgrades with the annual avoided CO_2, SO_2, NO_x, and $PM_{2.5}$ emissions (metric tons) for different energy efficiency (EE) upgrades in the state of PA. Each block represents an EE upgrade. The width of each block indicates the emission savings provided by the implementation of the upgrade, while the height of the block represents the net cost of conserved pollutant.

compared to loads which are more constant throughout the year (e.g. lighting loads). Overall, for all EEMs, we find that LED lighting, Central Air Source Heat Pumps (ASHP), DHPs, and Drill-and-fill wall insulation consistently provide the highest economic opportunities to reduce all pollutants. However, these results are sensitive to the choice of the discount rate selected. Because the magnitude of emissions reductions does not vary with the choice of discount rate, we compare the economic benefits i.e. $/ton of pollutants avoided for the different upgrades with discount rates of 3%, 7%, and 15%. Figure 4.3 compares these estimates for CO_2 emission reductions where we find that while all EEMs are cost-effective at very low discount rates (3%), only Central Air Source Heat Pumps (ASHP), LED lighting, DHPs, and ENERGY STAR refrigerators pass the cost-effectiveness criteria at much higher discount rates (15%). Appendix C.3 provides a sensitivity analysis for the different pollutant types with varying discount rates. These results are not surprising because the choices that were cost-effective at lower discount rates have very high lifetime values with annualized costs spread out over a long time. However, the options with lower lifetime values become more cost-effective as the discount rates increase. Other work finds that households may choose not to invest in options with long lifetime values as consumer implicit discount rates[13] are very high and would rather choose options with much lower lifetime values. It is very important for policymakers to take into consideration the key differences such as lifetime values

[13] The implicit discount rate can be defined as "…the value of the discount rate for a hypothetical net-present- value-maximizing consumer that best matches observed choice behavior")

and especially the choice of discount rates when making decisions between competing energy efficiency upgrades

4.3.3. Comparison of marginal and average emission reduction

We compare the estimates of the avoided average emission reductions from electricity generation for the different EEMs to serve as a comparison to our marginal emission factor estimates. Here, we find deviations of average emissions to marginal emissions for the different pollutants as CO_2: +11% to +13%, SO_2: -46% to +13%, $PM_{2.5}$: +1% to +3%, and NO_x: -3% to +2% (see Appendix C.4 for more details). For example, the largest discrepancy is in SO_2 emission estimates because of a greater difference between peak and off-peak marginal emission rates driven by the frequency of coal being the marginal generator. Because air conditioners are mostly used in the summer, with lower marginal rates compared to the rest of the year, avoided emission reductions using average values of SO_2 for air conditioners are overestimated by 13%. However, for upgrades like ductless heat pumps which have higher winter consumption compared to the summer, we underestimate the SO_2 emission reductions using average values compared to marginal values.

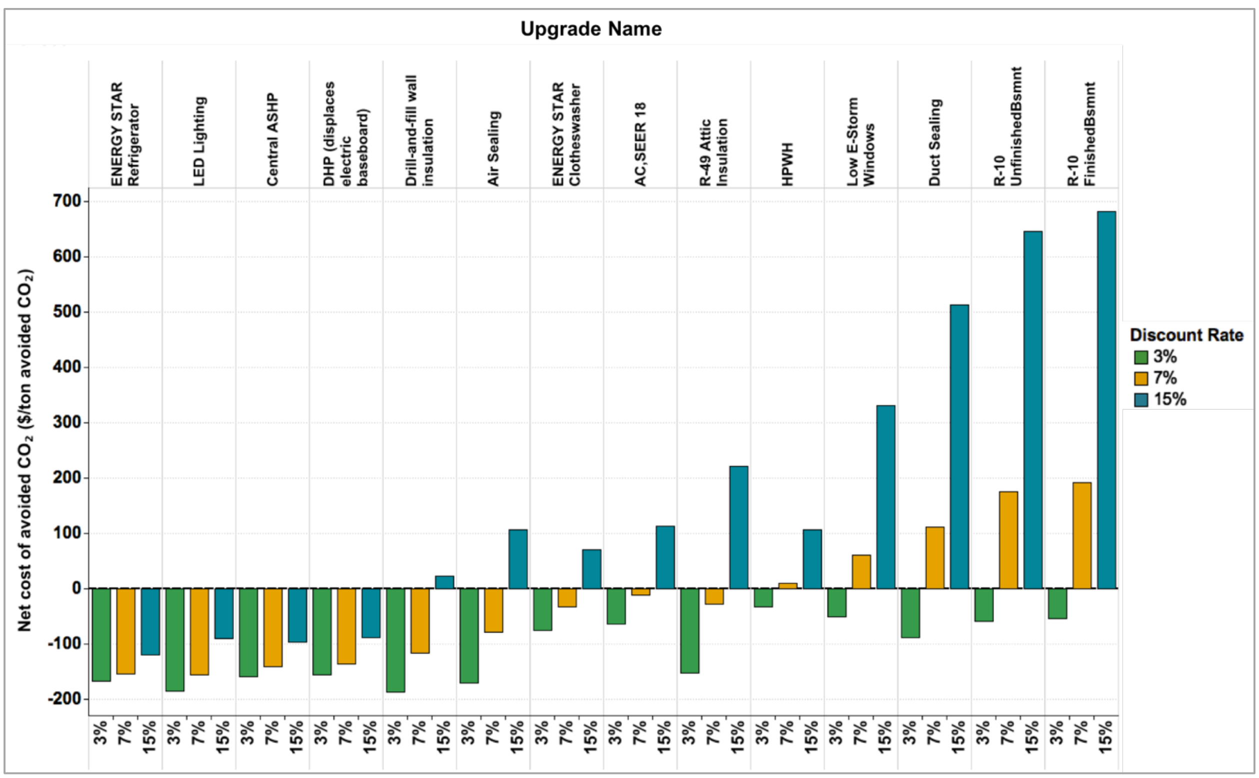

Figure 4.3 - Comparison of the net cost of avoided CO_2 for different EE upgrades using 3%, 7%, and 15% discount rates. Estimates less than 0 are cost-effective while those greater than 0 are not cost-effective.

4.3.4. Social benefits of energy efficiency upgrades

We monetize the total avoided emission reductions through the implementation of different EEMs. In Figure 4.4, we provide a comparison of the net cost of the different upgrades to the social benefits from the upgrades using our baseline discount rate of 7% (see Appendix C.5 for discount rates of 3% and 15%). Here, we sum the social benefits from CO_2, SO_2, $PM_{2.5}$, and NO_x into a total avoided damage $ value. Overall, we estimate total social benefits on the order of $2.4 billion per year with from CO_2, SO_2, $PM_{2.5}$, and NO_x savings accounting for 26%, 54%, 19%, and 1% of total benefits respectively (See Appendix C.5 for a breakdown of the benefits by EE upgrade and pollutant type). We find that majority of social benefits are from reductions of SO_2 which has been shown to have very harmful effects both to the health and the environment, for example, through its contribution to respiratory illnesses, acid rain, reduction of visibility in certain locations in the U.S.[14]

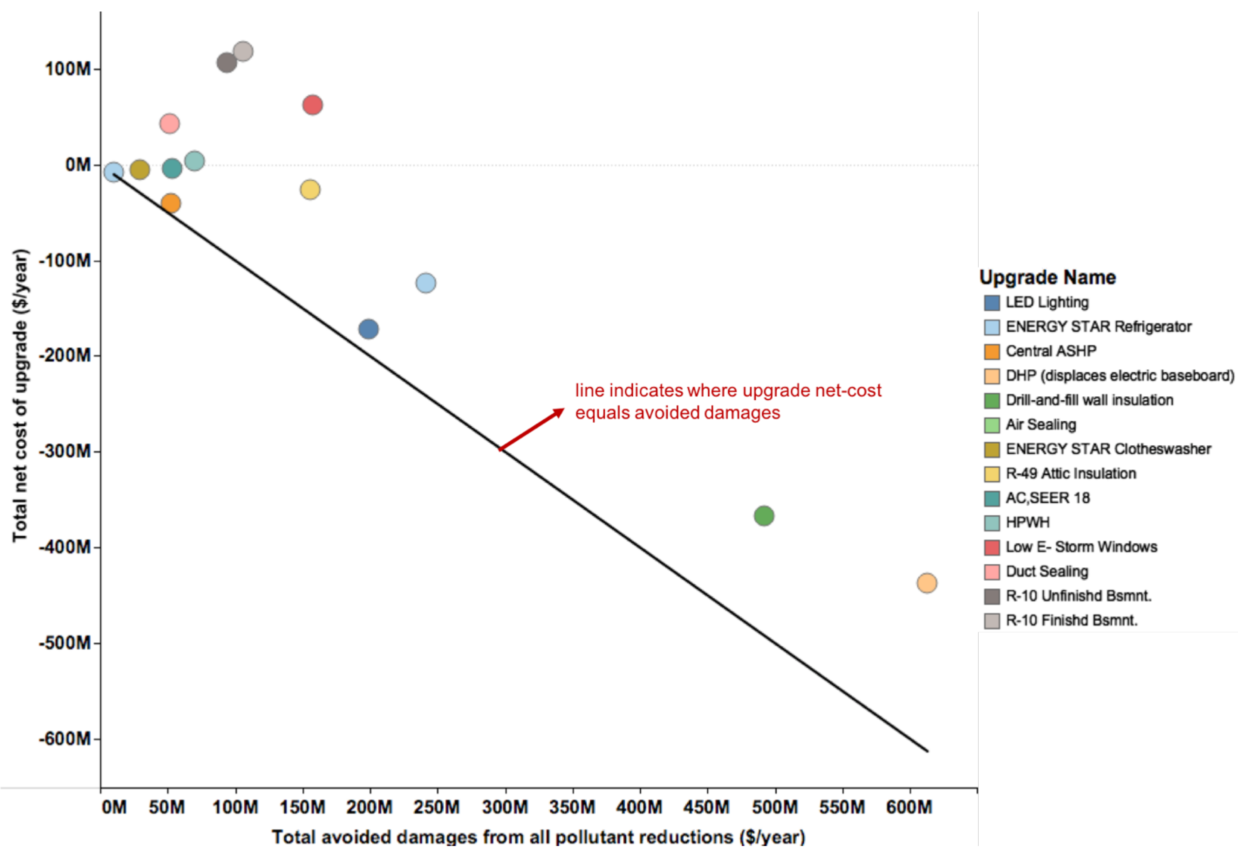

Figure 4.4 - Comparison of total net upgrade cost to total avoided damages from all pollutant emission reductions for different EE upgrades at a 7% discount rate

We also find that all the EEMs yield higher social benefits than private benefits which vary widely depending on the type of EEM considered. For example, it is more beneficial for the government to subsidize heat pump water heater (HPWH) upgrades even though it is not as cost-effective as central air source heat pumps (ASHP) upgrades as the social benefits for HPWH is higher than that of central ASHP

[14] https://www.epa.gov/so2-pollution/sulfur-dioxide-basics

upgrades (Total private net cost for HPWH vs central ASHP: +$4M vs -$40M, Avoided damages for HPWH vs central ASHP upgrades: $70M vs $53M). Overall, we find that with a discount rate of 7%, the top 4 upgrades which yield both high private net benefits as well as social benefits are drill-and-fill insulation, DHP, LED lighting, and air sealing upgrades. However, just like in section 4.3.2, the choice of these upgrades (especially when considering net private benefits) will change depending on the choice of the discount rates.

4.4. Discussion

In this work, we estimate the potential energy generation, emission reductions, private net benefits, and social benefits of implementing a variety of EE upgrades in the residential SFD housing stock in PA. Results from our analysis estimate a baseline consumption of 39TWh of annual electricity generation serving about 2.9 million homes in the state. We estimate reductions of 36%, 44%, 19%, and 43% in baseline electricity, gas, propane, and fuel oil consumption from the implementation of these different EE upgrades. These reductions are also associated with total avoided marginal emission reductions of 14M metric tons of CO_2, 16K metric tons of SO_2, 1.4K metric tons of $PM_{2.5}$, and 6K metric tons of NO_x per year. Putting this number in context, we estimate that the different EEMs could reduce the SFD carbon footprint by 34% compared to 2017 baseline levels and meet 6.3% of the total carbon reduction goal that has been set by Pennsylvania in 2050 compared to 2005 levels. Within the scope of our analysis, our discussion falls into three main categories.

4.4.1. The choice of marginal versus average emissions are important in estimating the potential for energy efficiency

From our analysis, we find deviations of average emissions to marginal emissions from the different pollutants ranging from as high as +11% to as low as -46% depending on the EE upgrade and the pollutant considered. These results indicate that the method chosen for an emission estimate can have serious implications for its results. As explained in section 3.2, because of the frequency of coal as the marginal generator in the U.S., there is a greater difference in on-peak and off-peak marginal emission rates. We note here that these results are not typical to the Pennsylvania region alone – for example, Smith and Hittinger estimated the differences between AEF and MEF reductions of CO_2 lighting upgrades by almost a factor of three in the upstate New York region (AEF reduction was estimated at 300kg/year compared to MEF reductions of 800kg/year)[111]. As NY's electricity is mostly composed of nuclear, natural gas, and hydro, the AEF emission, especially for upstate NY, is low as hydropower and nuclear plants produce no emissions. However, in NY, natural gas plants are the marginal power plant meeting demand when lighting is in use. As a result, the marginal emission reductions are higher than the average emission reductions as natural gas is meeting demand when the LED lights are in use. Therefore, it is beneficial to accurately capture these emission reductions as simpler AEF estimates may be misleading.

This is not to say that our estimation method is perfect. For example, our MEF estimates are gotten from the CEMS database which is limited to fossil-fuel generators greater than 25MW. Therefore, the MEF estimates do not account for renewable energy sources or small fossil-fuel generators indicating that our estimates are only valid if a CEMS-exempt generator does not operate on the margin[123]. As more renewables are being included in electricity dispatch, there is the possibility of the displacement of the marginal generator e.g. natural gas may be used more frequently instead of petroleum during peak periods. Similarly, we note that these estimates are based on 2017 power-plant data, indicating that these results may change as plants go out of commission or new ones are installed. It is therefore very important for future work to keep track of changes to the generation mix especially with the displacement of marginal generators as results may largely differ depending on these factors.

4.4.2. Bridging the gap between private and social benefits through energy efficient measures

Our analyses indicate that the selection of an EEM is highly dependent on the stakeholder and the type of reductions that they are most concerned about. For example, homeowners are more inclined to consider upfront investments when making their decision to choose an EEM while the government may be more interested in broader health and climate change implications. In 2015, Pennsylvania passed Act 129 where it set for Investor Owned Utilities (IOUs) amounting to yearly statewide electric energy incremental savings of 0.8% for 2016-2020 [126]. Since then, lighting programs have been overwhelmingly implemented --accounted for 70% of overall gross savings from energy efficiency in the state in 2018--as it has been identified as the greatest opportunity for demand reductions in the state[126], [127]. However, as the state is thinking more critically about broader climate impacts e.g. through the new greenhouse gas reduction goal in January 2019, it is important to examine which of the EEMs can provide both the private benefits i.e. in terms of cost reduction potential as well as provide the highest social benefits. Our results indicate that drill-and-fill insulation, DHP, LED lighting, and air sealing upgrades balance the choice of net-private and social benefits for the state. These results, however, are very sensitive to the choice of the discount rates e.g. drill- and-fill and air sealing upgrades are not cost-effective at higher discount rates of 15% as seen in Figure 3. Results have shown that the implicit discount rates[15] for consumers when making the choice of purchasing an EEM can range from as low as 0% to as high as 825% depending on the EEM considered[128], [129]. Therefore, it is highly important that the state identifies the implicit discount rates for households who may intend to purchase these EEMs and provide adequate financing to encourage households to invest in these EEMs.

4.4.3. Other considerations: Marginal Emissions Estimation approach, Social Cost of Carbon, and other co-benefits from energy efficiency

From this work, we highlight the importance of the use of the MEF approach to estimating emission reductions from the implementation of different EE upgrades. While we use an integrated air quality model (i.e. the AP3 model) to estimate the different emission reductions, we recognize that other dispatch or regression models exist[123], [130]–[136]. Although some studies have compared different integrated air quality models with results showing little sensitivity, we suggest that future work compare multiple models to ensure that the results are qualitatively identical[122].

[15] The implicit discount rate can be defined as "…the value of the discount rate for a hypothetical net-present- value-maximizing consumer that best matches observed choice behavior")

Secondly, we acknowledge that our valuation of social benefits may very low. For example, we value CO_2 reductions at $40 per metric ton[122]. While this number has been widely recognized and accepted, researchers and experts argue that it is far lower than the true cost of carbon pollution[137]–[139]. Therefore, it is important for future work to take into account the changes in the valuation of these different pollutants.

4.5. Conclusion

Based on our case study, we estimate that Pennsylvania could reduce its CO_2 emissions by 34% compared to 2017 baseline levels and its environmental health damages by $2.4 billion per year through residential EEMs in its SFD building stock. However, many of the EEMs examined in our study are relatively expensive and have relatively low private benefit. Given our results, we would recommend focusing on drill-and-fill insulation, DHP, LED lighting, and air sealing EEM technologies, which could reduce total Pennsylvania CO_2 emissions by 37% and its environmental health damages by $1.6 billion per year at a much lower abatement cost. Because our results are sensitive to the choice of discount rate, we suggest that Pennsylvania support these 4 EEM investments by offering the appropriate incentive and/or financing programs. However, it is important that these programs are structured equitably. A recent study by Jacobsen, for example, shows significant variation in the types of subsidies received by income levels. He compares tax credits, manufacturer/retailer rebates, and utility rebates and found the highest concentration of tax credits in higher-income households with the lowest concentration for utility rebate[140]. These results suggest that energy efficiency benefits may be disproportionately flowing to higher-income households if, for example, a larger amount of funds is allocated to tax credits compared to utility rebate programs. While different states in the U.S. are delivering specialized programs for low-income customers as a way to reduce the high energy burden experienced by these groups, it is also pertinent that the strategies being used are indeed effective.

Through the Act 129, Pennsylvania stipulated that each EDC obtains at least 5.5% of its consumption reduction from programs solely directed at low-income customers, available at no cost. We find that efficiency lighting and LED saturation is significantly higher in low-income homes than non-low-income homes. These results are not surprising because over 70% of gross savings in Pennsylvania came from lighting measures[127]. On the contrary, we find that low-income households have significantly higher (i.e. less efficient) air leakage rates compared to non-low income households. These results suggest that Pennsylvania's mandates may maximize participation rates and not achieve deep savings by individual households e.g. through the overwhelming number of lighting upgrades being implemented[141]. Although some low-income upgrades in Pennsylvania have focused on drill-and-fill wall insulation, air sealing, and DHPs upgrades, more penetration is needed so that these EEMs achieve the required health and climate change benefits. For example, only 4 out of the 7 EDC's implemented some DHP upgrades for low-income households in 2018.

We recommend that Pennsylvania also specifically align with existing efforts to serve low-income households. While Pennsylvania has begun attempts to coordinate the Weatherization Assistance Program (WAP) with its Low-Income Usage Reduction Program (LIURP) as well as its Act 129 Low-Income

Program in 2012, with an MOU in 2016 implemented to facilitate data sharing between all the agencies weatherization programs, this MOU has not been posted or made publicly available[142]. States such as Ohio and Massachusetts, however, have had successful low-income programs which benefited from a streamlined and effective delivery of state coordination serving low-income households e.g. through the Massachusetts Low-Income Energy Affordability Network (LEAN) and the Columbia Gas of Ohio's Warm Choice Program. LEAN works to standardize eligibility requirements, procedures, and standards to enable the delivery of various programs through Community Action Partnership agencies throughout the state[143], [144]. Ohio's Warm Choice program shares resources with Ohio's Home Weatherization Assistance Program and implementation contractors for both programs are reimbursed based on the services they provide[142], [143]. Similarly, states like Vermont supplement their Weatherization Assistance Programs with specific add-on measures which have included offerings such as mini-split heat pumps[142], [145]. However, it ensures that customers interact only with one program as these measures offered as part of the weatherization program. In this way, participation is convenient and more accessible to its customers. By adopting some of these best practices, Pennsylvania may be well on its way to delivering reductions needed through energy efficiency in its residential SFD homes.

Apart from the type of incentive programs, it is also very important to consider the size of these programs. Studies, for example, have shown the "free-rider" effect for many energy efficiency programs where participants would receive subsidies for programs that they would have done anyway[81], [146]. Although Pennsylvania conducts willingness-to-pay studies, it is beneficial to ensure that more targeted questions e.g. surrounding appliance purchase patterns and size of incentives are asked. For example, Pennsylvania residents indicate that they prioritize the performance of new measure and electricity bill savings for insulation and air sealing upgrades while for measures such as heat pumps, they prioritize improved reliability and reduced maintenance cost for the new EEMs[141]. Therefore, subsidies may indeed not be needed for some households, but more targeted information on performance, bill savings, and maintenance reductions may be adequate.

While our results are specific to Pennsylvania, the method can be applied to other states or cities in the United States and can help identify the most cost-effective EEM investments for meeting broader public environmental goals.

5. Conclusions and Policy Implications

This dissertation provides a critical look at the design and implementation of energy efficiency programs and policies. Specifically, I examine programs and policies that have been implemented in the past to provide insight into designing better policies in the future. I also examine the benefits of incorporating broader societal impacts into future policy design when examining the potential for energy efficiency. In this chapter, I highlight some of the main findings from each section along with some opportunities for informing policy making or advancing future research.

5.1. Public Policy Dilemma: to invest or not?

In Chapter 2, I examine the impact of various stakeholders in driving green building adoption. Specifically, I examine the impacts of local and federal policies while taking into account the simultaneous effect of USGBC LEED rating system improvements in encouraging green building retrofits. The conclusions of this study point to several areas of focus for policy makers:

Non-financial policies. After considering various local policies types, I find that non-monetary policies (i.e. requirement and density bonuses) are the most effective in driving commercial green building retrofits. More importantly, I find that non-monetary policies are more effective than policies which offer financial rewards for commercial building retrofits. The results suggest that as policy makers make decisions about the policies needed to driving green building adoption e.g. offering financial rewards or mandates, it is important to review the landscape which will yield the great impact for the building type. For example, while I was able to tease out the drivers for some LEED rating system types, I recommend that more analysis is done to examine the specific drivers for end-use building types e.g. commercial offices of different sizes will have varied needs compared to warehouses thereby allowing for more-tailored policy implementation.

The role of private actors in driving green building adoption. In this study, I also observe a significant role of the LEED rating system in driving green building adoption. I find significant improvements in green building adoption as the LEED certification process became more streamlined and easier to use. Although the government has been taking strides to encourage green building adoption e.g. through policy making and LEAD by example, where mandates where government-owned or certified buildings are required to be LEED certified, more collaboration between third-party certification systems such as LEED and the government may be very beneficial. For example, the government could help in playing a role in determining the kind of credits which would yield energy and/or carbon reduction points under the LEED rating system types. This could even be streamlined by location as studies have shown the potential for energy efficiency to vary by building location and type.

Better standardization of building policies. One of the most significant limitations in this study was the difficulty in categorizing the various policy types across different levels of the government e.g. making the distinction between policies affecting retrofits vs new construction for city, local, and federal policies. In moving this study forward, it will be very beneficial for states to have a standard format of delineating the building policies to ensure that adequate tracking and analysis can be made when examining program impacts.

Public disclosure of data. In Chapter 2, I assume that a LEED-certified building is more energy-efficient as the LEED documentation specifies that certain levels of energy reductions need to be achieved before the building can receive the stamp of approval as a LEED building. However, due to the proprietary nature of the energy data in many of these commercial buildings, this assumption is difficult to disprove. While 7 states in the U.S. have a commercial building disclosure policy which may make it easier to track energy consumption patterns in LEED-certified buildings[16], I recommend that policy makers strongly encourage the public disclosure of buildings to ensure that energy reductions are indeed being achieved as significant amount of time and/or money is being invested in promoting green buildings.

5.2. Evaluating Energy Efficiency Programs

As energy efficiency has been identified as a low-cost and reliable utility system resource and policy strategy to meet long-term energy and climate goals, significant investments have been made to encourage the implementation of a portfolio of energy efficiency programs and projects. However, this has also called for increased excellence in the way these programs are evaluated, measured, and verified. In Chapter 3, I shed light on some of the methods used in evaluating residential energy efficiency programs using a case study of a city in the U.S. The conclusions of this study provide the following insights for policy guidance.

Consider more robust mechanisms for estimating savings from energy efficiency programs. Most states in the U.S. require that program administrators conduct independent, third-party evaluation, measurement, and verification (EM&V) for their energy efficiency programs. However, due to time and expenses incurred, there is the risk of inadequately measuring the extent of these savings. For example, when using data-driven approaches to measure savings from energy efficiency programs, one could either use the randomized control trial (RCT) approach which is more accurate but expensive and time consuming or the quasi-experimental method (QEM) which is not as rigorous but is increasingly subject to some bias. Not surprisingly, many states, if at all, use some form of QEM for their EM&V process. Our study uses a first-level detection approach and finds evidence of bias even when using the QEM approach. Therefore, while policy makers are taking the right step to safeguard the EM&V process, it is also pertinent to ensure that the appropriate methods are implemented when measuring these energy efficiency program impacts. Using novel modeling processes, for example, studies are beginning to find evidence that ex-post evaluation of energy programs are much smaller than ex-ante estimates. With better data sharing, states and evaluators could collaborate with academic and research organizations in ensuring that the appropriate mechanisms are used in evaluating the portfolio of these energy efficiency programs.

[16] https://database.aceee.org/state/building-energy-disclosure

Survey implementation considerations. While the QEM approach was used to disentangle the effects of programs, this study would have been substantially improved if there was a better understanding of the motivation behind the reasons a customer is opting into a program. With this information, one can better understand the extent of factors such as free ridership, participant spillover, or other behavioral changes that may occur as a result of one joining a program. Similarly, program administrators are able to able to better tailor these energy efficiency programs to the needs of the customers. I suggest that adequate pre and post-tracking is implemented to program and non-program participants thereby significantly improving the energy efficiency evaluation process.

Non-financial energy efficiency programs. Just like in Chapter 2, I find evidence that behavioral programs provide more benefits than programs which offer financial rewards for energy efficiency. Although financial incentives are beneficial in promoting the use of more energy-efficiency equipment, more studies are beginning to lend support to the significant role of informational programs in promoting energy reductions. Therefore, policy makers should consider bridging the knowledge-gap so consumers are well equipped with the information needed to pursue energy efficiency – with or without financial incentive mechanisms in place. I also recommend that decision makers put appropriate survey and tracking mechanisms in place to determine the extent of changes that were implemented after these informational campaigns are put in place.

5.3. Inclusion of Health and Climate Benefits

The integration of health and climate impacts when examining energy efficiency reductions offers the opportunity to incorporate broader societal impacts when deciding to implement energy efficiency and may bolster support for these reductions. In Chapter 4, I explore not only the energy reductions but also examine the private and social benefits of implementing a wide range of energy efficiency upgrades to the residential building stock. I identify many areas for policy makers from this study and elaborate on two main points here

Designing policies with health and environmental considerations. Without explicitly estimating the reductions from the implementation of energy efficiency measures, it is expected that significant benefits will occur when considering the benefits to health and climate. However, it is important that the real extent of the benefits is captured as there are significant regional variations in the way energy is produced which may yield to suboptimal design of policies if neglected. In our study, for example, I find that policies which yield the highest private benefit may not necessarily yield the highest social benefits. As decision makers make the tradeoff between cost-effective measures and those which would yield the highest energy reductions, added considerations also need to be given to broader health and climate benefits.

Equitable distribution of energy efficiency incentives. In Chapter 4, I find that many of the energy efficiency measures are cost-intensive highlighting the need for better financing and/or incentive options. However, it has also been well documented that lower income homes are those that are more likely to have less energy-efficient homes but also find it very difficult to incorporate energy efficiency due to high costs. Also, some financing options have been realized to flow disproportionately to higher-income households indicating that without the proper design of energy efficiency programs, then climate goals would not be reached. Therefore, policy makers need to consider strategies that would reduce inequality in the distribution of financing and/or incentive options for these programs. For example, ensuring that energy efficiency programs are specifically tailored to lower-income households through adequate benchmarking and characterization of their needs.

5.4. Conclusion

This thesis offers both a retrospective and prospective look into the way energy efficiency programs and policies are designed with the aim of promoting energy reductions and ensuring the realization of broader climate goals. The three studies contained in this thesis provide insight into the considerations that need to be put in place by different actors when designing future energy policies and programs and provides insight on how to incorporate health and climate impacts into the decision- and policy making process. Ultimately, this thesis aims to provide a critical look into the way energy efficiency is viewed and designed thereby ensuring that decision makers can make more informed considerations to ensure a more sustainable future.

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Appendix A. Supplemental Information for Chapter 2

Appendix A.1. LEED Building Certification: summary information and characteristics

The U.S. Green Building Council (USGBC) was established in 1993 with a mission of promoting sustainable building practices in the building industry. The LEED version 1.0 was launched in 1998 and since then has evolved from the development of one standard for new construction to multiple standards across various building types[147]. Since its inception, there have been multiple versions of the LEED rating system ranging including v1.0, v2.0, v2.2, v2009 (previously named v3) and v4.

Until October 31, 2016 new projects were able to choose between LEED 2009 and LEED v4. Projects registering after October 31, 2016 must adhere to LEED v4 standards[147].

LEED standards apply to buildings of various types and categories. Under the LEED v4 standards, buildings can apply under the[148]:

- *Building Design and Construction (D+C)* applies to buildings that are newly constructed or going through a major renovation including New Construction, Core and Shell, Data Centers, Healthcare, Hospitality, Retail, Schools, and Warehouse and Distribution Centers.
- *Buildings Operations and Maintenance (O+M)* applies to existing buildings (i.e. buildings that are fully operational and have been occupied for at least one year) that are undergoing improvement with little to no construction, including Existing Buildings, Schools, Retail, Hospitality, Data Centers, and Warehouse and Distribution Centers.
- *Interior Design and Construction (ID+C)* applies to projects which interior spaces are a complete interior fit-out including Commercial Interiors (interior spaces that aren't dedicated to retail or hospitality functions), Retail, and Hospitality.
- *Neighborhood Development (ND)* applies to new land development or redevelopment projects that contain residential uses, non-residential uses or a mix
- *Homes* applies to single-family homes, low-rise and mid-rise multi-family homes (one to six stories).

In our work, we consider buildings certified under the LEED O+M (which we term LEED-EB), LEED Commercial Interiors(LEED-CI), and LEED Core and Shell (LEED-CS) rating systems. These rating systems updates, however, are not all implemented at the same period. Pilot testing for LEED-EB began in 2002 and in 2003 for LEED-CI[17]. LEED-EB and LEED-CI were launched together in November 2004 while the LEED-CS program launched in October 2003. LEED-EB got its first major update in 2008 and then a minor update with other rating system types with the introduction of LEED v2009. In November

[17] LEED-EB: https://www.usgbc.org/articles/more-decade-high-performing-buildings-out-now-edcs-february-issue; LEED-CI & LEED-CS: https://www.usgbc.org/articles/part-2-green-building-explosion-2003-2009

2013, all rating systems were updated to the LEED v4 program[18]. Therefore, there is the possibility to examine the effects of these updates on existing building certifications as they occurred in different years. However, LEED v2009 to LEED v4 coincides with ARRA-EECBG implementation as discussed in the main text. We decided to code ARRA instead of the LEED v2009 to LEED v4 while being cognizant that there may be bundled effect of the LEED update and federal funding disbursement.

LEED buildings can earn one of the four LEED rating levels: Certified, Silver, Gold, or Platinum[149]. These different rating levels can be pursued by earning points across several categories including energy use, air quality, water efficiency, and sustainable site development. The different points across different levels are as follows:

- LEED Certified: 40-49 points
- LEED Silver: 50-59 points
- LEED Gold: 60-79 points
- LEED Platinum: 80+ points

USGBC publishes information of buildings that have received LEED certifications under different LEED rating systems. The USGBC dataset collects information on building characteristics including project name, address, country, certification level, certification date, building type, and square footage. For this study, we extracted information on non-confidential building types that were certified from January 2000 to December 2016 to inform our results.

As of October 27, 2018, the USGBC had 137,140 buildings that had been registered who may have/have not received certifications. We subset those who registered and went on to certify their buildings data by 1) Location: US, 2) Non-confidential (as project owners may choose to have their projects confidential), and (3) Owner types: Non- Government. We also excluded "recertified buildings" as existing buildings have to undergo recertification every 5 years.

After all these exclusions, we were left with a total of 10,420 buildings certified under the LEED-EB, LEED-CI, and LEED-CS programs. Table A.1 provides a breakdown of the top 10 rating system versions considered in our dataset while Table A.2 provides the distribution of the top 10 LEED project types in our dataset. From Table A.1, we see that the highest versions of LEED buildings certified are from the LEED-CI and LEED-EB version 2009 programs. These results are intuitive because as stated above, projects could register for the LEED v2009 program till October 31, 2016. Also, from Table 2.1 in the main text, LEED has seen more significant growth especially in the CI program in more recent years. From Table A.2, we see that most of the buildings certified under the LEED existing buildings program are offices and retail spaces. Because our analysis is conducted at the Metropolitan Statistical Area level while the USGBC data has information on building data at the city level, we aggregate data up to the MSA level and use the information from 2002 to 2016 as explained in the methods section in the main text.

[18] LEED-v4: https://www.usgbc.org/articles/part-3-challenges-and-opportunities-2010-present

Table A.1 Top 10 rating system versions for existing buildings certified under the USGBC LEED rating system between 2002 and 2016

Rating System Version	Count	Percent of Total
LEED-CI v2009	2475	24%
LEED-EB:OM v2009	2305	22%
LEED-CI 2.0	1188	11%
LEED-CS v2009	998	10%
LEED-CI Retail v2009	948	9%
LEED-CS v2.0	710	7%
LEED-EB:OM	654	7%
LEED for Retail (CI) Pilot	633	6%
LEED-EB 2.0	274	3%
LEED-CS 1.0 Pilot	94	1%

Table A.2 – Top 10 project types for existing buildings certified under the USGBC LEED rating system between 2002 and 2016

Building Project Type	Count	Percent of Total
Office: Administrative/Professional	2321	22%
Commercial Office	1817	17%
Office: Mixed Use	866	8%
Retail	741	7%
Retail: Fast Food	687	6%
Retail: Other Retail	616	6%
Retail: Bank Branch	524	5%
Retail: Open Shopping Center	312	3%
Office: Financial	308	3%
Office: Other Office	288	3%

Appendix A.2. LEED building certifications by state and MSA

In Figure A.1, we show a map of the number of retrofitted commercial LEED by state and MSAs between 2002 and 2016. There is high regional variability in LEED certified buildings by state with majority of the LEED certified buildings in California. Within the different states, there is also a significant distribution of retrofitted LEED certified buildings by MSA, with majority of the retrofits clustered in larger MSAs (by population), such as Washington DC, New York, Los Angeles, and San Francisco.

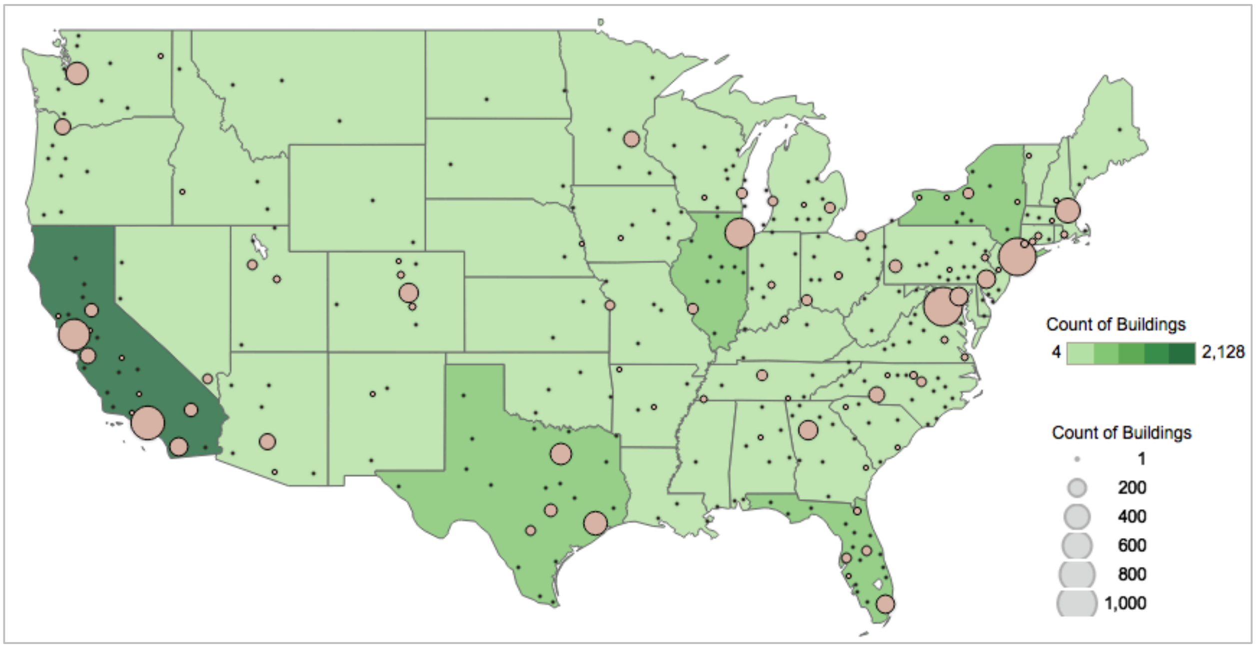

Figure A.1 - Total number of retrofitted commercial LEED buildings by state and variation by MSA from January 2002 to December 2016. The green background map indicates the number of retrofitted commercial buildings in the state. The pie charts show the distribution of the LEED certification levels for the different MSAs with the size of the pie chart indicating the total number of retrofits in each MSA. Compiled by authors from USGBC Policies database[3].

Appendix A.3. LEED policy categories by state and MSA

Based on the review of recent literature, we grouped the policies aimed at green building retrofits into 5 policy groups:

1) *Requirements,* meaning that new/renovated commercial buildings must meet LEED.
2) *Recommendations* that encourage LEED certifications, but buildings are not mandated to build LEED.
3) *Density/Height bonus* is a zoning tool that allows developers to build more housing units, taller buildings, or more floor space than normally allowed.
4) *Financial incentives* are monetary incentives e.g. tax credit programs, grant programs.
5) *Non-financial incentives*, incentives that are not necessarily monetary. Most policies in this category are expedited permitting policies.

Table A.3 shows the total count of initial policies added in each year by city, county, and state between 1999 and 2015. As stated in the main text, there was a ramp-up of policies enacted between 2007 and 2009 with a majority of policies enacted in 2009 coinciding with ARRA implementation. Figure A.2 shows a distribution of the policies by state and MSA.

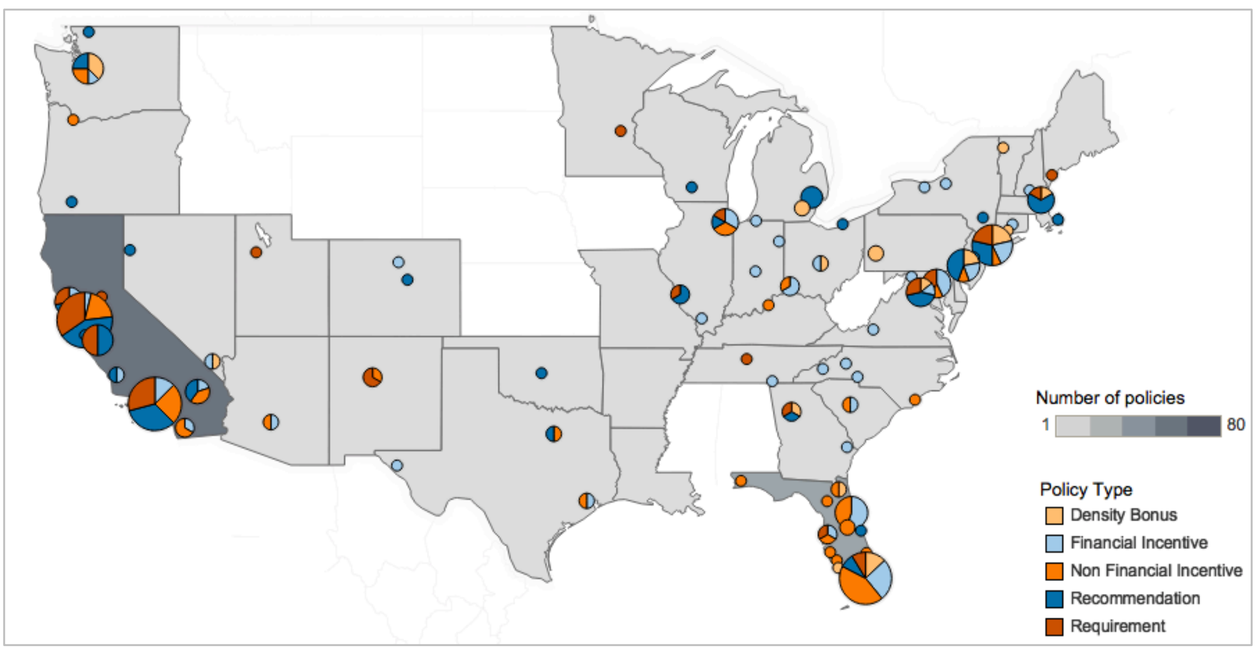

Figure A.2 - Total number of LEED certifications by state and total variations by MSA from Jan 2000 to December 2014. The blue background map indicates the number of incentives and policies available for the state. The pie charts show the type of policies available for the different MSAs with the size of the pie chart indicating the total number of policies available. Compiled by authors from USGBC Policies database[3].

Table A.3 – Policy counts by city, county, and state

LEED Policy Type	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Grand Total
Recommendation	0	0	1	0	1	1	4	4	15	19	10	12	5	1	1	0	0	74
Financial Incentive	1	1	1	0	0	0	0	5	14	9	22	7	2	3	4	2	0	70
Non Financial Incentive	0	0	0	1	2	1	3	4	5	11	21	3	3	1	1	0	0	56
Requirement	0	0	0	0	1	1	1	3	10	9	14	6	0	1	0	0	2	48
Density Bonus	0	0	0	0	0	0	2	3	5	2	9	1	1	1	1	0	0	25

Appendix A.4. Control Variables

Unemployment Data

We use unemployment data from the Bureau of Labor Statistics dataset at the county level and aggregated it to the MSA level for the purpose of our analysis.

GDP data

We use GDP data from the Bureau of Economic Analysis dataset available at the MSA level for the purpose of our analysis. We subtract Construction, Manufacturing, and Real Estate data from the GDP data as explained in the main manuscript

Solar PV Installations

We use data from the Lawrence Berkeley National Laboratory's Tracking the Sun Dataset for the size of solar PV installations in an MSA. We performed the following data cleansing tasks:

- Subset commercial/non-residential data from the dataset
- Matched zip code to county. In situations where zip code level information was not provided, we matched city to county
- All county information was then matched to the MSA level

This dataset of 30831 rows for solar PV installations (between 2000 and 2017) was then used for further analysis.

Alternative Fuel Stations dataset

We use data from the Alternative Fuel Station's dataset from the Office of Energy Efficiency and Renewable Energy for the total count of EV stations in an MSA. We perform the following data cleansing tasks:

- We select all "ELEC" stations from the "fuel_type_code" column
- We select all publicly available stations from the "groups_with_access code" column.
- We match zip code to city to county to the MSA level.

This dataset of 6017 rows for EV fuel stations (between 2000 and 2017) was then used for further analysis.

Appendix A.5. Year-over-year effects individual program types

We replicate Figure 2.3 in the main paper to show year-over-year effects for all years between 2002 and 2016 in an attempt to tease out federal and USGBC LEED updates. Figures A.3, A.4, and A.5 show the year-over-year effects for the LEED EB, CI, and CS rating system types. From Figures A.3, A.4, and A.5, we see the highest program impacts around 2008 and 2009.

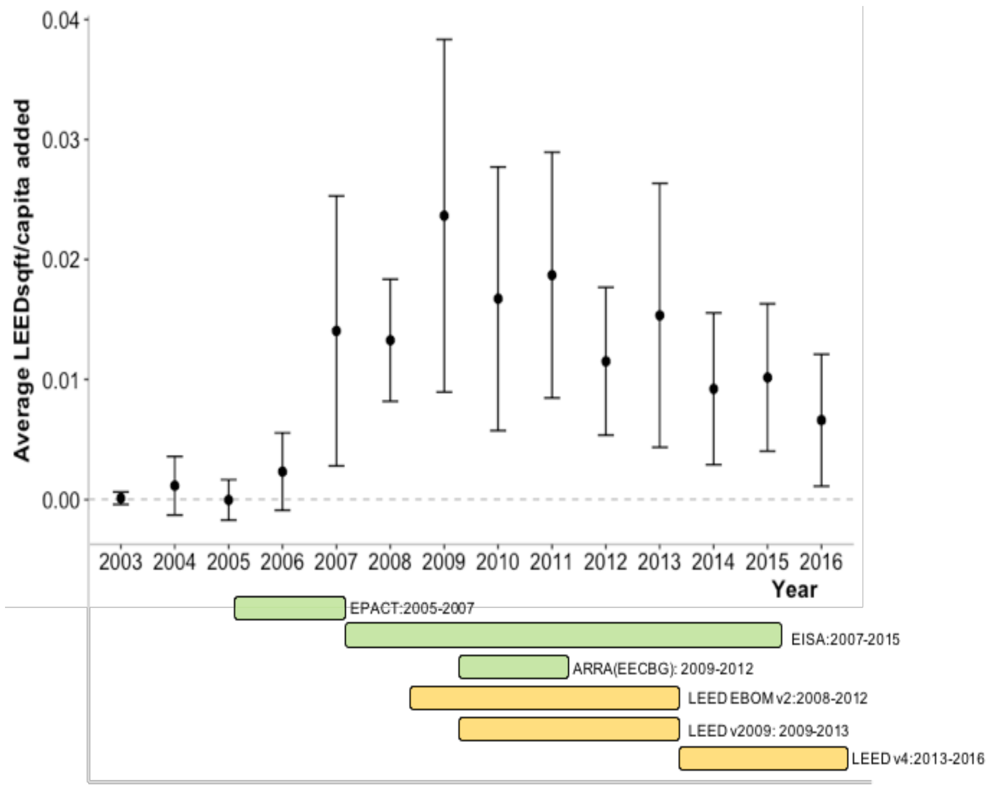

Figure A.3 - Year-over-year estimates showing the effects of federal and USGBC LEED rating system updates on programs certified under LEED-EB between 2003 and 2016 using 2002 as the base year. Blocks in green represent federal polices while blocks in yellow represent internal USGBC rating system upgrades.

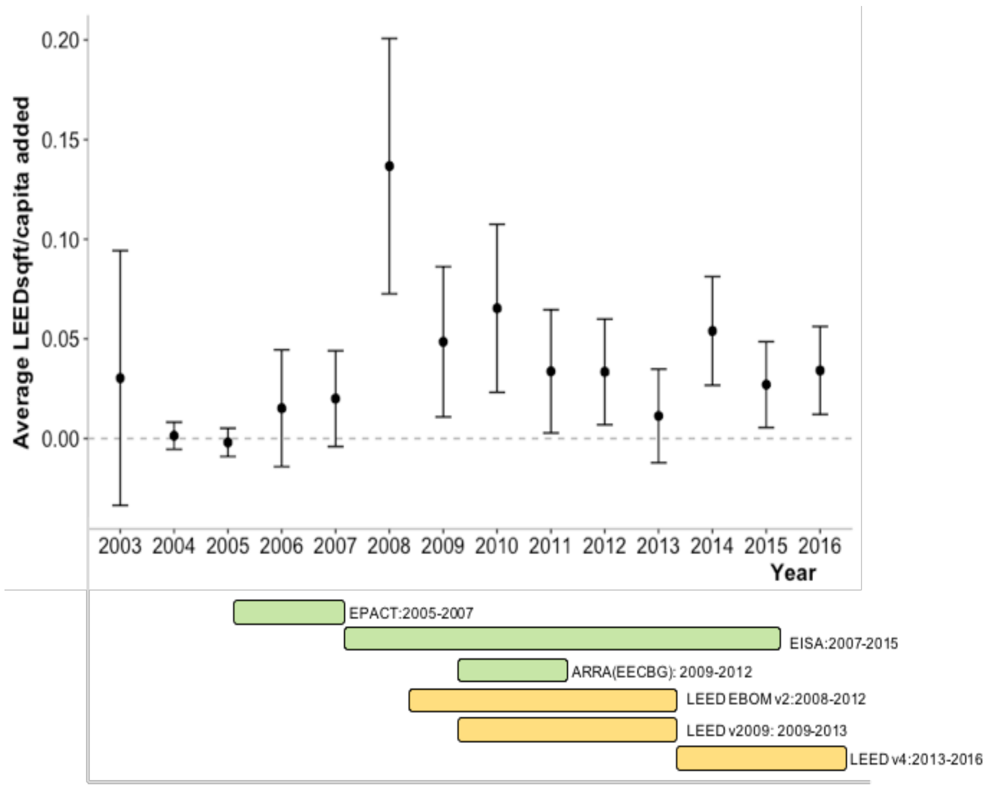

Figure A.4 - Year-over-year estimates showing the effects of federal and USGBC LEED rating system updates on programs certified under LEED-CI between 2003 and 2016 using 2002 as the base year. Blocks in green represent federal polices while blocks in yellow represent internal USGBC rating system upgrades.

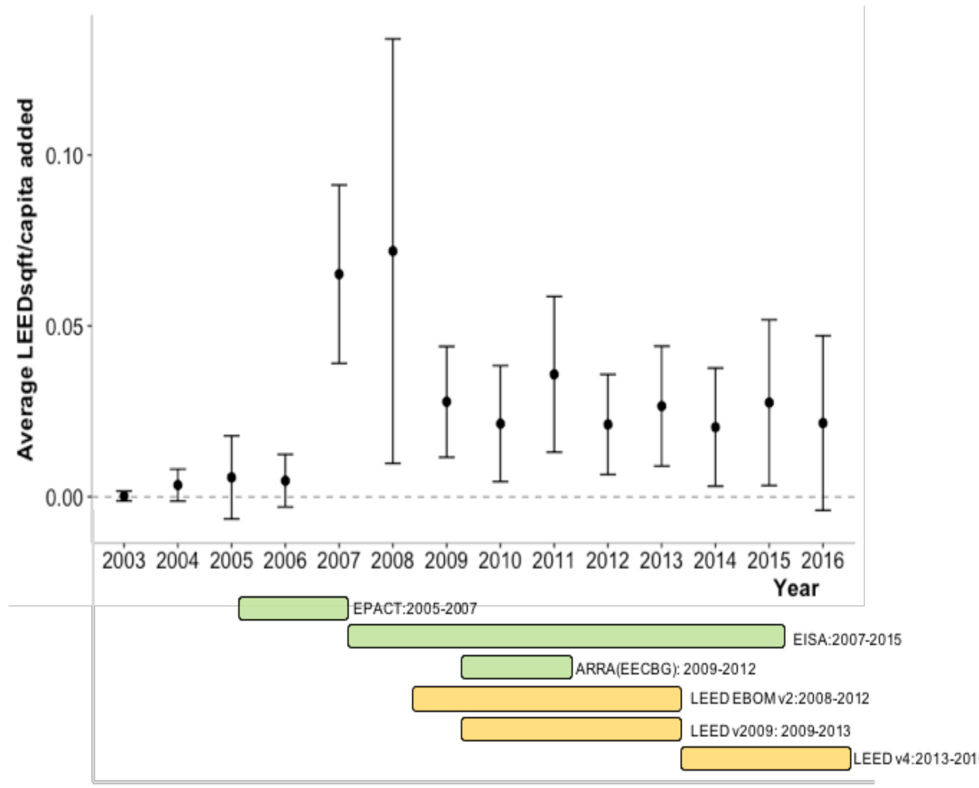

Figure A.5 - Year-over-year estimates showing the effects of federal and USGBC LEED rating system updates on programs certified under LEED-CS between 2003 and 2016 using 2002 as the base year. Blocks in green represent federal polices while blocks in yellow represent internal USGBC rating system upgrades.

Appendix A.6. Alternative model specification: federal and LEED rating system dummies

Table A.4 compares the estimated linear regression coefficients and standard errors from the main paper with one which excluded the year dummies (due to confounds with dummies related to federal policies and USGBC LEED updates). For all models, we include federal dummies for EPACT, EISA, and ARRA as explained in the main paper. We also include dummies indicating the start of LEEDv4 program in 2013. We also specifically add a dummy for the LEED-EB update in 2008 as articles in the LEED space indicated its significance. We modify equation (2.2) in the main paper for LEED-EB as:

$$Y_{i,t} = \alpha REQT_{i,t} + \beta RECOM_{i,t} + \gamma FINAN_{i,t} + \delta NOFINAN_{i,t} + \lambda DENSITY_{i,t} + \rho GDP_{i,t} + \mu UNEMPLOY_{i,t} + \varphi SOLARPV_{i,t} + \varphi EVCOUNT_{i,t} + \varrho AFTER_{EPACT_{i,t}} + \psi AFTER_{EISA_{i,t}} + \varsigma AFTER_{ARRA_{i,t}} + \sigma LEED_{EB2008_{i,t}} + \psi LEED_{v4_{i,t}} + MSA_i + \varepsilon_{i,t} \qquad (S1)$$

where $\sigma LEED_{EB2008_{i,t}}$ is a dummy variable that takes on the value of 1 between 2008 and 2013 and 0 otherwise indicating the LEED-EB update in 2008 . $\psi LEED_{v4_{i,t}}$ is also a dummy variable that takes on the value of 1 between 2013 and 2016 and 0 otherwise indicating the start of LEED version 4.

For the LEED-CI and LEED-CS programs, equation (2.2) is modified as:

$$Y_{i,t} = \alpha REQT_{i,t} + \beta RECOM_{i,t} + \gamma FINAN_{i,t} + \delta NOFINAN_{i,t} + \lambda DENSITY_{i,t} + \rho GDP_{i,t} + \mu UNEMPLOY_{i,t} + \varphi SOLARPV_{i,t} + \varphi EVCOUNT_{i,t} + \varrho AFTER_{EPACT_{i,t}} + \psi AFTER_{EISA_{i,t}} + \varsigma AFTER_{ARRA_{i,t}} + \psi LEED_{v4_{i,t}} + MSA_i + \varepsilon_{i,t} \qquad (S2)$$

From Models (S2) in Table A.4, we specifically note the positive impact of programs occurring in 2008 (specifically LEED-EB update) and the negative impact of ARRA programs. However, from the year-over-year effects estimate in Figures S3-S5, we see that the 2009 effect is positive but smaller than the 2008 effect. Therefore, the ARRA dummy is capturing the reduction between 2008 and 2009 as negative even though the impact is still overall positive. We decide to go on with the Year-over-year estimate in the main paper as the results, although similar, is more difficult to interpret in Model (S2).

Appendix A.7. Alternative model specification: LEED Volume program

We attempt to capture the effect of the LEED Volume program by examining the count of buildings certified under the different rating system types. As stated in the main paper, LEED Volume aims at certifying projects of the similar type making the certification process easier. Therefore, in the case of LEED-CI projects for example, the impacts may not be seen in terms of square footage but counts of buildings certified.

We modify the dependent variable of equations S1 and S2 to be the count per 100,000 persons in the MSA population. As a sensitivity analysis to capture the effects of LEED Volume, we exclude companies who participated in the LEED pilot program for the LEED-EB rating system as well as top companies who have certified buildings under each of the rating systems and are a part of the LEED Volume program.

For the LEED-EB program we exclude: Stop and Shop, MEPT-Bentall Kennedy, Kohl's Department Stores, Cushman and Wakefield, Wells Fargo Bank North America, and Bank of America. For the LEED-CI program, we exclude: Verizon Wireless, Wells Fargo Bank North America, PNC, and Starbucks. For the LEED-CS program, we exclude Prologis and Liberty Property Trust[19][20].

[19] LEED Volume program participants: https://www.usgbc.org/articles/potential-retrofits-launch-leed-volume-program-operations-maintenance

[20] LEED Volume participants as of 2014: https://www.usgbc.org/articles/green-tools-leed-users-project-certification-options

Table A.4 - Alternative model specifications – Model results examining the effects of different local policy types on retrofitted LEED square footage in commercial buildings (1) accounting for MSA and year effects and (2) including federal and USGBC LEED program updates excluding year effects

Variable	Coefficient and Robust Standard Errors							
	All programs		LEED-EB		LEED-CI		LEED-CS	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Requirement	**0.22****	**0.22****	**0.07***	**0.08***	**0.30**	**0.30**	0.08	0.08
	(0.10)	**(0.10)**	**(0.04)**	**(0.04)**	**(0.02)**	**(0.02)**	(0.08)	(0.08)
Financial Incentive	0.01	0.01	-0.01	(0.01)	-0.0004	-0.001	0.03	0.03
	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
Non Financial Incentive	0.09	0.09	0.01	0.02	-0.004	-0.005	0.09	0.09
	(0.08)	(0.08)	(0.06)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
Density Bonus	0.03	0.03	**0.13****	**0.13****	**0.04*****	**0.05*****	-0.11	-0.11
	(0.10)	(0.10)	**(0.06)**	**(0.06)**	**(0.02)**	**(0.02)**	(0.08)	(0.08)
Recommendation	0.003	0.003	0.02	0.02	0.02	0.02	-0.03	-0.03
	(0.06)	(0.06)	(0.06)	(0.06)	(0.01)	(0.01)	(0.03)	(0.03)
GDP (in billions of dollars)	**0.004*****	**0.004*****	**0.002****	**0.002****	**0.0005*****	**0.0005*****	**0.0009*****	**0.0009****
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
PV System Size (in GW)	-0.006	-0.009	-0.005	-0.008	0.001	0.001	-0.002	-0.002
	(0.02)	(0.02)	(0.01)	(0.01)	(0.002)	(0.002)	(0.01)	(0.01)
EV Charging Stations (Count)	-0.0005	-0.0006	0.0003	0.0001	**-0.0002***	**-0.0002****	**-0.006*****	**-0.005****
	(0.001)	(0.001)	(0.007)	(0.001)	**(0.0001)**	**(0.0001)**	**(0.002)**	**(0.002)**
Unemployment rate (%)	-0.004	-0.003	0.003	0.003	-0.0009	-0.0001		0.004
	(0.005)	(0.004)	(0.004)	(0.003)	(0.0006)	(0.0006)		(0.004)
EPACT		0.001		-0.004		0.001		**0.06*****
		(0.01)		(0.01)		(0.001)		**(0.02)**
EISA		**0.09*****		0.01		**0.01*****		**-0.04 ***
		(0.02)		(0.01)		**(0.003)**		**(0.02)**
ARRA		**-0.14*****		**-0.09*****		0.001		**-0.04 ***
		(0.05)		**(0.03)**		(0.004)		**(0.02)**
LEED(2008-2013)		**0.12*****						
		(0.04)						
LEED-EB(2008)				**0.11*****				
				(0.03)				
LEEDv4		-0.03		0.01		**-0.004**		**-0.04 ***
		(0.02)		(0.01)		**(0.003)**		**(0.01)**
Intercept	**-0.24*****	**-0.23*****	**-0.11****	**-0.10*****	**-0.03****	**-0.03****	-0.08	-0.08
	(0.07)	**(0.07)**	**(0.04)**	**(0.01)**	**(0.01)**	**(0.01)**	(0.07)	(0.07)
MSA dummies	Included	Included	Included	Included	Included	Included	Included	Included
Year dummies	Included	Non-included	Included	Non-included	Included	Non-included	Included	Non-included
Observations	5730	5730	5730	5730	5730	5730	5730	5730
Number of groups	382	382	382	382	382	382	382	382

Robust standard errors in parentheses

***p < 0.01, **p< 0.05, *p<0.1.

Notes: LEED(2008-2013): dummy for all updates to all existing building rating systems between 2008 and 2013 ; LEED-EB(2008): dummy indicating update to the LEED-EB program between 2008 and 2014 ; LEED v4:dummy indicating the LEED update between 2013 and 2016.

Table A.5 compares the estimated linear regression coefficients and standard errors for the counts of LEED certified buildings per 100,000 persons in the MSA with the sensitivity model which excludes

Table A.5 - Alternative model specifications – Model results examining the effects of different local policy types on count of LEED buildings per 100,000 persons in the MSA accounting for MSA, federal, and USGBC LEED upgrades for (1) all buildings and (2) excluding top LEED volume participants

Variable	Coefficient and Robust Standard Errors					
	LEED-EB		LEED-CI		LEED-CS	
	(1)	(2)	(1)	(2)	(1)	(2)
Requirement	**0.08*** (0.03)**	**0.03 (0.03)**	0.06 (0.04)	**0.07* (0.04)**	0.03 (0.02)	0.02 (0.02)
Financial Incentive	-0.002 (0.01)	-0.0008 (0.007)	0.01 (0.01)	0.008 (0.01)	-0.005 (0.006)	-0.06 (0.006)
Non Financial Incentive	0.04 (0.04)	0.03 (0.04)	0.01 (0.03)	-0.002 (0.03)	0.02 (0.02)	0.01 (0.02)
Density Bonus	0.006 (0.04)	0.05 (0.03)	**0.14*** (0.03)**	0.03 (0.03)	-0.006 (0.03)	(0.01) (0.02)
Recommendation	0.04 (0.04)	0.04 (0.04)	0.03 (0.03)	0.05 (0.03)	0.01 (0.01)	0.01 (0.01)
GDP (in billions of dollars)	**0.0008** (0.0003)**	**0.0008** (0.0003)**	**0.001*** (0.0004)**	**0.001*** (0.0003)**	**0.0005*** (0.0002)**	**0.0005***** (0.0002)
PV System Size (in GW)	-0.01 (0.01)	-0.003 (0.005)	**0.08*** (0.03)**	**-0.009** (0.004)**	-0.002 (0.005)	-0.0005 (0.004)
EV Charging Stations (Count)	-0.0003 (0.0002)	-0.0001 (0.0002)	0.0001 (0.0004)	-0.0002 (0.0002)	**-0.0005** (0.0002)**	-0.0005 (0.0002)
Unemployment rate (%)	**-0.003* (0.002)**	-0.001 (0.001)	-0.0008 (0.002)	**0.004** (0.002)**	-0.001 (0.001)	-0.001 (0.001)
EPACT	(0.00) (0.002)	-0.0008 (0.002)	**0.01*** (0.04)**	**0.01*** (0.004)**	**0.01*** (0.003)**	**0.009*** (0.003)**
EISA	0.007 (0.005)	**0.008* (0.005)**	**0.04*** (0.006)**	**0.04*** (0.01)**	**0.03*** (0.006)**	**0.03*** (0.006)**
ARRA	0.01 (0.01)	-0.001 (0.008)	**0.03** (0.01)**	-0.02 (0.01)	**-0.02*** (0.007)**	**-0.02*** (0.007)**
LEED-EB(2008)	**0.04*** (0.01)**	**0.03*** (0.08)**				
LEEDv4	**0.04*** (0.007)**	0.007 (0.006)	**0.04*** (0.01)**	**-0.02*** (0.007)**	**-0.03*** (0.006)**	**-0.03*** (0.006)**
Intercept	-0.02 (0.02)	-0.02 (0.02)	**-0.09*** (0.03)**	**-0.11*** (0.03)**	0.006 (0.01)	0.01 (0.01)
MSA dummies	Included	Included	Included	Included	Included	Included
Year dummies	Not-included	Not-included	Not-included	Not-included	Not-included	Not-included
Observations	5730	5730	5730	5730	5730	5730
Number of groups	382	382	382	382	382	382
Robust standard errors in parentheses						
***p < 0.01, **p< 0.05, *p<0.1.						
Notes: LEED-EB(2008): dummy indicating update to the LEED-EB program between 2008 and 2014 ; LEED v4:dummy indicating the LEED update between 2013 and 2016.						

the companies stated above for the different rating systems. Since LEED Volume was implemented in 2011 and LEED v4 in 2013, we are expected to see reductions, if any, in the LEED v4 dummy estimates as there are no year effects in the model specification. From Table A.5, comparing models (1) and (2) for the different rating systems, we note significant reduction in estimates of the LEED v4 program especially in the LEED-EB and LEED-CI case. Therefore, LEED Volume has a big role to play in also encouraging commercial green building adoptions. We do not see reductions in the LEED-CS case which we hypothesize is due to lack of observations in buildings certified under this rating system type

Appendix A.8. Alternative model specification: First Differences and Anderson-Hsaio Model

Table A.6 examines the sensitivity of our model approach and provides the estimated linear regression coefficients for using the first differences and Anderson-Hsaio estimator for our main regression model. It specifically examines the first differences and Anderson-Hsaio estimates and standard errors for Column (1) of Table (2.1) of the main paper. We find large discrepancies from Table A.6 where the first differences and Anderson-Hsaio estimates are similar but very different from the fixed effects estimates. Upon further examination, we realize that the first-differences model is not appropriate for our analysis. Hence, a lagged model such as the Anderson-Hsaio cannot be used for this work. We provide a sample case comparing the fixed effects and first differences model in the sub-sections below

Explanation of First Differences(FD) and Fixed Effects (FE) Model

For the FE and FD models, we examine two cases: 1) where an entire MSA gets a policy which is enacted midway through the timeframe of the program and LEED-sqft increases immediately, and 2) lagged effects case where policy effects are not seen in the first year of the program

First Differences Model

Table A.7 shows a case of no-year lags i.e. program effects are seen immediately the policy is enacted. We implement the first differences (as seen on the right side of the table) by subtracting our estimates of each year from its previous year.

Figure A.6 provides a visual representation of Table A.7. Here, we see that although the LEED-sqft is increasing, the first differenced approach shows a negative trend. The negative trend is worse when we have a lagged effect as seen in Table A.8 and Figure A.7. These results however, are different from the fixed effects model where a positive trend is seen.

Table A.6 - Alternative model specifications – (2) Model results examining the effects of different local policy types on retrofitted LEED square footage in commercial buildings accounting using the 1) fixed efffects approach , 2) first differences approach, 3) Anderson Hsaio approach

Variable	**Coefficient and Robust Standard Errors**		
	Fixed effects	**First differences**	**Anderson Hsaio**
Lagged LEEDsqft (2 years)			**0.09***
			(0.04)
Requirement	**0.22****	0.22	0.23
	(0.10)	(0.15)	(0.15)
Financial Incentive	0.02	0.004	0.01
	(0.03)	(0.04)	(0.04)
Non Financial Incentive	0.09	-0.10	-0.10
	(0.08)	(0.12)	(0.13)
Density Bonus	0.03	**-0.58***	**-0.56***
	(0.10)	**(0.33)**	**(0.33)**
Recommendation	0.003	0.02	0.01
	(0.06)	(0.08)	(0.08)
GDP (in billions of dollars)	**0.004*****	0.0006	0.0009
	(0.001)	(0.001)	(0.001)
PV System Size (in GW)	-0.006	-0.04	-0.05
	(0.02)	(0.07)	(0.07)
EV Charging Stations (Count)	-0.0005	0.0008	-0.0006
	(0.001)	(0.001)	(0.001)
Unemployment rate (%)	-0.004	**-0.01****	**-0.01****
	(0.005)	**(0.005)**	**(0.004)**
Intercept	**-0.24*****	**0.008*****	0.005
	(0.07)	**(0.002)**	(0.003)
MSA dummies	Included	Not included	Not included
Year dummies	Included	Not included	Not included
Observations	5730	5348	4966
Number of groups	382	382	382
Robust standard errors in parentheses			
***p < 0.01, **p< 0.05, *p<0.1.			

Fixed Effects Model

We implement a similar model structure as the FD model where we have cases of no-year and one-year lags in Tables A.9 and Table A.10. The FE model was estimated by subtracting each estimate from its time-averaged mean value. The results depicted in Figures A.8 and A.9 respectively are very different from the FD approach as it better captures the trends we expect to see. We also see consistent results in the case of one-year lags as well as the FE results still captures that increasing trend. We settle on the fixed effects model as it better captures the time trends we expect to see compared to the first differences approach.

Table A.7 - Base and first difference cases with no-year lags of policy implementation and LEED-sqft increase

Case 1a: No Year Lags				First Differences	
Year	Policy	LEED-sqft		Policy	LEED-sqft
1	0	0		NA	NA
2	0	0		0	0
3	1	200		1	200
4	1	500		0	300
5	1	900		0	400
6	1	1100		0	200

Table A.8 - Base and first differences case with one -year lags of policy implementation and LEED-sqft increase

Case 1b: 1 Year Lag				First Differences	
Year	Policy	LEED-sqft		Policy	LEED-sqft
1	0	0		NA	NA
2	0	0		0	0
3	1	0		1	0
4	1	200		0	200
5	1	500		0	300
6	1	900		0	400

Table A.9 - Base and fixed effect cases with no-year lags of policy implementation and LEED sqft increase

Case 1: No Year Lag				Fixed Effects	
Year	Policy	LEED-sqft		Policy	LEED-sqft
1	0	0		-0.67	-450
2	0	0		-0.67	-450
3	1	200		0.33	-250
4	1	500		0.33	50
5	1	900		0.33	450
6	1	1100		0.33	650

Table A.10 - Base and fixed effect cases with one-year lags of policy implementation and LEED-sqft increase

Case 1b: 1 Year Lag				Fixed Effects	
Year	Policy	LEED-sqft		Policy	LEED-sqft
1	0	0		-0.67	-266.67
2	0	0		-0.67	-266.67
3	1	0		0.33	-266.67
4	1	200		0.33	-66.67
5	1	500		0.33	233.33
6	1	900		0.33	633.33

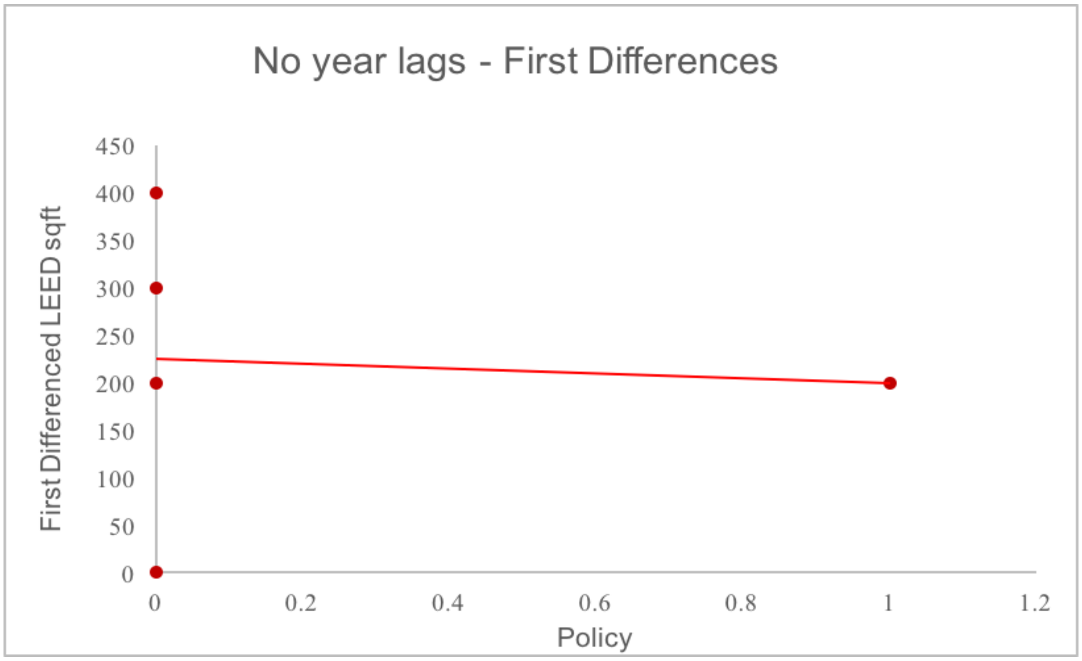

Figure A.6 - Relationship between policy implementation and LEED-sqft using the FD approach with policy effects seen the year policy was implemented

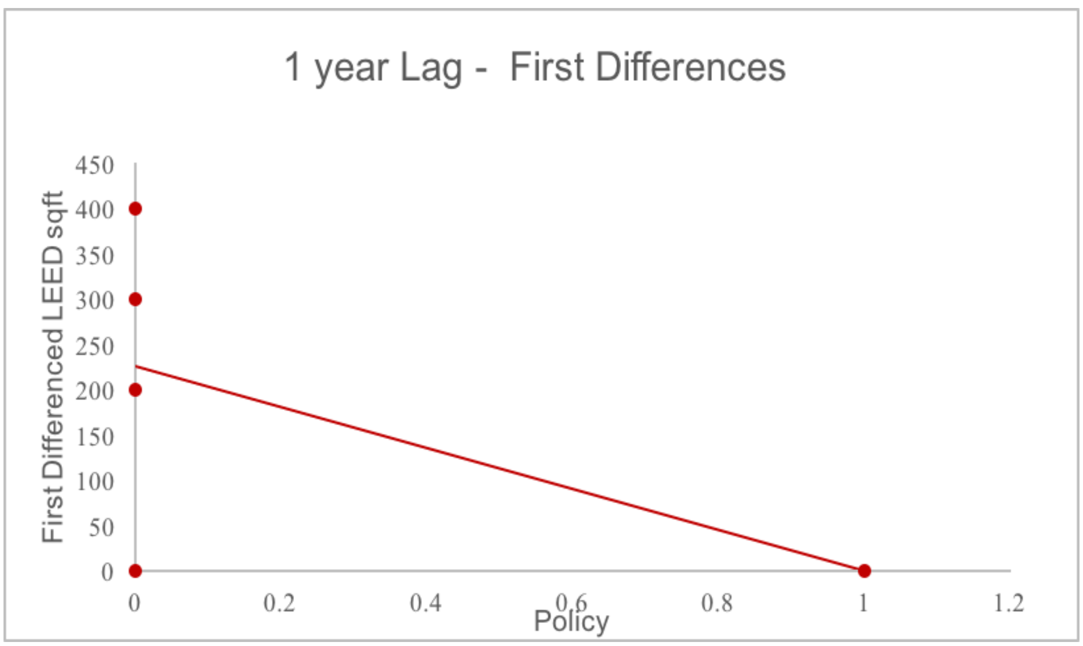

Figure A.7 - Relationship between policy implementation and LEED-sqft using the FD approach with policy effects seen one year after the year policy was implemented

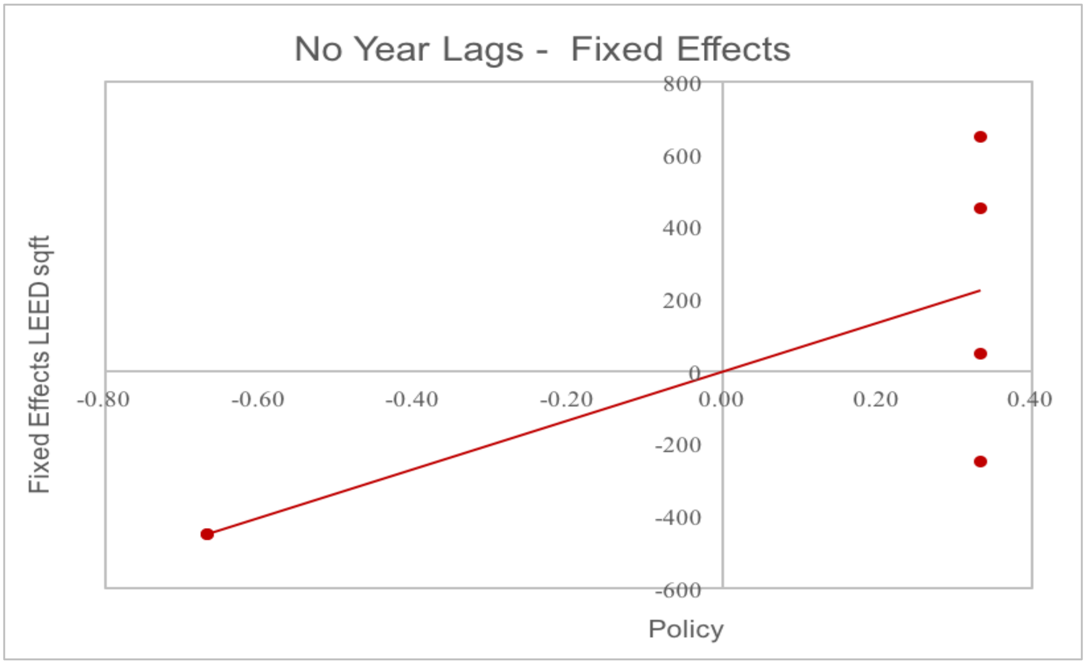

Figure A.8 - Relationship between policy implementation and LEED-sqft using the fixed effects approach with policy effects seen one year after the year policy was implemented

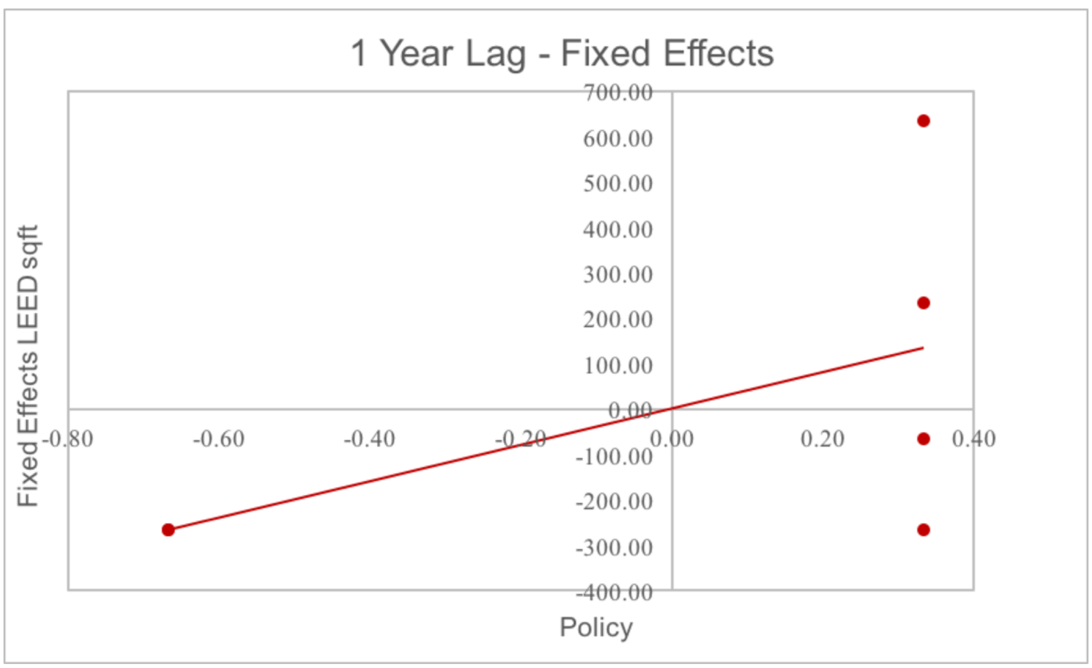

Figure A.9 - Relationship between policy implementation and LEED-sqft using the fixed effects approach with policy effects seen one year after the year policy was implemented

Appendix A.9. Evaluation of specific financial incentive LEED programs

We attempt to quantify the level of incentives that different existing commercial buildings across the US will receive if LEED certified by examining policies which could potentially be estimated e.g. tax abatement policies. In estimating these costs, we use the following simplifying assumptions: first, we assume a hypothetical 10,000-square-foot building. This assumption is needed as some incentives vary their benefits depending on the building size, while others vary benefits depending on building value. We use $178/sqft as the base sale price; the average sales price of a typical green commercial building in Philadelphia, PA over the past 10 years[21]. We then use the 2014 RSMeans Building Construction Costs Handbook, which has information on construction cost indices (CCI), as a proxy for sale price indices that we can use to scale costs in other cities relative to Philadelphia. We thus assume the sale prices for different cities to be:

$$Saleprice_{cityi} = \frac{Saleprice_{PA} * CCI_{cityi}}{CCI_{PA}}$$

We use these different sale prices to estimate the monetary benefits that commercial building owners/developers will receive if they become LEED certified under the rating systems stated in the data section above. We also assume varied land values by state retrieved from the Lincoln Institute of Land and Property values database[22].

Note: The ($) estimates calculated from the incentives were for a 10,000sqft LEED building. The amounts presented in the paper was then divided by 10,000sqft to elicit a ($/sqft) value. Lower end estimates (in situations where there are ranges of incentives that could be gotten) were used in presenting the results in the paper. While we have estimates of financial incentive costs for 36 different cities, counties, and states, we show example calculations for four different policy categories below.

8.1 Building Permit Fee Refunds

Policy Name: US-NC-Mecklenburg County-2007-Mecklenburg County Green Building Rebate Program
County: Mecklenburg County, North Carolina
Magnitude of Incentive: Rebates increase proportionate to the level of certification achieved: 10% reductions for LEED Certified, 15% for LEED Silver, 20% for LEED Gold and 25% for LEED Platinum.
Link to Incentive Calculation:
http://charmeck.org/mecklenburg/county/LUESA/CodeEnforcement/Documents/fees.pdf

Using sale price of $126, a land value percentage of 31.6%, the total building value is $1,658,000 for a 10,000sqft building. Permit fee rebates are estimated and presented in Table A.11 and we see that permit fee savings range between $720 - $1800.

[21] Sourced from CoStar real estate company: http://www/costar/com/

[22] Retrieved from Land and Property Values in the US, Lincoln Institute of Land and Policy, http://datatoolkits.lincolninst.edu/subcenters/land-values/

8.2 Tax Credit/Abatement Program

Policy Name: US-NY-Onondaga County-2013-Onondaga County Uniform Tax Exemption Policy
County: Onondaga, New York
Magnitude of Incentive: UTEP provides LEED Gold and LEED Platinum certified buildings to receive tax exemptions in accordance with the Community PILOT schedule. The Community PILOT schedule offers a tax exemption percentage schedule of 100% down to 10% on a graduated basis, and for a period of 12 years.
Link to policy: http://syracusecentral.com/Onondaga/media/Onondaga/OCIDA/OCIDA-Handbook-update-3-3-15.pdf

With a total estimated value of $1, 284, 448 (where land value is estimated at $305,448 and building value is estimated at $979,000), the amount of tax saved in $ in seen in Table A.12. The estimated tax saved is about $63,000 over 12 years.

8.3 Certification fee refunds

Policy Name: US-TN-Chattanooga-2009-Engineering and Water Quality Sustainable Sites Program
City: Chattanooga, TN
Magnitude of Incentive: Commercial and residential projects that achieve LEED certification with at least 5 points under the Sustainable Sites category (including SS 6.1 and 6.2), will receive a fee credit up to 60%.

With an impervious building area of 10,000sqft, estimated savings are around $150 as seen in Table A.13.

8.4 Grant program

Program Name: US-PA-2013-High Performance Building Program
State: Pennsylvania
Magnitude of Incentive: Grants of up to $500,000 or 10% of the total project cost (whichever is less) are available to appropriate projects, with loans of up to $2 million (small businesses) and up to $100,000 (residential projects) are also offered. Amortizations can be structured to a maximum of 25 years and a 10-year loan term. In order to receive these funds, all projects must achieve one of the following or higher: LEED Gold certification

Assume: 40% of building was renovated
Total building costs: (40% * 95% * $153/sqft * 10000) = $581,400
Incentive: 10% of building cost: $58,140

Total incentive costs estimated for this grant program is around $58,000.

Table A.11 - Certification level percentage and incentive amount for a building permit refund program in Mecklenburg County

Certification level	Rebate (%)	Incentive Amount ($)
Certified	10	$718
Silver	15	$1077
Gold	20	$1437
Platinum	825	$1796

Table A.12 - . Estimated tax savings calculation for a Tax Credit program in Onondaga County

Year	Tax Abatement	Tax Paid	Deduction	Taxable AV	Tax Rate	Tax Paid	Tax Saved
1	100%	0%	1,284,448	-	0.8032	$-	$10,317
2	100%	0%	1,284,448	-	0.8032	$-	$10,317
3	100%	0%	1,284,448	-	0.8032	$-	$10,317
4	90%	10%	1,156,003	142,000	0.8032	$1,141	$9,285
5	80%	20%	1,027,558	284,000	0.8032	$2,281	$8,253
6	70%	30%	899,114	426,000	0.8032	$3,422	$7,222
7	60%	40%	770,669	568,000	0.8032	$4,562	$6,190
8	50%	50%	642,224	710,000	0.8032	$5,703	$5,158
9	40%	60%	513,779	852,000	0.8032	$6,843	$4,127
10	30%	70%	385,334	899,114	0.8032	$7,222	$3,095
11	20%	80%	256,890	1,027,558	0.8032	$8,253	$2,063
12	10%	90%	128,445	1,156,003	0.8032	$9,285	$1,032
						Total Tax saved	**$63,042**

Table A.13 - Estimated savings calculation for a certification fee refund program in Onondaga county

in Equivalent Residential Units (ERU)	3.125	ERU
Water Quality fee ($)	221.4	in 2009
Fee credit ($)	249.075	in 2016
Fee credit (60% of total fees)	**$149.445**	

Appendix A.10. Initial LEED model specification results

As stated in the results section of our main paper, our primary analysis was a deviation from our preplanned and preregistered analysis (osf.io/e7qzk) because we observed very large lagged effects three years after policy implementation. Upon further examination, we realized USGBC LEED updates as well as federal policy implementation needed to be explicitly included in the model. This section details the initial model used for this study.

Initial model specification

The preplanned model is documented at the Open Science Framework (osf.io/e7qzk). In our initial model, we implemented a first differences approach with time and MSA fixed effects to examine the relationship between LEED policies and LEED square footage. The first differences, time and MSA fixed effects allowed us to eliminate first order time trends, time, and MSA invariant heterogeneity that may have been observed in our model thereby leading to omitted variable bias and causing errors in our coefficient estimates. The base model specified was:

$$\Delta Y_{i,t} = \alpha\Delta REQT_{i,t} + \beta\Delta ENCRG_{i,t} + \gamma\Delta CHECK_{i,t} + \delta\Delta \mathrm{BNUS}_{i,t} + \lambda\Delta EXPED_{i,t} + \mu\Delta FINAN_{i,t} + \rho\Delta OTHER_{i,t} + \psi\Delta PROG_{i,t} + \omega\Delta GRANT_{i,t} + \phi\Delta PRMTRBT_{i,t} + \upsilon\Delta REQTINCEN_{i,t} + \epsilon\Delta EXPEDINCEN_{i,t} + s(\Delta GDP_{i,t}) + s(\Delta UNEMPLOY_{i,t}) + \lambda_t + factor(MSA) + \Delta\varepsilon_{i,t} \qquad (S3)$$

here *i* represents an MSA and *t* represents the time period (2000 – 2014) $\Delta Y_{i,t}$ represents the change in LEED square footage per capita in each MSA from one year to the next. $\Delta REQT_{i,t}$, $\Delta ENCRG_{,t}$, $\Delta CHECK_{i,t}$, $\Delta BNUS_{i,t}$, $\Delta EXPED_{i,t}$, $\Delta FINAN_{i,t}$, $\Delta OTHER_{i,t}$, $\Delta PROG_{i,t}$, $\Delta GRANT_{i,t}$, $\Delta REQTINCEN_{i,t}$, and $\Delta EXPEDINCEN_{i,t}$range between 0 and 1 and represent the change in the fraction of total MSA population *i* affected by the presence of the respective policies from one year to the next including requirement, encouragement, LEED project checklist, height/density bonus, expedited permitting, other incentive, LEED program/initiative, grant program, permit fee rebate, requirement with incentive, and expedited permitting with incentive, respectively. $\Delta GDP_{i,t}$ and $\Delta UNEMPLOY_{i,t}$represent the changes in GDP and unemployment rate respectively in each MSA from one year to the next. $\lambda_t\Delta\varepsilon_{i,t}$represent time dummy variables and the error term, respectively.

We also included a model with lagged effects between policy implementation and LEED certifications as noted by Bond and Devine[26], who show that green incentive policies elicit the greatest change two to three years after their implementation. We slightly modified the preplanned analysis model as:

$$\Delta Y_{i,t} = \sum_{-1}^{k=3}(\alpha\Delta REQT_{i,t-k} + \beta\Delta ENCRG_{i,t-k} + \gamma\Delta CHECK_{i,t-k} + \delta\Delta \mathrm{BNUS}_{i,t-k} + \lambda\Delta EXPED_{i,t-k} + \rho\Delta OTHER_{i,t-k} + \psi\Delta PROG_{i,t-k} + \omega\Delta GRANT_{i,t-k} + \phi\Delta PRMTRBT_{i,t-k} + \upsilon\Delta REQTINCEN_{i,t-k} + \epsilon\Delta EXPEDINCEN_{i,t-k} + s(\Delta GDP_{i,t-k}) + s(\Delta UNEMPLOY_{i,t-k})) + \lambda_t + factor(MSA) + \Delta\varepsilon_{i,t} \qquad (S4)$$

where *k* is the number of years.

We also calculated the average effects and 95% confidence intervals of our model using a clustered bootstrap approach, which allows for within-group dependence of errors[150]. To do this we resampled the MSAs with replacement, estimated the model, and repeated 1000 times to get a distribution of estimated model parameters. The average effect and 95% confidence interval estimates were then the mean, 2.5, and 97.5 quantiles of the distribution. To calculate the total effect of each policy we sum the estimated model parameters from a lag of 0 to 3 years after policy implementation, with average and quantiles calculated similarly. Figure A.10 presents the results of the regression analysis for the top 5 policy types. Figure A.11 presents results of the total effects of the policy three years after implementation using our initial model specification. We also include some sensitivity analysis where we drop a few highly influential variables that may affect our regression results thereby leading to high leverage and overestimating our regression results. We assess the sensitivity of our preplanned model by including these dropped variables in our model, and also by performing the regressions without the control variables as seen in Figure A.12.

Requirements had the total largest effect of 2 sqft/capita (95% CI: -0.2 to 8.2) (which is very large compared to our updated model which showed that requirement policies had an average effect of 0.12sqft/capita before ARRA and 0.46sqft/capita after ARRA). Density bonuses, tax credits, and "other incentive" programs in this model also show slightly smaller total increases of 1.2 sqft/capita (95%CI: -1.6 to 4.8), 0.9sqft/capita (95%CI: -1.7 to 3.3), and 0.4 (95%CI: -1.2 to 1.6) respectively.

We noticed that we were estimating very large effects for most of these policies three years after policy implementation with quite large confidence intervals. While these results were consistent with some studies which have found lagged effects of the policies, we were wary of the interpretation of the results because for many of the policies, that lag occurred around 2009. Our updated model then included federal policies including the Energy Policy Act of 2005 (EPAct), the Energy Independence and Security Act of 2007 (EISA), and the American Recovery and Reinvestment act of 2009 (ARRA). Also, we collapsed the initial 12 policy groups into 5 policy groups for the final model specification as we realized that there was not enough variation in some of the policies to make a definitive conclusion.

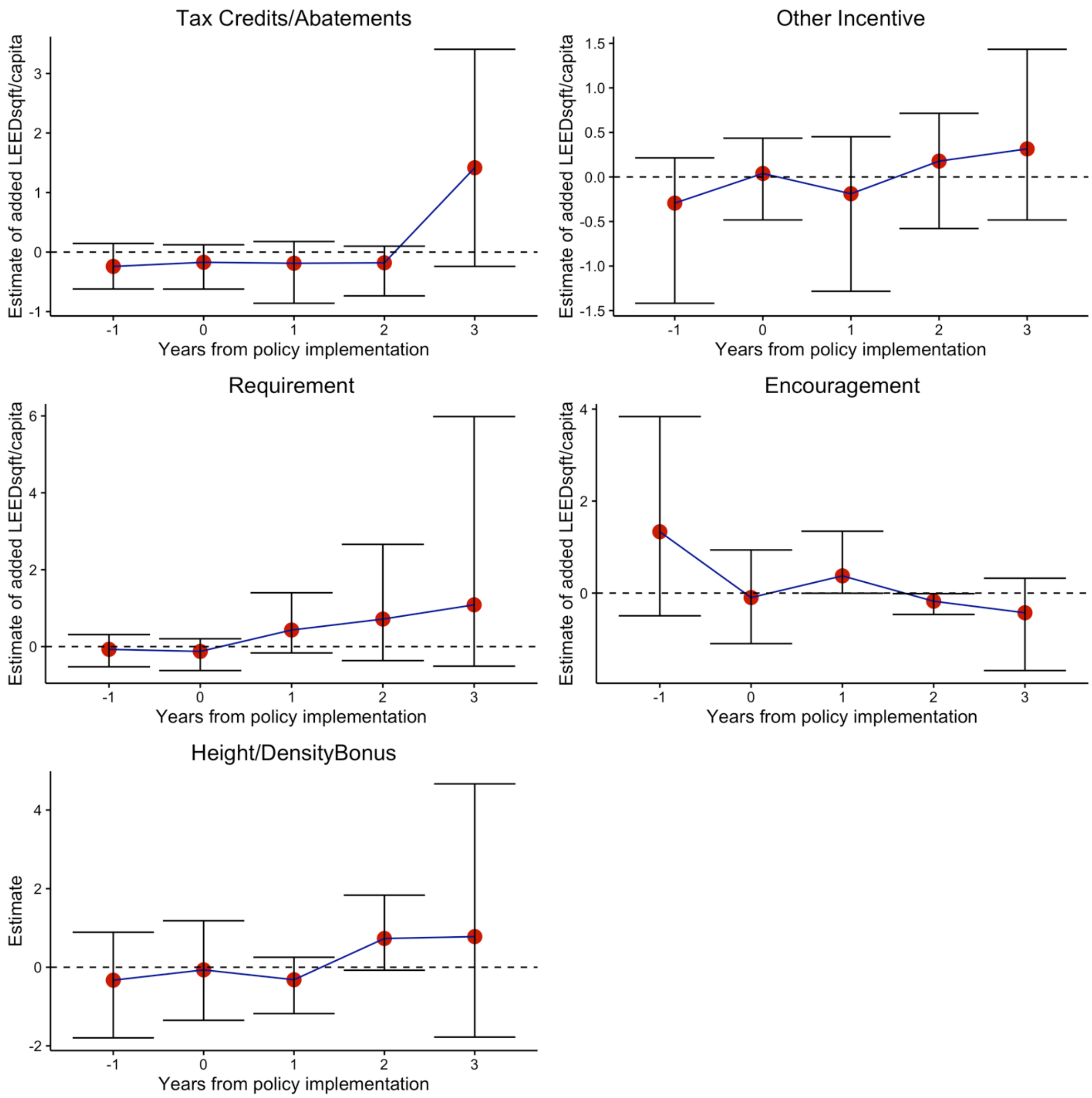

Figure A.10 - Regression results including one year-lead, and one to three year lags of policy implementation. Titles refer to policy names. They y-axis represents the coefficient estimates (from Model 2 as described in the methods section) for each policy variables in LEED-sqft per capita. The x-axis describes the coefficient outcome as a function of years from one year before policy implementation to three years after policy implementation. Point represent the average effect and error bars represent the 95% confidence intervals.

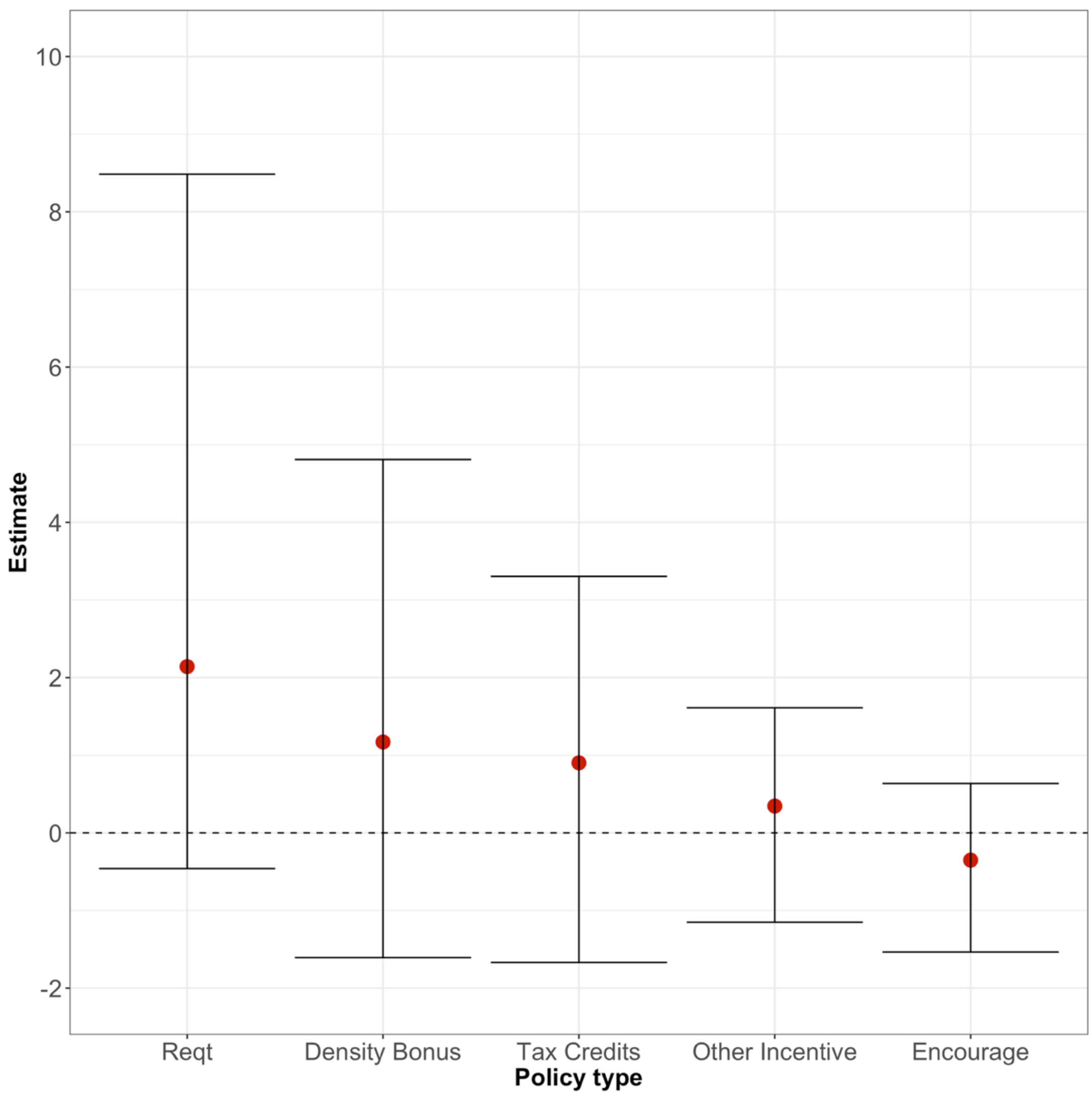

Figure A.11 – Total average effects of LEED-sqft per capita three years after policies implementation. Errors represent 95% confidence interval.

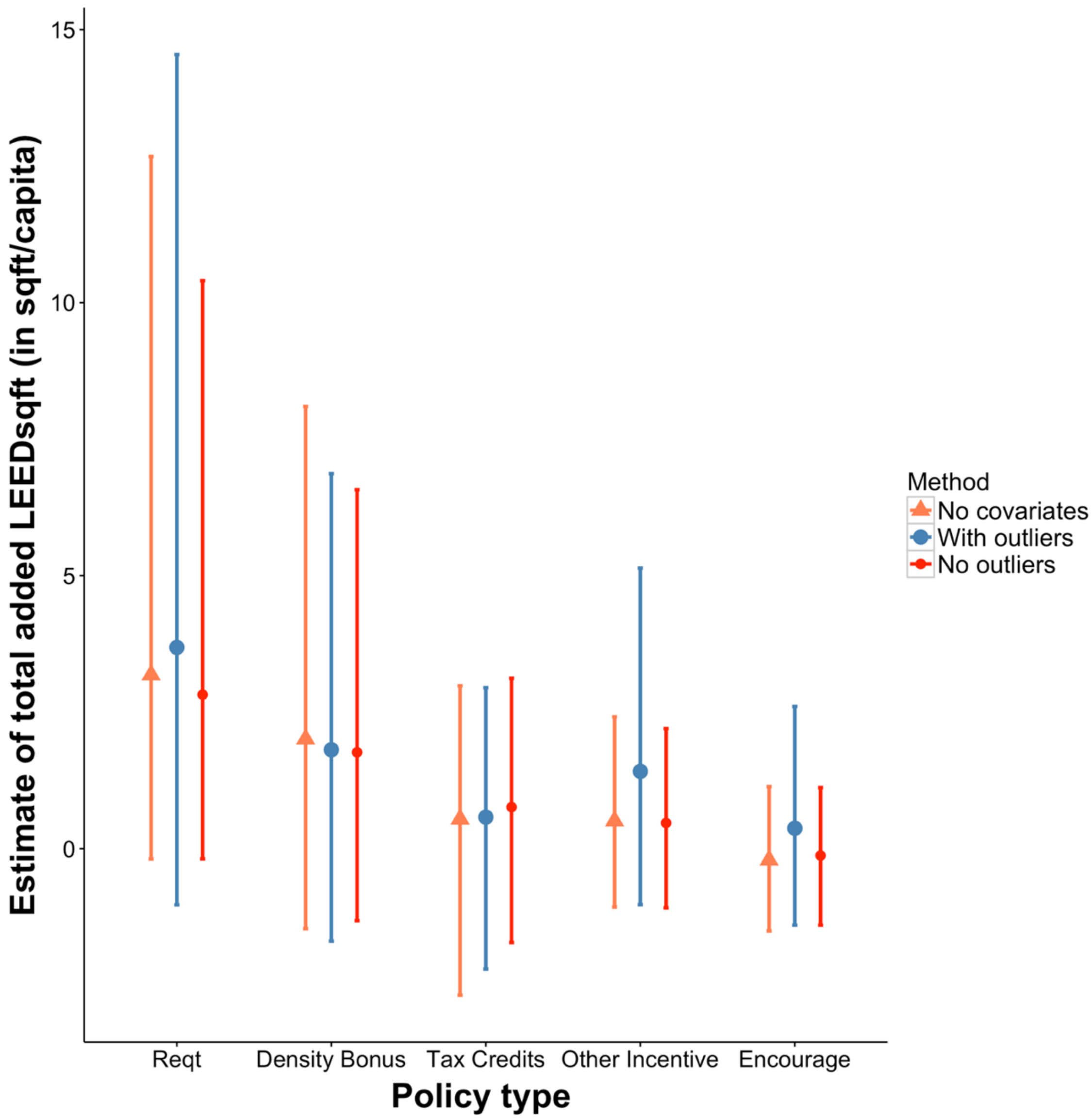

Figure A.12 – Sensitivity analysis of total average effects of LEED policies. Orange, blue, and red points represent the mean total effects with no covariated included, influential observations included, and influential observations removed respectively. The error bars represent the 95% confidence intervals.

Appendix B. Supplemental Information for Chapter 3

Appendix B.1. Energy program overview

Transformation for electricity and gas consumption

Figure B.1a, b compares the base and log transformation of electricity and gas consumption respectively for all years i.e. 2010 to 2016 in our dataset. Just like Figure 3.2 in the main text, the log-transformation for both electricity and gas yields a more normal distribution pattern and hence is used for the purpose of our analysis.

Energy Efficiency programs by quarter

Table B.1 shows a table of the number of households that received an energy efficiency program by the quarter of the year the program was received.

Table B.1 – Number of energy efficiency programs received by households by quarter

Program Type	2009 Q1	2009 Q2	2009 Q3	2009 Q4	2010 Q1	2010 Q2	2010 Q3	2010 Q4	2011 Q1	2011 Q2	2011 Q3	2011 Q4	2012 Q1	2012 Q2	2012 Q3	2012 Q4	2013 Q1	2013 Q2	2013 Q3	2013 Q4	2014 Q1	2014 Q2	2014 Q4	2015 Q4	Grand Total
Smart Energy	4	12	141	152	150	182	161	169	169	285	131	123	149	136	105	75	68	53	70	137	93	6	5	1	2,144
LED 2/$8					1	668	50	17	173		1														865
LED Holiday Light				240	101			216	5			94	108			109	184			1	136				832
Refrigerator Recycling			11	4	11	12	41	14	27	4	34	22	17	16		9	15	4			41	5			281
Green@home Acterra					9	11	11	3	16	17	14	11	16	11	13	13	20	8	4		18				195
Home Energy Kit							140	17																	155
CFL Flood Light Program								101	8	2						8									119
REAP					6			4	5	15	5	10	8	1	16	12	11		7	6	7	2			104
Grand Total	4	12	148	387	271	834	390	509	391	318	172	255	290	161	133	217	284	63	81	144	290	13	5	1	3,480

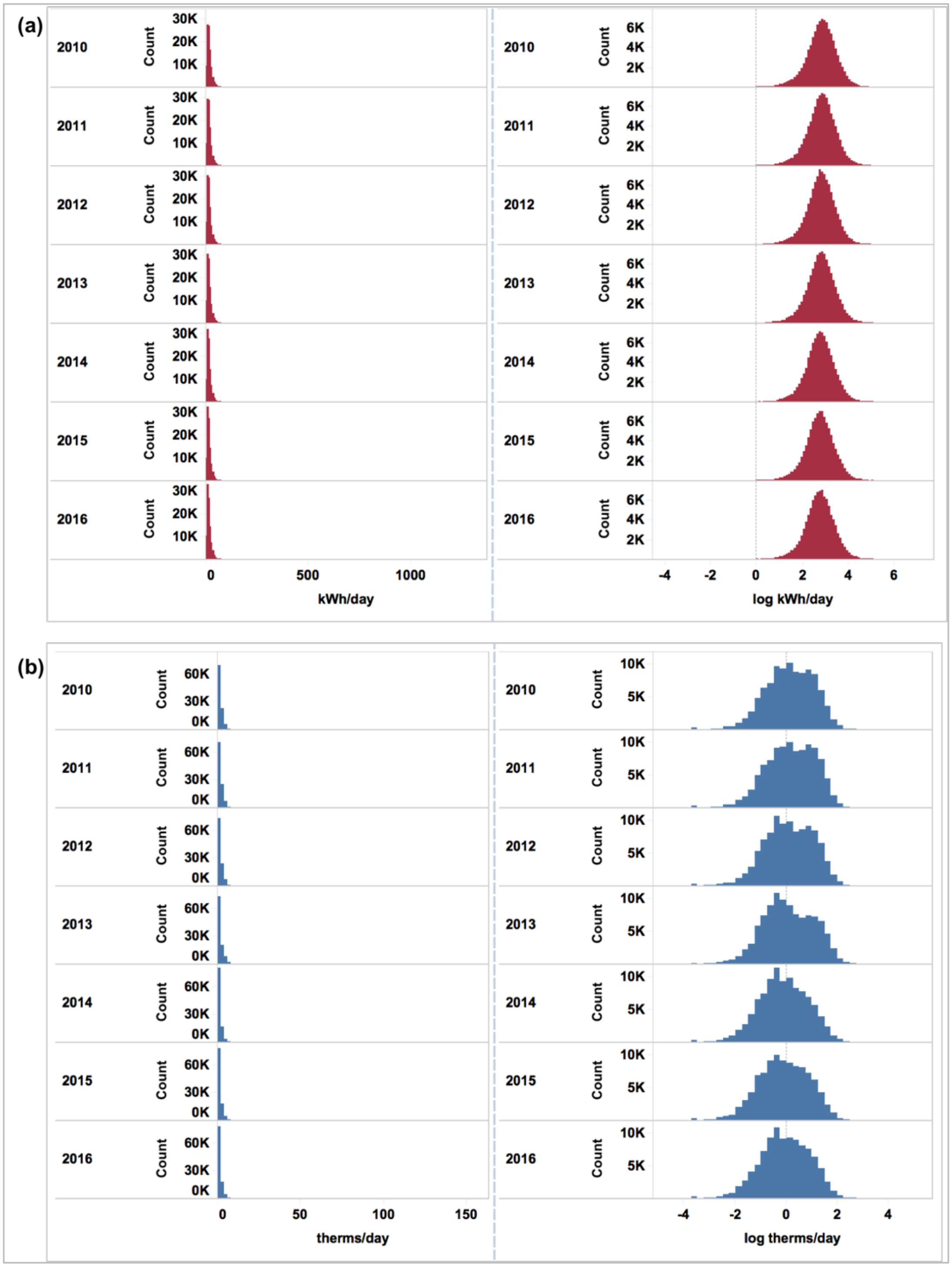

Figure B.1 - (a) Histogram of average electricity consumption per day (left) and log average electricity consumption per day (right) for all years in timeframe – 2010 to 2016. (b) Histogram of average gas consumption (left) and log average gas consumption for all years in timeframe – 2010 to 2016

Appendix B.2. Alternative model specifications

Full model results

Table B.2 presents the full model results from Equations (3.1) and (3.2) in the main text.

Table B.2 - Effects on energy efficiency programs on (1) electricity consumption per day and (2) gas consumption per day

	ln (kWh/day)	ln (therms/day)
Independent variable	(1)	(2)
REAP	-0.06 (0.04)	-0.04 (0.03)
Smart Energy	-0.02*** (0.01)	0.01 (0.01)
Home Energy Kit	0.04 (0.02)	0.04** (0.02)
Refrigerator Recycling	-0.04** (0.02)	0.06*** (0.02)
CFL Flood Light	-0.01 (0.02)	-0.01 (0.02)
Green@Home Acterra	-0.06*** (0.02)	-0.06*** (0.02)
LED 2/$8	(-0.004) (0.01)	-0.03** (0.01)
LED Holiday Light	-0.04*** (0.01)	-0.02* (0.01)
Observations	722,108	722,108
Groups	15,968	15,968
Household effects	Yes	Yes
Month Number dummies	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Seasonality effects

We implement an alternative model approach where we account for seasonality effects. We modify equations (3.1) and (3.2) in the main text by subsetting the heating degree days in terciles of low, medium, and high temperatures. Table B.3 provides regression results for the different temperature groups for electricity and gas consumption. From Table B.3, we find that estimates do not vary significantly as a result of the different temperature ranges, therefore we are not concerned about seasonality effects.

Table B.3 - Effects on energy efficiency programs on electricity and gas consumption per day accounting for periods of low, medium, and high temperatures.

	ln(kWh/day)			ln(therms/day)		
Independent variable	Low	Med.	High	Low	Med	High
REAP	-0.07 (0.05)	-0.08* (0.05)	-0.06 (0.04)	-0.03 (0.04)	-0.10** (0.05)	-0.03 (0.04)
Smart Energy	-0.03*** (0.01)	-0.01 (0.01)	-0.02** (0.01)	0.02 (0.01)	0.03** (0.01)	0.01 (0.01)
Home Energy Kit	0.04 (0.03)	-0.15 (0.03)	0.06*** (0.02)	0.02 (0.03)	0.002 (0.03)	0.08*** (0.02)
Refrigerator Recycling	-0.06*** (0.02)	-0.04 (0.03)	-0.02 (0.02)	0.08*** (0.02)	0.07*** (0.03)	0.06** (0.03)
CFL Flood Light	-0.002 (0.02)	0.01 (0.03)	-0.02 (0.02)	-0.01 (0.03)	-0.01 (0.04)	-0.01 (0.02)
Green@Home Acterra	-0.07** (0.03)	-0.05* (0.03)	-0.05** (0.03)	-0.06** (0.03)	-0.03 (0.03)	-0.06*** (0.02)
LED 2/$8	0.01 (0.03)	0.004 (0.02)	-0.01 (0.01)	0.03 (0.03)	0.01 (0.02)	0.002 (0.01)
LED Holiday Light	-0.05*** (0.02)	-0.04** (0.02)	-0.02 (0.01)	-0.01 (0.02)	-0.02 (0.02)	-0.03* (0.02)
Observations	239,655	241,798	240,655	239,655	241,798	240,655
Groups	14,699	14,991	15,176	14,699	14,991	15,176
Household effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Number dummies	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

Long and Short-run effects

Figure B.2 shows a plot of the total number of households for each month in the time frame of our analysis. We find here that the total number of households is not constant, as some months contain less number of households compared to others e.g. November and December 2014 which contains around 7500 households as opposed to the average of about 9000 households per month. Although electricity and gas consumption data will usually average out when estimating results, we are concerned about the presence of outliers e.g. data available for only one month, which may influence our results.

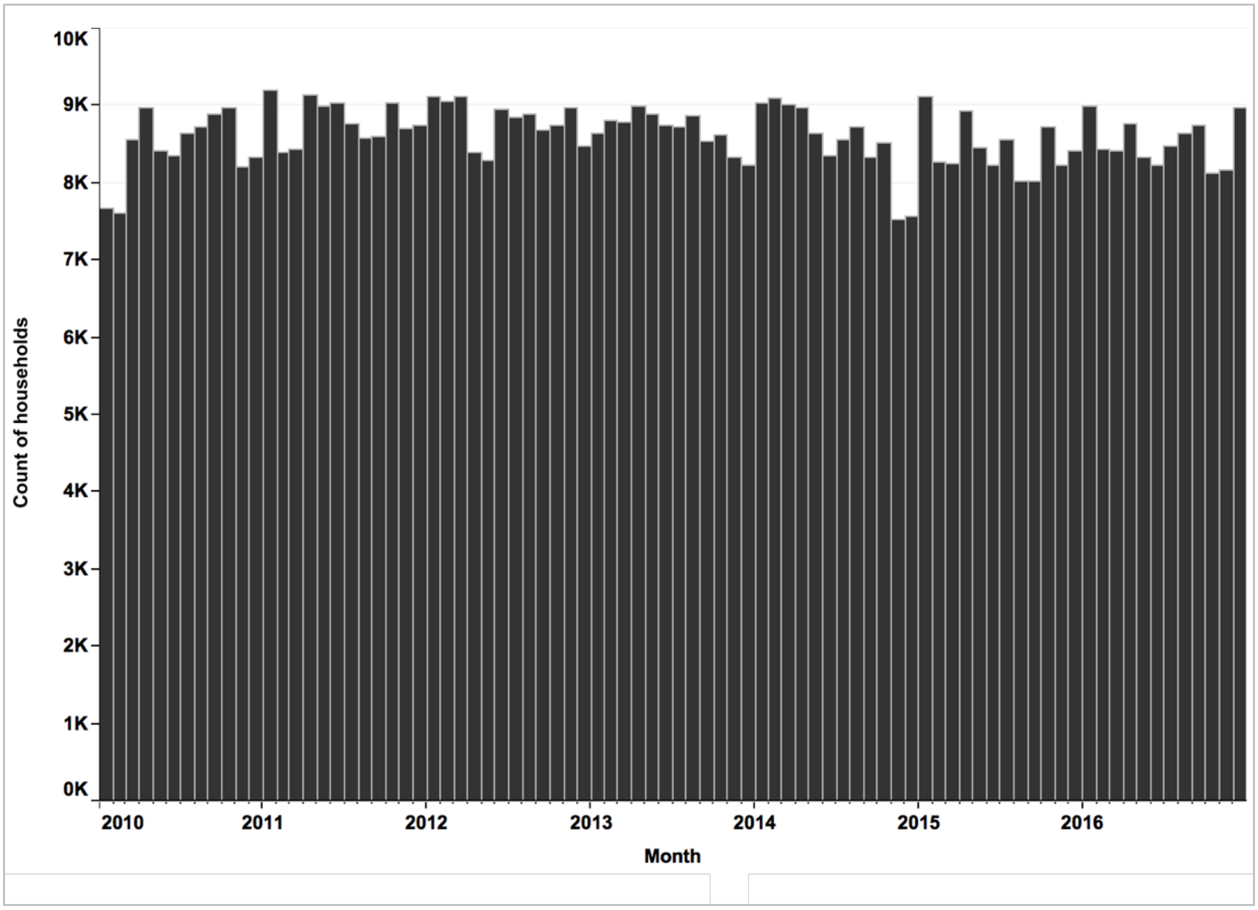

Figure B.2 - Number of households in each month from 2010-2016 from the City of Palo Alto

For each energy efficiency program, we subset households with at least one year of pre and post-treatment data in an 18-month window to account for long and short-run effects as explained in the main text. The Home Energy Kit, CFL Flood Light, and LED 2/$8 program did not have enough pre-treatment information so we subset households with at least 6months, 9months, and 6 months of pre-treatment information respectively. For those who never got a program, however, we subset households with at least 2years of data. Table B.4 provides more details on the number of treated and control groups in the base case and long/short run case. As we have more than one energy efficiency program and households receive programs at different times, we use the number of households that meet the criteria for each program in evaluating its long and short run effects. For example, we have 4744 (69+4675) unique households in the REAP program while the Smart Energy program has 5507 (832+4675) unique households. Models (3.1) and (3.2) in the main text is then re-run for each program and we extract the estimate and standard errors for the energy efficiency program of interest. Table B.5 presents the full model results for the long and short-run estimates for electricity and gas consumption. The explanation of these results is presented in the main text.

Table B.4 - Number of households in the treated and control groups for the base and long/short run case for each energy efficiency program

	Base Case		Long/Short run case	
Energy Efficiency Program	Treated	Control	Treated	Control
REAP	104	15864	69	4675
Smart Energy	1878	14090	832	4675
Home Energy Kit	155	15813	92	4675
Refrigerator Recycling	267	15701	133	4675
CFL Flood Light	119	15849	59	4675
Green@Home Acterra	195	15773	112	4675
LED 2/$8	649	15315	300	4675
LED Holiday Light	86469	15104	138	4675

Event History Modeling

We present results of the event history modeling approach for electricity and gas consumption in Figures B.3 and B.4. From Figure B.3, we find that the results approximate roughly a step function as expected with the difference in differences approach. We find evidence of not enough pre-treatment observations with the CFL, Home Energy Kit, and LED 2/$8 programs as expected. From Figure B.4, we also find the step function reductions of the gas programs with the exception of the LED 2/$8 which has a weird cyclic pattern. We are not able to explain the results for the cyclic pattern obtained in this case but overall, results are pretty consistent. As a result, we use the difference-in-differences approach for the interpretation of our results.

Table B.5 - Effects on energy efficiency programs on electricity and gas consumption per day accounting for long and short-run effects

	ln (kWh/day)		ln (therms/day)	
Independent variable	Long-run	Short-run	Long-run	Short-run
REAP	-0.08** (0.04)	-0.08*** (0.03)	-0.06 (0.04)	-0.04 (0.03)
Smart Energy	-0.05*** (0.01)	-0.03*** (0.01)	-0.02 (0.01)	-0.01 (0.01)
Home Energy Kit	-0.004 (0.02)	0.01 (0.01)	0.01 (0.03)	0.01 (0.02)
Refrigerator Recycling	-0.06**	-0.06***	0.03	0.02

	(0.03)	(0.02)	(0.03)	(0.02)
CFL Flood Light	-0.05 (0.03)	-0.004 (0.02)	-0.03 (0.03)	0.02 (0.02)
Green@Home Acterra	-0.06** (0.02)	-0.07*** (0.02)	-0.09*** (0.02)	-0.06*** (0.02)
LED 2/$8	-0.03** (0.02)	-0.01 (0.02)	-0.03** (0.02)	-0.01 (0.01)
LED Holiday Light	-0.06*** (0.02)	-0.02 (0.01)	-0.05*** (0.02)	-0.02 (0.01)
Observations	Varies by IV	Varies by IV	Varies by IV	Varies by IV
Groups	Varies by IV	Varies by IV	Varies by IV	Varies by IV
Household effects	Yes	Yes	Yes	Yes
Month Number dummies	Yes	Yes	Yes	Yes

Note: IV = Independent variable, the number of groups for each Independent variable is in columns (3) and (4) in Table B.3 and the number of observations for each group is the number of groups multiplied by 84 months.
Robust standard errors in parentheses
*** p<0.01, **p<0.05, *p<0.1

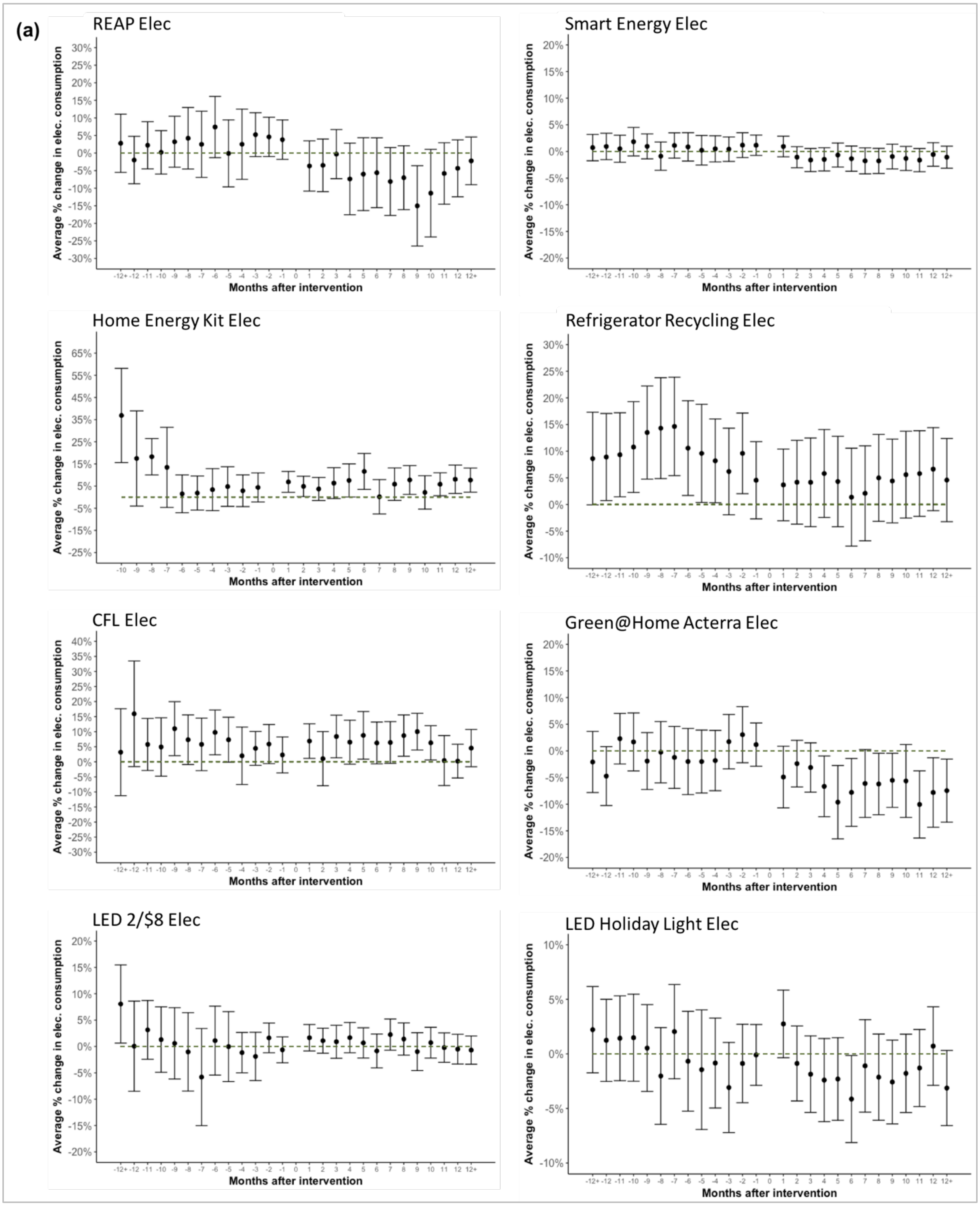

Figure B.3 - Event history plots accounting for 12 months before and after program implementation for electricity consumption

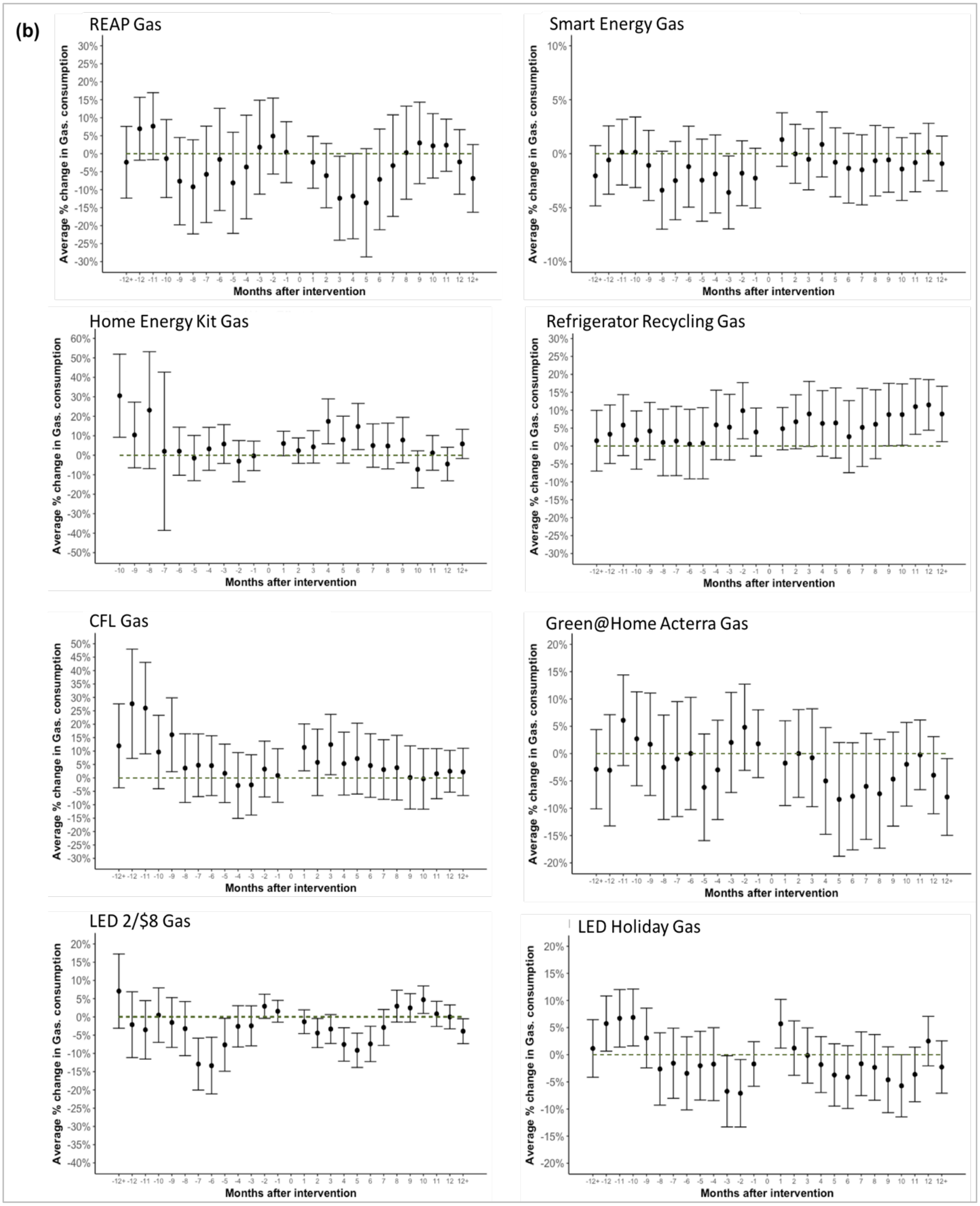

Figure B.4 - Event history plots accounting for 12 months before and after program implementation for gas consumption

Appendix B.3. Shuffle test

We implement the "shuffle test" to ensure our model specification is indeed correct. The shuffle test includes a mixing of the treatment and control group information such that households which originally receive a treatment become controls (i.e. behave as if they did not receive a treatment) while some control households randomly receive a treatment using a random selection process. As the number of households in the control group is much higher than that in the treated group, we randomly shuffle the control group multiple times so that different households which originally were not treated randomly "receive" a treatment in different iterations. We expect that this mixing approach would yield no significant reductions in electricity or gas use if the energy efficiency program indeed has an effect. However, if we see reductions with this mixing approach, then it indicates an error with the model selection approach.

We provide an illustration of the shuffle test in Table B.6 below. In Table B.6, under the original data columns, we find that the treatment group reduces its value over time by 2 units while the control group has no changes over time. If we shuffle the values, as in the shuffle data columns, there is a mixing of effects such that the treatment then has no effect as the control group is acting as if "treated" and the treated group is now given a "control" value. We implement this approach for our full dataset where we randomly shuffle control households which get a treatment, repeat model (3.1) and model (3.2) regressions in the main text 25 times, then average the estimates and robust standard errors with results presented in Table B.7. We find that, as expected, none of the results are significant lending credibility to our regression approach.

Table B.6 – Illustration of the shuffle test

		Original Data		Shuffle data	
Time	Group	Treat/Control	Value	Group	Value
1	A	Control	20	Treat C.	20
2	A	Control	20	Treat C.	18
3	A	Control	20	Treat C.	18
1	B	Control	25	A	20
2	B	Control	25	A	20
3	B	Control	25	A	20
1	C	Treat	20	Control B.	25
2	C	Treat	18	Control B.	25
3	C	Treat	18	Control B	25

*For original data: treatment effect is a reduction of 2, For shuffled data: treatment effect is an increase of 1

Table B.7 - Effects of energy efficiency programs on electricity and gas consumption using shuffle test approach

Energy Efficiency Program	ln (kWh/day)	ln(therms/day)
REAP	-1% (95%CI: -9% to 7%)	-1% (95%CI: -10% to 7%)
Smart Energy	-2% (95%CI: -4% to 1%)	-1% (95%CI: -3% to 2%)
Home Energy Kit	-0.1% (95%CI: -7% to 7%)	-1% (95%CI: -9% to 8%)
Refrigerator Recycling	-1%(95%CI: -6% to 4%)	-1% (95%CI:: -7% to 5%)
CFL Flood Light	-1% (95%CI: -8% to 6%)	2% (95%CI: -7% to 11%)
Green@Home Acterra	-2% (95%CI: -9% to 4%)	-2% (95%CI: -9% to 5%)
LED 2/$8	-1% (95%CI: -4% to 2%)	-2% (95%CI: -6% to 2%)
LED Holiday Light	-1% (95%CI: -5% to 3%)	-1% (95%CI: -5% to 4%)

Appendix B.4. Comparison of study estimates with ex-ante and ex-post savings from the CPAU

In accordance with the SB 1037 California State bill, the CPAU produces an annual report detailing all utility program expenditures, expected, and annual energy savings. These savings are conducted by independent contractors also in accordance with the State's 2021 Assembly bill which indicates that independent evaluations for these energy efficiency programs must be adequately measured and verified. As a result, we have access to information on the annual electricity and gas savings from its programs over the years:

2010 report: https://www.cityofpaloalto.org/civicax/filebank/documents/25906
2011 report: https://www.cityofpaloalto.org/civicax/filebank/documents/30481
2012 report: https://www.cityofpaloalto.org/civicax/filebank/documents/31809
2013 report: https://www.cityofpaloalto.org/civicax/filebank/documents/42470
2014 report: https://www.cityofpaloalto.org/civicax/filebank/documents/47266
2015 report: https://www.cityofpaloalto.org/civicax/filebank/documents/52187
2016 report: https://www.cityofpaloalto.org/civicax/filebank/documents/58115

Therefore, we are able to compare the electricity and gas savings claimed by some of these energy efficiency programs over the years. We compare the results of our main result estimates i.e. models (1) and (2) of the main text with that of the CPA to examine the differences in our study estimates with that of the CPA and presented in the Table B.8. We calculate our study estimates as follows:

$$Annual\ savings = \%reduction \times \frac{average\ consumption}{day} \times \frac{365days}{year}$$

We use Table B.8 to determine the percentage reductions for each of the electricity and gas programs and use the average consumption for all households which did not receive a program (i.e. control group) to determine the average kWh/day and therms/day estimates.

Table B.9 compares the energy savings the results of our statistical analyses (i.e. savings from Figure 3.4a, b) with that of Table B.8. Our estimates include the average and 95% confidence intervals for the different energy efficiency programs. As the energy efficiency programs implemented by the CPAU lasted for at least a year, we are able to obtain a range of energy savings for some of the programs. We did not make comparisons for the Green@Home Acterra and Home Energy Kit program as these savings were not available in the annual reports. As the Green@Home Acterra program is a volunteer program, the CPAU could not estimate immediate results from the audits and therefore did not provide energy savings for this program. We also could not find claimed savings in the annual reports for the Home Energy Kit programs but hypothesize that since this program contained a variety of energy saving measures, the CPAU did not feel the need to separately estimate the savings for these programs. We also did not compare savings for the Smart Energy and REAP programs as a variety of appliances potentially qualify for rebates and are eligible for low-income upgrades respectively. Therefore, these savings would vary widely from appliance to appliance. Although we can estimate the average savings per unit, we are wary to compare their results directly.

Table B.8 – CPA's energy efficiency program estimates

	Report Year	Annual elec. savings	Annual gas savings
Refr. Recycling	2013	842	0
	2014	616	0
	2015	620	0
	2016	643	0
CFL Flood light	2013	32	0
LED 2/$8	2010	38-40	0
LED Holiday light	2010	24	0
	2013	40	0

From Table B.9, we find some differences when comparing our study estimates with that of the CPAU. We find much smaller average reductions with the Refrigerator Recycling program of our estimates compared to that of the CPAU (although our upper bound estimate is almost the same as the CPAU's lower bound estimate). While the LED 2/$8 lower estimates from the CPAU are about the same as our study estimates i.e. 38kWh and 32kWh respectively, we find a wider range of savings of our estimates compared to that of the CPAU. The LED Holiday Light program, as expected shows a stark difference in both estimates with respect to electricity and gas use. The CPAU in its estimates uses an engineering modeling approach where it estimates reductions from the substitution of incandescent lightbulbs to LED lightbulbs. Using California Public Utilities Commission interactive effects which capture change in HVAC electricity and gas usage from the installation of an energy saving measure of 1.02kWh/kWh and -0.02therms/kWh respectively for a 40W to 7W LED to CFL lightbulb switch, we find estimated reductions of 19kWh (33W × 541hours/year × 1.04) but increased gas consumption of 0.4therms (33W × 541hours/year × -0.02). These values show that our mean study estimates for around 32kWh for 2 LED bulbs in indeed plausible. We can, in fact, get annual electric savings of up to 190kWh for 2 lightbulbs if the bulbs are turned on for up to 2770hours in a year. However, these electricity savings also be associated with an annual gas consumption increase of 3.7therms. From Table 3.2 in the main paper, we find simultaneous decreases rather than increases in gas consumption estimates. Our study results go on to indicate that the extreme savings we see for LED bulbs are highly implausible to be due to just lighting replacement. However, data-driven approaches may reveal other characteristics of households who opt into energy efficiency programs, for example, households undergoing renovations may be the ones taking advantage of the rebates. This is not to say that the LED programs have no impact, as they are meant to serve as an introduction to a new energy efficiency measure that households may otherwise have not known about. It is, however, difficult to use data to disentangle if this is indeed the case.

Table B.9 - Annual electricity and gas savings from the City of Palo Alto estimates and our study estimates. Numbers in parenthesis correspond to negative values, i.e., an energy consumption increase.

	City of Palo Alto own estimates		Our Study average effect estimates	
Program	**KWh/unit**	**Therms/unit**	**kWh/unit**	**Therms/unit**
Refrigerator Recycling	620 – 840	0	320: 30 – 610	34: 11 - 57
CFL Bulb	91	0	38: (260) – 330	6: (21) – 33
LED 2/$8	38 - 80	0	32: (130) – 190	17: 2 – 32
LED Holiday Light	24 - 40	0	270: 70 – 460	13: (1) – 28

* Individual annual savings are 19 - 40KWh/unit,

** Numbers in parentheses indicate an increase rather than a decrease in consumption.

*** Numbers after colon indicate 95% confidence bands.

Appendix B.5. Difference-in-differences and event history approaches using test data

We use our trained data to predict the last 20% of our dataset using the difference-in-differences and event history model approaches. We estimate the root- mean squared error (rMSE) for both electricity and gas consumption. For electricity consumption, the calculated rMSE is:

- Difference-in-differences: 7.36
- Event history: 7.34

For gas consumption the rMSE is:

- Difference-in-differences: 0.5358
- Event history: 0.5355

Since the event history only performs slightly better than the difference-in-differences model, we use the difference-in-differences model results for ease of interpretation

Appendix C. Supplemental Information for Chapter 4

Appendix C.1. Energy Efficiency Measures

We consider 14 different energy efficiency measures (EEMs) for upgrades to the residential single-family detached housing stock in Pennsylvania. These upgrades were chosen for two main reasons: they have been identified by NREL ResStock as upgrades which present the highest savings in terms of economic potential in the state of Pennsylvania (as presented in Figure D-36 of the attached NREL Residential Building Stock Documentation) and these upgrades can be reasonably modeled using the ResStock's Parametric Analysis Tool (PAT). The description of these upgrades can be found in the attached ResStock Documentation with some slight modifications to some of the EEMs specified as follows:

Ductless Heat Pump: This upgrade involves installing one or more high-efficiency ductless heat pump (DHPs) in homes heated with electric baseboards. While the ResStock documentation indicates a 60% load displacement, we use a 100% load-displacement for ease of analysis.

LED: While the ResStock Documentation replaces 95% of the lamps in every home with high-efficacy light-emitting diode (LED) lamps, we assume that 100% of the lamps in every home will be replaced instead.

Table C.1 provides the incremental cost and lifetime values for the different EEMs which was imputed into the ResStock PAT tool. These values were specified either through the ResStock Documentation or averages from NREL's Residential Efficiency Measures Database.

Table C.1 - Incremental costs and life time values for different EEMs

Upgrade Name	Lifetime	PAT Tool Option (Upgrade)	Upgrade Description	Cost ($)	Reference
Air Sealing	999	Wall Area, Above-Grade Conditioned	25ACH50 – 20ACH50	1.2	Baseline (do nothing)
			20ACH50 – 15ACH50	1.2	
			15ACH50 – 10ACH50	1.2	
			10ACH50 – 8ACH50	0.5	
Drill-and-fill wall insulation	999	Wall Area, Above-Grade Conditioned	Uninsulated – R-13	2.21	Baseline (do nothing)
Duct Sealing	999	Duct Surface Area	L: 10% Uninsulated – 10% R-8	1.4	Baseline (do nothing)
			L: 20% Uninsulated – 10% R-8	1.8	
			L: 30% Uninsulated – 10% R-8	2.2	
			L: 20% R-4 – 10% R-4	0.4	
			L: 30% R-4 – 10% R-4	0.81	
			L: 20% R-6 – 10% R-6	0.4	
			L: 30% R-6 – 10% R-6	0.81	
			L: 20% R-8 – 10% R-8	0.4	
			L: 30% R-8 – 10% R-8	0.81	
Low E-Storm Windows	30	Window Area	Clear,Double,Metal, Air – Low-EStorm on Double,Metal Air	8.3	Baseline (do nothing)
R-10 Finished Basement	999	Wall Area, Below-Grade	Unfinished – R 10 Wall	3.1	Baseline (do nothing)
R-10 Unfinished Basement	999	Wall Area, Below-Grade	Unfinished – R-10 Wall	3.1	Baseline (do nothing)
R-49 Attic Insulation	999	Floor Area, Attic	Uninsulated – R-7	2.4	Baseline (do nothing)
			Uninsulated – R-13	1.9	
			Uninsulated – R-19	1.6	
			Uninsulated – R-30	1.4	
			Uninsulated – R-38	0.87	
			Uninsulated – R-49	0.5	
Ductless Heat Pumps (DHP) - (displaces electric baseboard)	15	Heating System (kBtu/h)	Electric Baseboard – MSHP,SEER 29.3, 14 HSPF	95	Baseline (do nothing)
Heat Pump Water Heater (HPWH)	12	Fixed	Electric Standard OR Electric Premium – Electric Heat Pump, 50 gal	1700	Upgrade baseline to Electric Premium, Fixed Cost at $590, $4.5/Water Heater Gal capacity.
Central Air Source Heat Pumps(ASHP)	15	Fixed	ASHP: SEER 10, 6.2HSPF; SEER 13, 7.7HSPF; SEER 15, 8.5HSPF to SEER 22, 10 HSPF	4200	Upgrade baseline to SEER 14, 8.2HSPF at $3200 and $4.2/Heating System capacity
		Heating System (kBtu/h)		42	
AC,SEER 18	16	Fixed	AC: SEER 8, SEER 10, SEER 11, SEER 12, SEER 13 to SEER 18	3200	Upgrade baseline to SEER 13

		Heating System (kBtu/h)			(SEER 13) at $2700 at $42/Heating System capacity
ENERGY STAR Clotheswasher	14	Fixed	Usage: 80% STANDARD to 80% ENERGY STAR	880	Upgrade to Fed. Min. Standards (387kWh/yr) at $560
			Usage: 100% Standard to 100% ENRGY STAR	880	
			Usage: 120% Standard to 120% ENERGY STAR	880	
ENERGY STAR Refrigerator	17.4	Fixed	Upgrade to EF 19.9	670	Upgrade to Fed. Min. Standards (EF 17.4) at $660
LED Lighting	78.28	Lighting Floor Area	Upgrade to 100% LED	0.12	Baseline (do nothing)

* HVAC = Heating, Ventilation, and Air Conditioning,

** Reference scenario represents the business-as-usual point of comparison for upgrade scenarios. For some upgrades, such as insulation upgrades, the reference is the existing condition. For other upgrades, such as equipment upgraded at wear out, the reference is the current federal standard.

Appendix C.2. Modeling Approach

ResStock Building Simulation background

The NREL ResStock analysis framework was developed in an attempt to develop a high level of granularity when understanding the technical and economic potential of end-use energy efficiency in the U.S. single-family detached (SFD) housing stock. As a majority of studies either rely presently on average savings values from literature or simulations from a small number of prototype buildings, these results may not depict actual energy consumption in a particular location or the actual building characteristics in an area. For example, there may be more direct interactions between envelope efficiency upgrade and HVAC equipment efficiency whereas an envelope component upgrade savings may only be weakly influenced by the level of insulation of the rest of the envelope. It is therefore very important not only to understand the baseline housing characteristics in a particular location but also the interactions between the different household characteristics when implementing an upgrade as they vary from one building type to the other.

The ResStock methodology involved 6 major steps to characterize and understand the technical and economic potential for the U.S. RSF baseline housing stock: 1) Housing Stock Characterization where a data model was used to represent the energy-related characteristics of the U.S. Single family detached (SFD) housing stock. A hierarchical process was used which defined over 100 components of a building which was aggregated from 11 different sources including the U.S. Census, U.S. EIA Residential energy consumption survey and many others, 2) Statistical Sampling which involves a Latin hypercube sampling method which selected representative homes defined by the housing stock data model. Using convergence testing, 350,000 homes are selected as the number of building/location models needed to represent the current U.S. housing stock. Weighting factors were then used to scale these results from 350,000 to the 80 million SFD homes included in the analysis. 3) Baseline Building Simulation which used EnergyPlus building simulations for each of the 350,000 building location models to evaluate detailed subhourly annual energy consumption for the baseline housing stock, 4) Validation comparing the modeled consumption against the U.S. EIA Residential Energy Consumption Survey 2009 with iterative changed to make sure modeled results were in better agreement with the reference consumption, and 5) Energy Efficiency Upgrade Simulations which defined over 50 energy efficiency upgrades for application to the baseline housing stock. Each upgrade applied only to a subset of the 350,000 building/location models as an upgrade may not be appropriate for a home e.g. a home may already have the upgrade needed so is excluded from the analysis. Using a combination of EnergyPlus input files, corresponding models, and incremental costs for the base case and upgrade scenarios, detailed energy consumption results were defined for the baseline and upgrade scenarios, and 6) Technical and Economic Potential Calculations where technical potential was calculated as the aggregated annual savings in all homes which qualify for an upgrade. Economic potential was calculated as the aggregated annual savings for upgrades which pass a cost-effectiveness threshold of NPV > 0 or a simple payback period of less than 5 years. This economic potential for each state was then aggregated annually and presented in the attached ResStock documentation. More detailed results of this approach is also in the attached ResStock documentation and can be found at Wilson et. al.[57]

Our approach for using ResStock Building Simulation tool

The ResStock technical and economic potential estimates presented by NREL, although granular, is estimated on an aggregate annual level. As our analysis needs more granular/detailed results and PAT tool is publicly available, we can obtain hourly resolutions needed for our work in estimating hourly resolutions for the baseline and upgrade scenarios. We follow the ResStock methodology very closely as presented in Figure C.1.:

First, we select 8 out of the 216 TMY3 regions presented in the PAT tool which capture the Pennsylvania area. With the capabilities of Energy Plus, the PAT tool determines the hourly energy consumption of the representative baseline homes. These hourly resolution outputs are then combined and scaled up to represent the 2.9 million residential SFD homes in Pennsylvania. Next, we re-simulate the baseline housing stock using the PAT tool with the assumption that the baseline homes have been "replaced" with the new EEM. With these simulations, we can compare the baseline energy consumption with that of the energy efficient case for the different EEMs. These results are then utilized for further analyses.

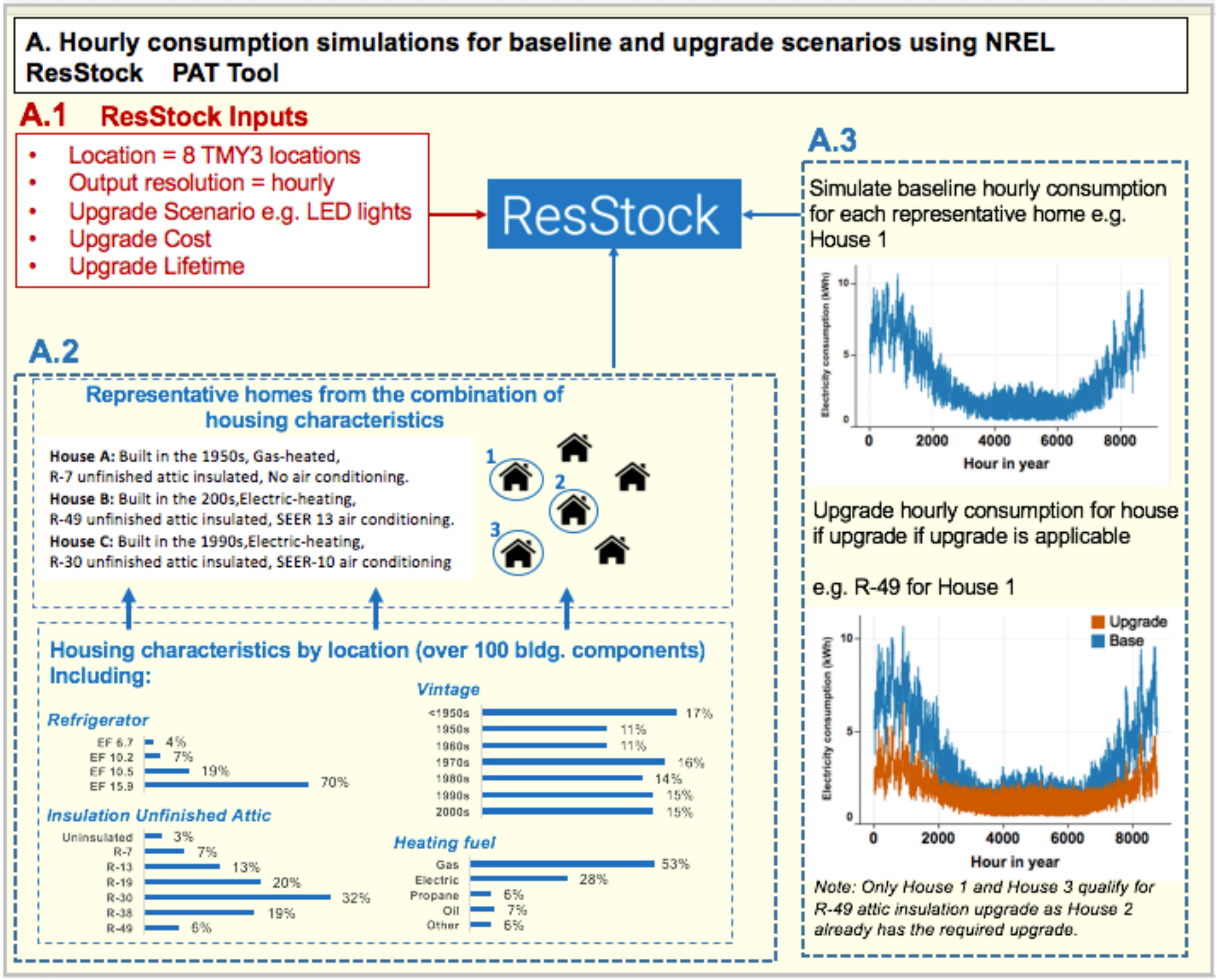

Figure C.1 - Modeling approach: (A.1) We select inputs to be used in estimating the baseline and upgrade scenarios for PA's housing stock using the NREL ResStock PAT tool (A.2, A.3) NREL's PAT tool uses underlying housing characteristics for the region of PA to estimate baseline and upgrade hourly consumption scenarios for different upgrade'

Appendix C.3. Sensitivity Analysis: Mitigation Supply Curves and Economic Benefit Plots

Here, we compare the mitigation supply curves and economic benefit plots for all EEMs at varying discount rates. In Figures C.2 and C.3, we show the mitigation supply curves at discount rates of 3% and 15% respectively. In Figures C.4-C.6, we compare the economic benefits (i.e. \$/ton of pollutant avoided) for SO2, NOx, and $PM_{2.5}$. As expected, with lower discount rates, all EEMs are considered cost-effective. However, as the discount rates increase, more EEMs become not cost-effective. We find that only Central Air Source Heat Pumps (ASHP), LED lighting, DHPs, and ENERGY STAR refrigerators pass the cost-effectiveness criteria at much higher discount rates (15%).

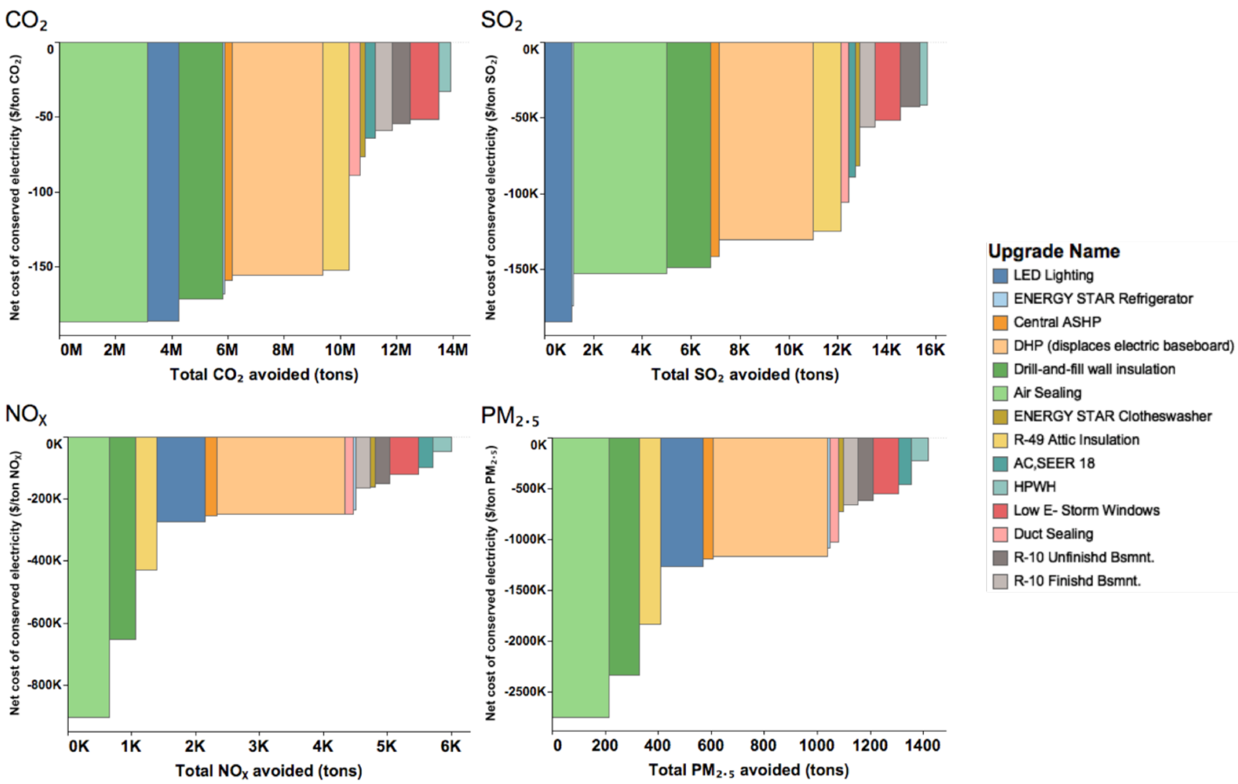

Figure C.2 - Mitigation supply curves comparing the private net-cost of different EE upgrades with the annual avoided CO_2, SO_2, NO_x, and $PM_{2.5}$ emissions (metric tons) for different energy efficiency (EE) upgrades in the state of PA at a 3% discount rate. Each block represents an EE upgrade. The width of each block indicates the emission savings provided by the implementation of the upgrade, while the height of the block represents the net cost of conserved pollutant.

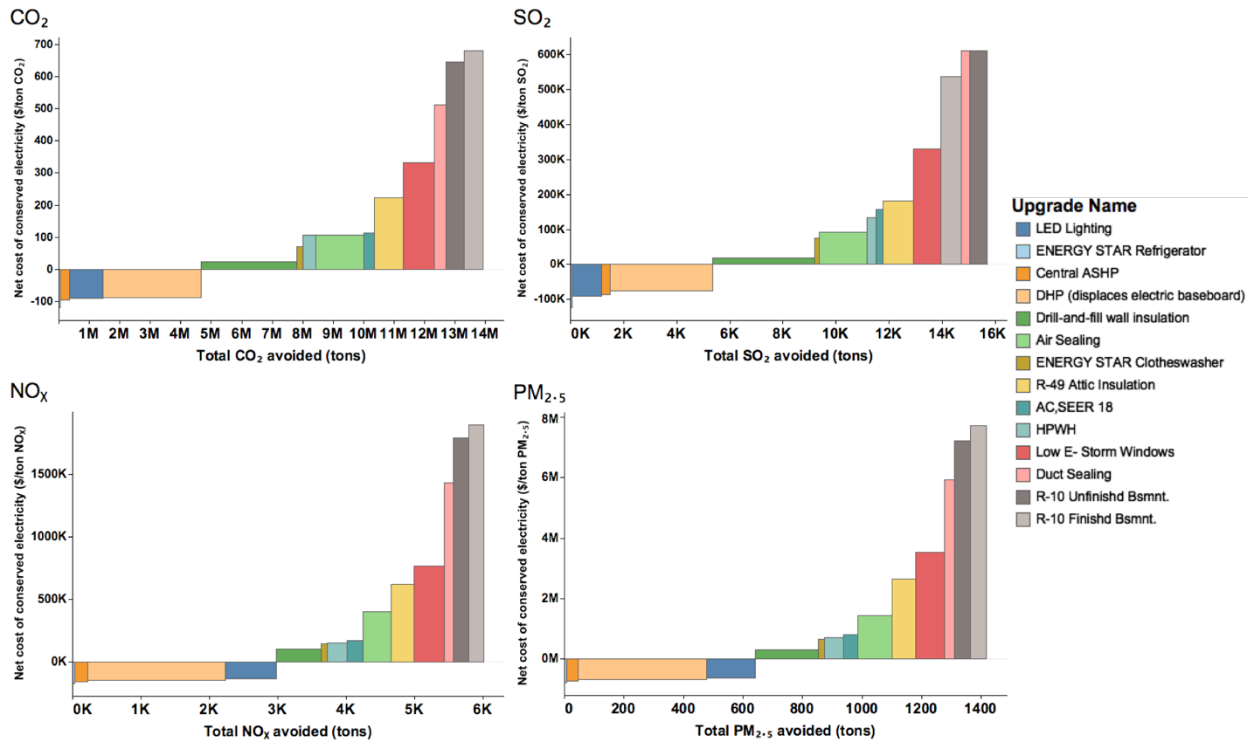

Figure C.3 - Mitigation supply curves comparing the private net-cost of different EE upgrades with the annual avoided CO_2, SO_2, NO_x, and $PM_{2.5}$ emissions (metric tons) for different energy efficiency (EE) upgrades in the state of PA at a 15% discount rate. Each block represents an EE upgrade. The width of each block indicates the emission savings provided by the implementation of the upgrade, while the height of the block represents the net cost of conserved pollutant.

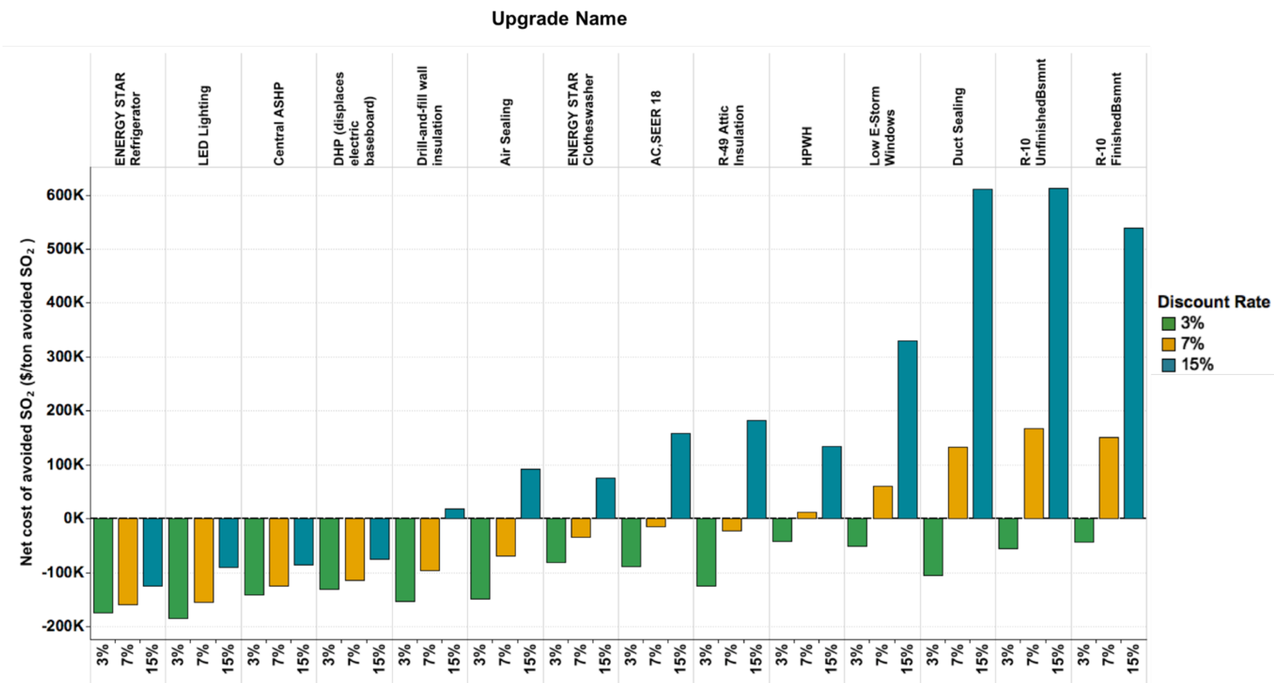

Figure C.4 - Comparison of the net cost of avoided SO_2 for different EE upgrades using 3%, 7%, and 15% discount rates. Estimates less than 0 are cost-effective while those greater than 0 are not cost-effective.

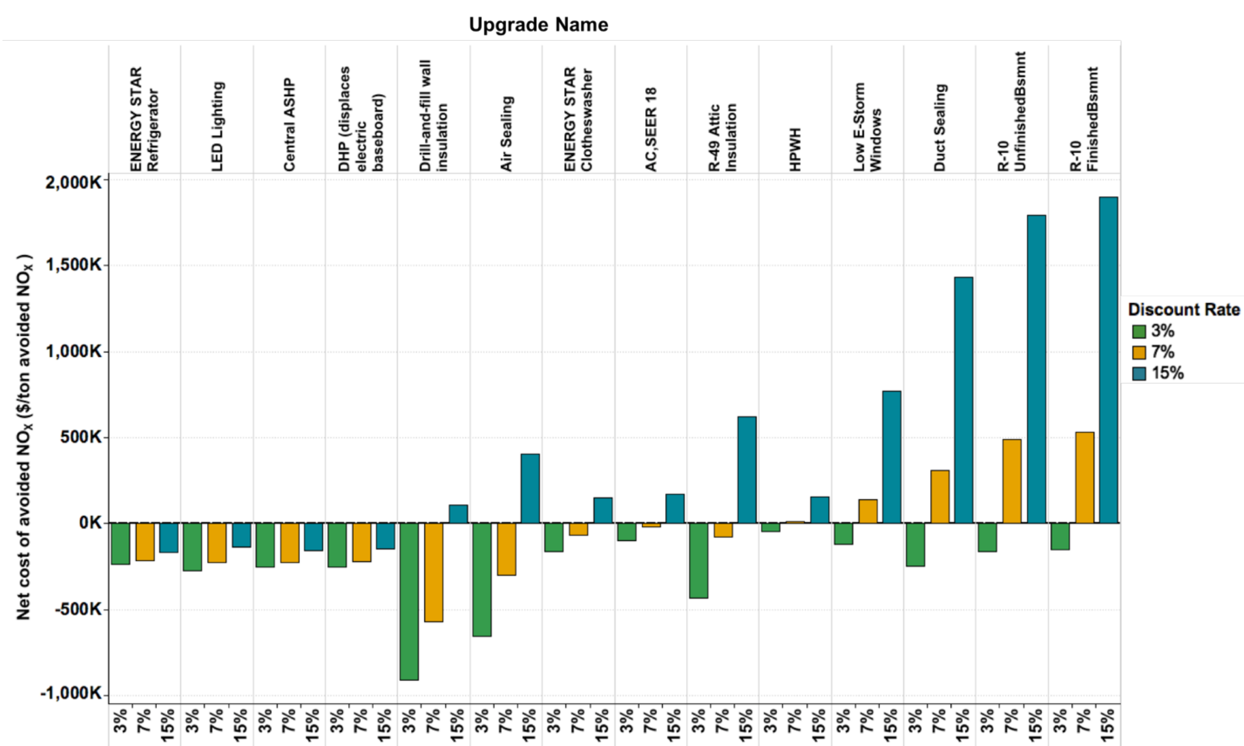

Figure C.5 - Comparison of the net cost of avoided NO_x for different EE upgrades using 3%, 7%, and 15% discount rates. Estimates less than 0 are cost-effective while those greater than 0 are not cost-effective

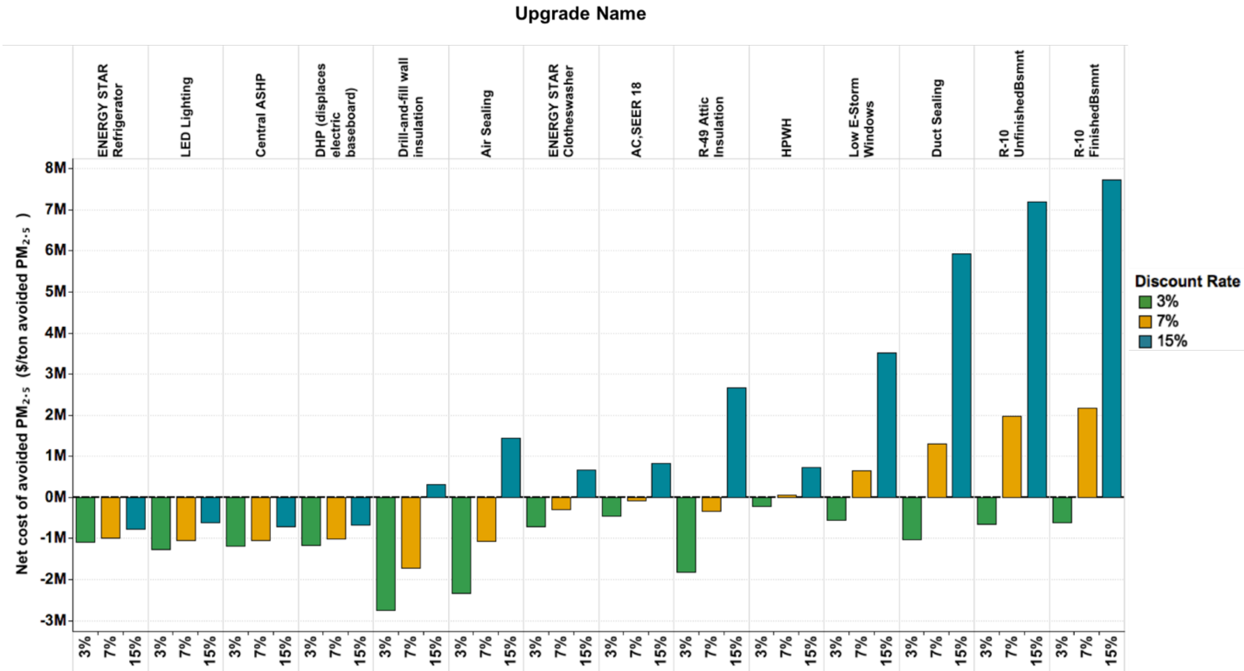

Figure C.6 - Comparison of the net cost of avoided $PM_{2.5}$ for different EE upgrades using 3%, 7%, and 15% discount rates. Estimates less than 0 are cost-effective while those greater than 0 are not cost-effective

Appendix C.4. Comparison of average to marginal emissions

In Table C.2, we compare the deviation of the avoided average to marginal emissions reduction estimates for CO_2, SO2, $PM_{2.5}$ and NO*x*. Here, we find deviations of average emissions to marginal emissions for the different pollutants as $CO_{2:}$ +11% to +13%, $SO_{2:}$ -46% to +13%, $PM_{2.5:}$ +1% to +3%, and $NO_{x:}$ -3% to +2%. These results indicate that average emissions estimates could deviate from the marginal factor estimates by a significant amount thereby misleading us to think that EE upgrades are saving more (or less) than they are. As explained in the main text, the largest discrepancy is in SO_2 emission estimates because of a greater difference between peak and off-peak marginal emission rates driven by the frequency of coal being the marginal generator. For example, because air conditioners are mostly used in the summer, with lower marginal rates compared to the rest of the year, avoided emission reductions using average values of SO_2 for air conditioners are overestimated by 13%. However, for upgrades like ductless heat pumps which have higher winter consumption compared to the summer, we underestimate the SO_2 emission reductions using average values compared to marginal values. Therefore, while average emission estimates may be used for back of the envelope calculations, marginal emission values are more appropriate in quantifying the size of interventions especially due to variability in the demand profile over the year.

Table C.2 - Deviations of avoided average to marginal emission estimates for CO_2, SO_2, NO_x, and $PM_{2.5}$ reductions

Upgrade Name	CO_2	SO_2	NO_x	$PM_{2.5}$
Air Sealing	11%	-45%	1%	4%
DHP (displaces electric baseboard)	11%	-46%	1%	4%
Drill-and-fill wall insulation	12%	-41%	1%	4%
Duct Sealing	12%	-24%	0%	3%
LED Lighting	12%	-20%	0%	3%
Low E-Storm Windows	12%	-23%	2%	3%
R-10 Finished Basement	11%	-37%	1%	3%
R-10 Unfinished Basement	11%	-32%	1%	3%
R-49 Attic Insulation	12%	-33%	1%	3%
AC, SEER 18	13%	13%	0%	2%
ENERGY STAR Clothes washer	11%	-26%	-3%	4%
HPWH	11%	-15%	-1%	3%
ENERGY STAR Dishwasher	12%	-28%	0%	2%
Central ASHP	11%	-38%	1%	3%
ENERGY STAR Refrigerator	11%	-22%	1%	1%

Appendix C.5. Social discount rates

In Figures C.7 and C.8, we provide comparisons of the net cost of the different upgrades to the social benefits from the upgrades using our baseline discount rate of 7%. As expected, the results are sensitive to the choice of discount rates because as the discount rate increases, the social benefits become higher than the private benefits of the upgrades. At a 15% discount rate, it is beneficial to implement all these EEM measures.

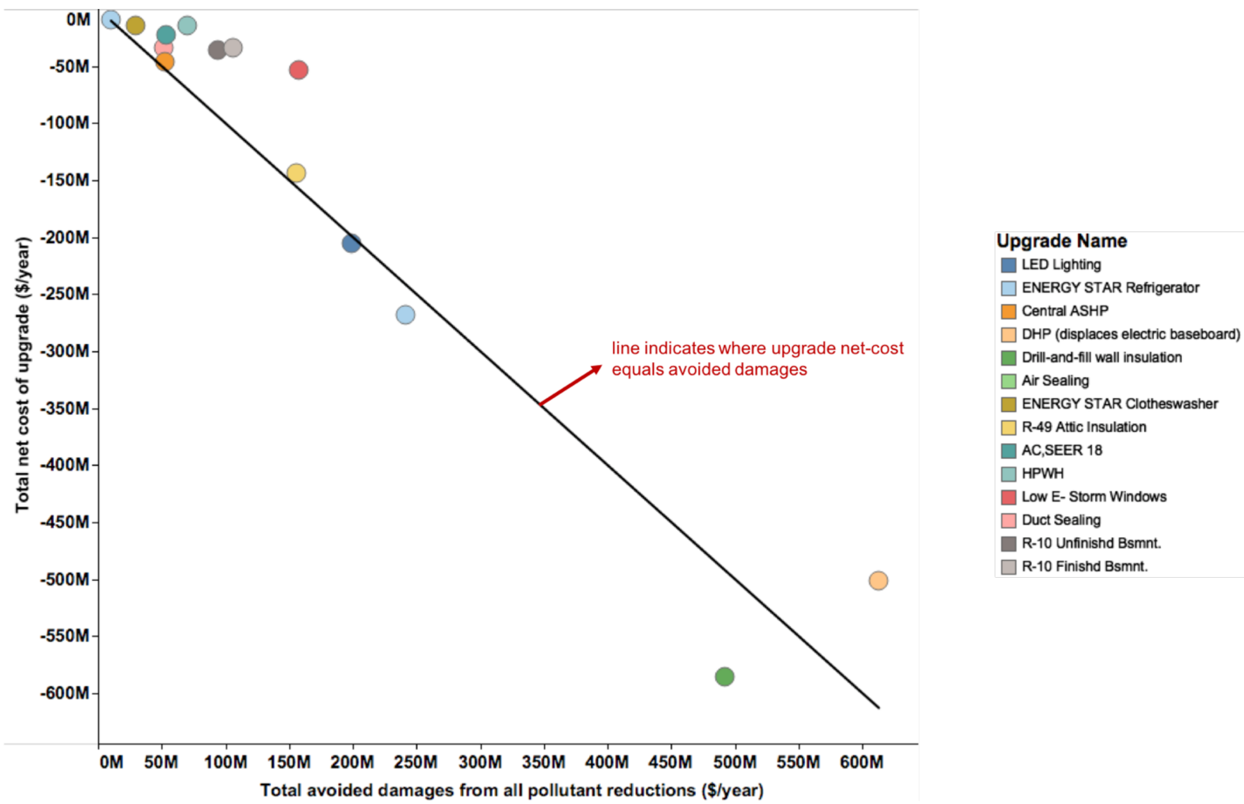

Figure C.7 - Comparison of total net upgrade cost to total avoided damages from all pollutant emission reductions for different EE upgrades at a 15% discount rate

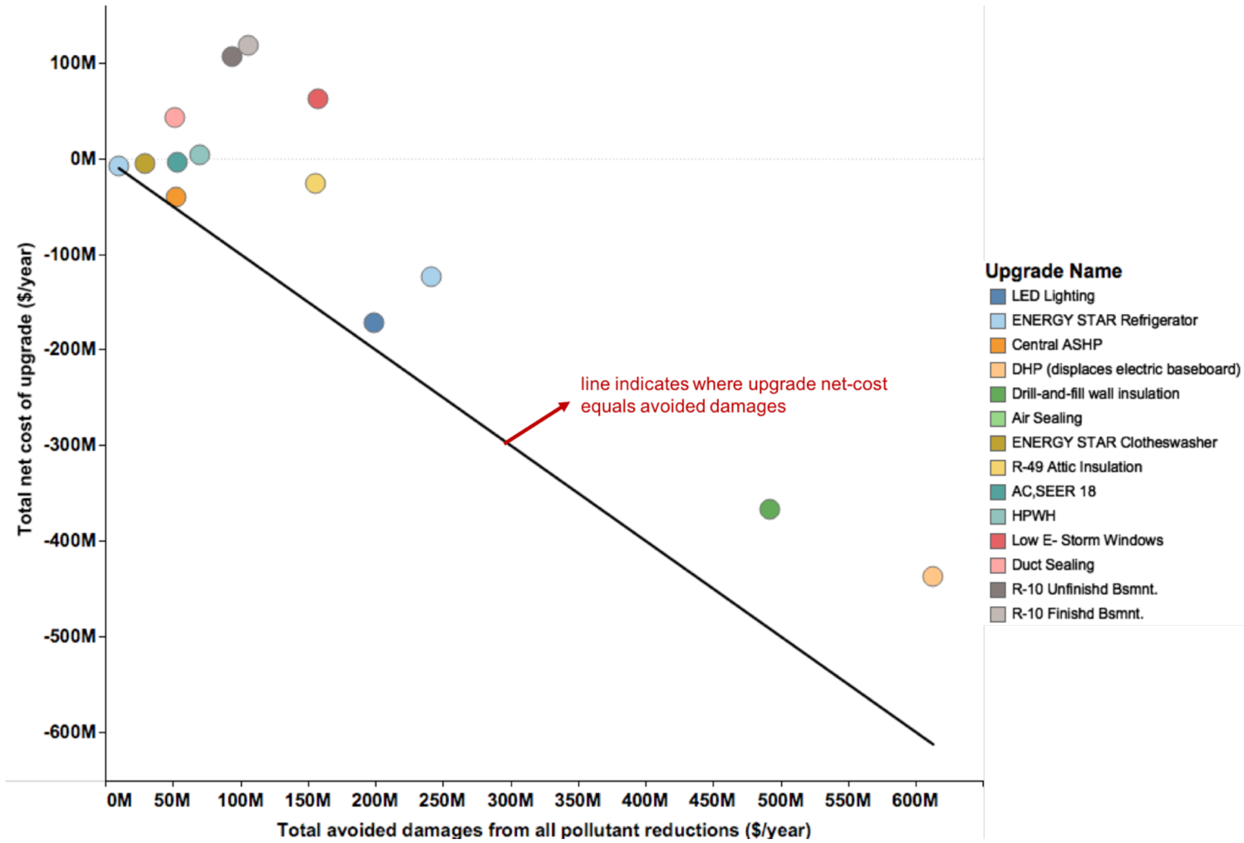

Figure C.8 - Comparison of total net upgrade cost to total avoided damages from all pollutant emission reductions for different EE upgrades at a 15% discount rate