Household benefits from energy efficiency retrofits: Implications for net zero housing policy*

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Abstract

Decarbonizing the housing stock while maintaining household welfare is critical to the public acceptance of climate policy. A challenge in meeting this goal is our incomplete understanding of the distribution of realized benefits from policies designed to reduce greenhouse gases in residential buildings. Our study provides new insights on key variables that contribute to household and social welfare by quantifying both the level and distribution of energy savings, bill savings, and rebates disbursed from Canada's national energy efficiency retrofit program. Using a unique dataset consisting of all single-family homes in a Canadian city, we find that retrofits reduce natural gas consumption for up to 10 years in the average participating home by about 21%. Whole-envelope retrofits reduce natural gas consumption by 35%, only half of model-predicted savings. Several recommended retrofits save zero energy. While program-induced gas bill savings are higher among some households with below average property values, retrofit rebates were disbursed equally across the house wealth distribution. These findings indicate that significant challenges that remain in identifying effective, scalable policies that meet both climate goals and deliver welfare-promoting net zero technology investments across the housing stock.

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1 Introduction

Climate policy scenarios that meet economy-wide net zero carbon emission targets consistently emphasize the need for dramatic reductions in built environment energy consumption (IEA, 2021; Ürge-Vorsatz et al., 2020). Since over two-thirds of the current global building stock will still be operational in 2050, identifying effective approaches to dramatically reduce emissions in existing buildings while maintaining household welfare is an urgent policy goal. This is compounded by the reality that greenhouse gas (GHG) emissions in most industrialized countries are not falling anywhere near a rate that is consistent with net-zero by mid-century (UNEP, 2023).

Recognizing this imperative, Canadian policymakers have enacted, or are in the process of enacting, numerous programs and policies aimed at the building sector. This includes increasingly stringent model energy codes for new buildings, a new "net-zero ready" energy code, and subsidy programs for house retrofits such as insulation, air sealing, and high efficiency heating and cooling equipment. Canada's mandatory carbon tax, one of the most stringent carbon pricing policies globally, is set to rise from CA$65 per ton today to $170 per ton by 2030.[1] This escalating carbon price will help incentivize energy conservation in buildings, yet it also raises energy affordability and equity concerns (Romero-Lankao et al., 2023). Regressive outcomes from energy programs threaten their widespread public acceptance, which can potentially be mitigated by subsidizing investments that reduce energy demand while maintaining the welfare derived from energy services (Goulder et al., 2019; Metcalf, 2009).

Building simulation models are currently widely used in energy retrofit programs to identify the most impactful investments to undertake. However, recent studies have identified that modeled predictions of retrofit energy savings fall significantly short of observed reductions across many common energy efficiency investments (Fowlie et al., 2018; Burlig et al., 2020; Christensen et al., 2021; Chuang et al., 2022; Alekhanova et al., 2023).

Despite these concerning outcomes, important gaps remain in our understanding of the realized performance of home energy efficiency retrofit programs and their potential for contributing towards net-zero goals while maintaining or enhancing household welfare. This includes a dearth of evidence on total household energy savings realized from whole-envelope or "deep" retrofits that are key to meeting climate policy targets in existing buildings (Tozer et al., 2023; Giandomenico et al., 2022; Ang et al., 2023); no existing studies on the realized distribution of retrofit program benefits across house-level demographic variables that directly impact household welfare from low-carbon investments; sparse documentation of the long-term persistence of retrofit savings; and few studies on programs available to the general population rather than with means-tested eligibility criteria. In particular, the lack of analyses using participant-level data to document the distribution of benefits from energy conservation programs is a blind spot in our understanding of the welfare outcomes that drive the acceptance, or rejection, of public policies aimed at reducing environmental externalities (Anderson et al., 2013; Romero-Lankao et al., 2023; Tullock, 1983).

This is the first study to comprehensively fill these gaps. We combine house-level observations from Canada's EnerGuide for Homes (EGH) program and match them to a 13-year history of monthly electricity consumption, natural gas consumption, and energy prices for all single-family houses in a

[1] All figures in the paper are in Canadian Dollars (CA$). Average exchange rate in 2024 is 0.74 USD

medium-sized Canadian city.[2] The city's population is served by a single municipally-owned utility, and they heat their homes almost exclusively with natural gas, so that our combined electricity and gas data represent whole-house consumption for almost all of the houses in our sample.[3] These rich data enable us to quantify total energy savings from houses that completed "whole-house" envelope retrofits in addition to savings from a number of individual measures. Finally, our municipal collaborator also provided us with address-level tax assessment data with detailed property information including house size, year of construction, and property assessed value, which we use to conduct our distributional analysis.

The EGH database has existed since 1998 and records detailed house-level characteristics arising from in-home energy audits. This includes model-predicted energy savings for a range of potential investments such as energy efficient heating and cooling equipment, air sealing, basement, wall, and attic insulation; energy-using equipment type and model number at baseline and after a retrofit is complete; post-audit recommended retrofits; and retrofits completed. The database has observations for close to 2 million housing units, representing about 15% of the current housing stock in Canada. Federal home energy audit and retrofit rebate programs in place today and historically have been available to any Canadian household, so that houses across the income spectrum are eligible to participate.

Our analysis focuses on the ecoEnergy initiative, an energy efficiency rebate program that was in place in Canada between 2008 and 2012, and provides a comprehensive assessment of realized energy savings together with bill savings and rebates disbursed from adopted retrofits across the house wealth distribution. We follow a difference-in-difference approach, comparing the energy consumption of newly-retrofitted (treated) homes with their energy consumption prior to the retrofit, and to similar (control) homes that are not retrofitted. We show that our results are highly robust to several alternative choices of control group, including a control group restricted to homes that are eventually treated, as well as control groups formed by matching on pre-treatment observed variables including building characteristics and furnace type. We also show that our results are robust to potential bias that may arise from "staggered" treatment (Goodman-Bacon, 2021), which is possible in our setting as program participation takes place over a multi-year period.

We find that house energy consumption fell by about 15% on average as a result of participating in the program. Almost all of the energy savings occurred in natural gas consumption, which declined by 21% for up to 10 years, whereas electricity use declined by 0%-5%.[4] The individual retrofits generating the largest average usage reductions were new furnace adoption and wall insulation, which each reduced natural gas consumption by 15-20%. Complete-envelope retrofits reduced natural gas and total energy consumption by 35% and 25%, respectively. An event study analysis indicates that savings following retrofit adoption persist at roughly the same level throughout our sample period, which on average is about ten years post-adoption.

While the natural gas savings are considerable, pre-retrofit modeled savings predictions for adopted retrofits were almost two times higher than realized savings. The average realization rate, which is the

[2] Our timeframe includes at least 1 year of pre-program baseline data and up to 11 years after program participation.

[3] We base our statement about the primary heating source in the city from conversations with the City utility. In addition, the city is referred to as "The Gas City", a moniker included on the utility's energy bills, due to its low natural gas prices.

[4] The electricity savings results are not robust across specifications, with small point estimates that are often statistically insignificant. This is not surprising given that almost all homes heat with natural gas and adopted retrofits were primarily home envelope and new furnace investments.

share of model-predicted savings that actually occurred after a retrofit, is 60% for natural gas savings. Complete envelope retrofits have a realization rate of 50%. Gas realization rates for individual retrofits vary widely: the realization rate for attic insulation, wall insulation and natural gas furnaces is 77%, 61% and 64% respectively, whereas the gas realization rate is statistically zero for basement and foundation header insulation, energy efficient air conditioners, and new windows and doors. The average electricity realization rate is statistically indistinguishable from zero.[5]

The only measure with higher than predicted energy savings is air sealing, with a natural gas realization rate of 145%. However, while air sealing is a popular measure that was undertaken by a majority of participating houses, both the predicted and realized air sealing savings are modest: about a 5% reduction in natural gas and total energy use.

Using house assessed value as a proxy for wealth among program participants, together with energy prices provided to us by the utility and rebate data obtained from the federal government, we go on to document the distribution of program participation rates, energy bill savings, and rebates disbursed across the property value distribution.[6] Program participation rates overall were relatively low, with participation peaking at 12% among houses just below the mean of property values. Gas bill savings peak among lower wealth houses, though only 4% of houses in this group participated in the program. Average total rebate payments were disbursed equally across the assessed value distribution and averaged $1,100, significantly less than the maximum potential rebate of $5,000. Finally, we show that the variation in the distribution of bill savings cannot be attributed to specific retrofit measures, consistent with a selection channel driving the higher savings among lower wealth houses.

Taken together our results provide strong suggestive evidence that private household benefits are lower than program participants would have expected based on the information provided to them during their energy audit. Many households paid substantial sums out of pocket, net of rebate payments, for retrofits that did not reduce their energy bills or reduced them significantly less than predicted. These findings indicate that the current approach to retrofit program delivery leads to investment misallocations that detract from meeting net zero targets on time and in a manner consistent with maintaining household welfare.

A further cause for concern from a climate policy perspective is that most of the energy savings from retrofits arose from the adoption of furnaces with energy efficiency ratings above 80%. Given that the maximum potential efficiency of a furnace is 100%, and that market transformation regulations in place in both Canada and the U.S. have now halted the sale of furnaces with efficiencies lower than 90% for over a decade, further opportunities for energy usage declines from furnace adoptions in the coming years are limited.[7]

These findings point to the urgency of developing and applying new approaches to retrofit program design that improve upon the current status quo and help guide households towards investments that result in significantly higher energy savings (Christensen et al., 2022). This necessitates the development of data-sharing frameworks for utility data, which reflect the outcome of occupant decision-making after a retrofit has been adopted. This is a key methodological improvement that can be made to avoid having

[5]In the Canadian context, one other study has documented that electricity savings from heat pumps are significantly below engineering projections Papineau et al. (2021), with a realization rate of 21% relative to theoretical heat pump potential.

[6]Our use of assessed value as a proxy for wealth in Canada is explained further in the following Sections.

[7]Furnaces with efficiencies below 80% have been phased out since the 1990s and furnace upgrades are no longer supported by the federal rebate program.

to incorporate "best guess" assumptions about the house characteristics and behavioral parameters that impact energy consumption predictions in the building energy models currently used to provide retrofit guidance to households.

The rest of the paper is organized as follows. Section 2 reviews the EGH program; Section 3 describes the data we make use of in our analysis; Section 4 presents our estimation methods and robustness checks; Section 5 describes our results and Section 6 concludes.

2 Program description

The ecoEnergy Retrofit Homes program (ecoEnergy) was announced by the Canadian federal government in 2007 and in place until 2012. It was initially expected to be a $300 million program (Department of Finance Canada, 2007) but was expanded by $300 million in 2009 as a result of unexpectedly high demand and to stimulate the building industry in the wake of the 2008 financial crisis (Department of Finance Canada, 2009).[8] It ran until March 31, 2012, when its budget was exhausted. ecoEnergy was one iteration in a line of similar residential retrofit programs in Canada. The EnerGuide for Houses (EGH) Retrofit Incentive was available between 2003 and 2006 as part of the 2002 Climate Change Plan for Canada, with a budget of $73 million (Government of Canada, 2002).[9] Most recently in 2021 Canada launched the Greener Homes program, which has a budget of $2.6 billion.

Each of these programs largely follow the same model. To qualify for a grant a homeowner must complete a pre-retrofit audit by a certified energy auditor. An audit consists of a detailed home inventory that includes house dimensions, orientation, number of windows and doors, and HVAC equipment characteristics including air conditioner, water heater, and furnace type and model number. It also includes a blower door test, which measures the air leakage rate of a home envelope. Information from the audit is then entered into simulated building energy consumption program used by federal departments and agencies in Canada (the HOT2000 model), which provides an estimate of total building energy consumption, including separate predictions for electricity and natural gas consumption.[10] Based on the results of the pre-retrofit audit, houses are provided with a list of suggested grant-eligible retrofit options. An example of these retrofit recommendations from a home audit is shown in Figure 1. Recommended retrofits are prioritized based on potential energy savings, the life expectancy of the home's components, interactions between systems, the homeowner's potential renovation plans, and costs to perform the retrofits. Finally, to qualify for retrofit rebates houses are required to undertake a post-retrofit audit to confirm upgrades within 18 months of the pre-retrofit audit.

Various iterations of the program have had different rules for which upgrades qualify for a grant. The following retrofits were eligible for a rebate under ecoEnergy: Air sealing, energy-efficient furnaces and air conditioners, new windows and doors, attic insulation, basement insulation, foundation header/joist insulation, and wall insulation. (Government of Canada, 2009).[11] While retrofit grants were offered for

[8] During part of this period, houses were also eligible to apply for the Home Renovation Tax Credit, and some provinces offered home retrofit incentives that piggy-backed on the federal program (Rivers and Shiell, 2016).

[9] See https://www.canada.ca/en/news/archive/2003/10/energuide-houses-retrofit-incentive-launched.html.

[10] The software was developed and is maintained by Natural Resources Canada, a federal government department, to support the EnerGuide initiative.

[11] In the 2003-06 version of the program, grants were performance-based, depending on the improvement in home energy efficiency rating achieved (as determined by the building energy performance simulation model) . In the 2021 version of the program, natural gas furnace upgrades no longer qualify for grants.

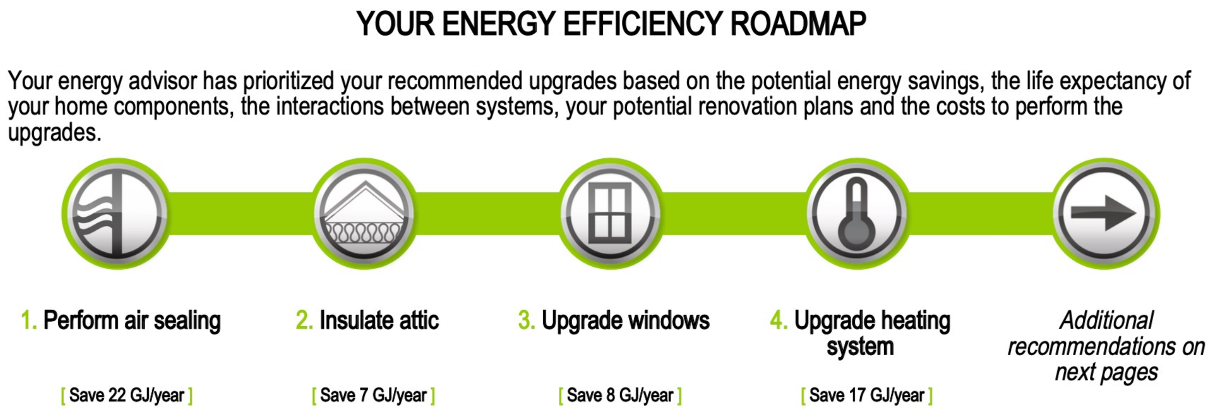


Figure 1: Example home audit output

different upgrades in different iterations of the program, in each case the total incentive for an individual house was limited to $5,000, and houses were free to decide which recommended upgrades (if any) to undertake. The rebates offered under each iteration of the program were not intended to cover the full cost of a retrofit, but rather to subsidize a portion of the total costs paid by participants (Consumers Council, 2017).

3 Data

Our analysis is focused on Medicine Hat, a Canadian city in the province of Alberta with approximately 75,000 residents. We combine data from three distinct sources to conduct our analysis. First, information on rebate payments, house characteristics, recommended retrofits, retrofits undertaken, and predicted energy consumption from the first and second energy audits during the ecoEnergy timeframe are from the federal government's EnerGuide for Homes (EGH) database. Some of these variables, such as predicted consumption before and after a retrofit, are generated from the HOT2000 software.[12] We observe data for 1,684 houses that completed both pre and post energy efficiency audits through the EGH program in the Medicine Hat metropolitan area between 2008 and 2012.

Second, address-level property assessment data were provided by the City of Medicine Hat. Property-level tax assessment variables include information on house size, type (detached or attached, number of stories) and year of construction as well as an assessment of the property's value. Third, monthly electricity and natural gas consumption observations for a 13-year period spanning 2007-2019 were provided by the municipal electricity and natural gas utility. Both the property tax and energy consumption data include all single-family properties in the city: approximately 20,000 houses.[13]

Out of the 1,684 EGH database observations from the Medicine Hat area, we address-matched 1,459 houses to the City's property assessment data. The unmatched observations were due to one or more of

[12] The software is available here: https://www.nrcan.gc.ca/energy-efficiency/homes/professional-opportunities/tools-industry-professionals/20596.

[13] Multi-unit residential, small commercial and some mixed-use buildings were excluded from the analysis as these were not defined as single-family houses by the City.

the following reasons: incorrectly recorded addresses in the EGH database, missing property assessment data, or some EGH addresses not being within official Medicine Hat city boundaries (this includes Redcliff, a suburb of Medicine Hat where some homes participated in ecoEnergy). These data were then merged with the utility consumption dataset which resulted in a total of 1,453 homes with matched data on retrofits, model-predicted predicted natural gas and electricity consumption, property assessments, and realized energy consumption.[14] The six unmatched houses were due to missing energy consumption data.

We also retain energy consumption and property assessment information from houses in Medicine Hat that are non-participants in the retrofit program. For these non-participant households we do not observe energy efficiency audit and retrofit adoption variables. We matched property assessment and energy consumption data for 18,284 non-participating homes.

Table 1: Summary statistics

	Program participants		Non-program participants	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Property Assessment Data				
Total assessed value ($)	276,665	87,090	289,405	123,025
Lot size (square feet)	6,910	3,165	8,783	20,182
Building size (square feet)	1,270	420	1,302	463
Effective year built	1971	18	1981	23
Energy Consumption Data				
Actual energy consumption (GJ/year)	144	45	148	48
Actual pre-retrofit energy consumption (GJ/year)	178	57		
Actual post-retrofit energy consumption (GJ/year)	133	44		
EnerGuide for Homes Data				
Predicted pre-retrofit energy consumption (GJ/year)	195	60		
Predicted post-retrofit energy consumption (GJ/year)	149	40		
Air sealing	0.82	0.38		
Attic insulation	0.64	0.48		
Basement insulation	0.13	0.33		
Central AC	0.13	0.34		
Foundation Header insulation	0.09	0.28		
Natural Gas furnace	0.68	0.47		
Walls insulation	0.04	0.21		
Windows and Doors upgrades	0.18	0.39		
Total observations	1,453		18,284	

Notes: The table displays the means and standard deviations of the variables used in the analysis from three datasets: property assessment data, energy consumption data, and Energuide for homes data (audit data). Columns (1) and (2) present data for the 1,453 houses that participated in the program, while columns (3) and (4) provide data for the remaining single-family homes in the city—18,284 houses that did not participate in the program.

Summary statistics for the data are provided in Table 1. The data contain observations from all 1,453 houses that participated in the retrofit program in the city along with the remaining 18,284 houses that

[14] We define energy consumption is the sum of electricity and natural gas consumption. Given historically low natural gas prices in this part of Canada and Medicine Hat's status as "The Gas City", we were advised by City utility staff that this is a reasonable assumption.

did not participate. The most popular retrofits undertaken by participants were air sealing (82% of participating houses), natural gas furnace upgrades (68% of participating houses), and attic insulation upgrades (64% of participating houses). Compared to non-participant houses, the Table shows that program participants have smaller lot sizes and slightly smaller building sizes and assessed values. Program participants also live in houses that are on average a decade older than non-participant houses. Total energy consumption is presented in this Table as an annual average over the 13-year sample period, and include both pre- and post-retrofit observations. Over this period, there is little difference in energy consumption between participating and non-participating houses.

Among participant houses, Table 1 documents significant differences between model-predicted and actual energy consumption. Both pre- and post-retrofit modeled predictions of total energy consumption are higher than actual energy consumption.[15] For example, pre-retrofit total energy consumption is over-predicted by about 10%. The over-prediction of baseline consumption are consistent with previously documented modeling biases in the NEAT model used by the U.S. Department of Energy Weatherization Assistance Program (Fowlie et al., 2018; Christensen et al., 2021).

Comparing the unconditional pre- and post-retrofit predictions of total energy consumption in Table 1, the typical participating house was projected to reduce energy consumption by about 24%.[16] Our analysis described in the following section uses utility billing data and a difference-in-difference framework to determine whether these savings materialized, and if so whether savings align with the modeled predictions shown to households during their energy audit.

4 Methods

4.1 Graphical evidence: event study

To determine program effects over time and the persistence of energy efficiency retrofits, we begin our analysis with an event study that exploits a unique feature of our data: we observe houses up to five years before and 11 years following a retrofit. This enables us to determine the persistence of the energy savings associated with home energy retrofits and assess if they decay after adoption, relative to the control group. Decay could result from physical degradation of the measures, such as air leaks opening following sealing, or from improvements over time in the control group relative to the treatment group, such as from eventual replacement of a furnace with a more efficient model in the untreated control group.

For our event study specification we begin by aggregating monthly energy consumption to calendar year.[17] We regress the logarithm of energy consumption on a retrofit dummy variable that takes on a value of 1 if a house has completed an energy efficiency retrofit under the ecoEnergy program, and zero otherwise interacted with a time-to-treatment variable ($\text{retrofit}_{iym}\mathbf{1}[y - D_i = h]$). We estimate a separate coefficient associated with leads and lags of a retrofit (the index h), as follows:

[15] Appendix Table A1 includes pre and post-retrofit predictions for electricity and natural gas and show a similar pattern.

[16] Appendix Table A1 indicates that the average participating household was predicted to decrease natural gas consumption by approximately 28% and electricity consumption by 1.3%

[17] As we show below in Table 2, aggregating the data from the monthly to annual frequency has no substantial effect on the results.

$$log(e_{iy}) = \sum_{\substack{h=-5 \\ h \neq -1}}^{h=11} \beta_h \text{retrofit}_{iym} \mathbf{1}[y - D_i = h] + \alpha_i + \gamma_y + \epsilon_{iy}, \tag{1}$$

where $log(e_{iy})$ is the logarithm of energy consumption, i indexes houses and y indexes year. The variable D_i in Equation (1) is the year of the post-retrofit audit for house i. We drop all observations between the pre-retrofit audit and the post-retrofit audit for each house. h measures number of years before or after a retrofit occurred in a given house i. House fixed effects are denoted α_i and year-of-sample fixed effects are denoted γ_y. As is standard, we normalize the estimates by dropping the indicator variable for the year prior to retrofit.

Since retrofit adoptions occur over a number of years in the data, our research design is a "staggered" difference-in-difference. Goodman-Bacon (2021) shows that such research designs, in the presence of dynamic or time-varying treatment effects, can lead to bias in standard two-way fixed effects (TWFE) estimators (such as Equation (1)). This bias derives from estimating treatment effects that compare newly-treated units with previously-treated units. Sun and Abraham (2021) and Callaway and Sant'Anna (2021) propose alternative estimators for this setting that avoid comparing units treated at different times. We augment our event study specification with these two estimators, and compare the savings over time from these modified estimators to the standard two-way fixed effects results.

We also compare two different samples in our analysis to assess any potential concerns about staggered adoption and selection bias: the full sample including program participants who retrofitted their houses and non-participant controls (19,737 houses), and the "Participants-only" sub-sample of houses who participated in the program (1,453 houses). In the latter sample houses that have yet to be treated form the counterfactual control group against which earlier-treated houses are compared. Since all participating houses retrofit their homes between 2009 and 2012, the treated-only subsample can only recover estimated coefficients for up to three years post-retrofit since a credible counterfactual cannot be constructed once all or almost all houses are treated.

There are benefits and drawbacks to using each of these samples. Using the non-participant controls enables us to estimate retrofit savings over the full 11-year timeframe we observe each house for, which is one of the goals of our study. On the other hand, untreated houses may differ from treated houses based on unobservable, time-varying characteristics. As described in the next sub-section, to address both potential sources of bias (staggered adoption and selection) we apply dynamic TWFE corrections together with several different matching estimators using our rich set of observable characteristics in regressions including the non-participant controls. Our results presented in Sections 5.1 and 5.2 show that these regression estimates recover highly stable coefficients across all specifications.

4.2 Two-way fixed effects analysis

We next identify the overall average treatment effect on the treated (ATT) of participating in the retrofit program with a differences-in-differences estimator using both monthly and annual energy consumption. As in the event study, we report estimates for both the full and treated-only sample and augment our TWFE approach with adjustments for heterogeneous treatment effects. Since the retrofit program is voluntary, we also employ a number of matching approaches to assess whether selection into treatment may lead to biased inference.

Our specification assesses the average impact of participating in the program on energy, natural gas and electricity consumption. We regress the natural logarithm of each monthly energy consumption measure ($log(e_{iym})$, where e denotes either natural gas, electricity or their sum), on the retrofit indicator variable retrofit$_{iym}$. This specification includes house fixed effects α_i as well as month-of-sample fixed effects γ_{ym} (e.g., February 2017), and takes the following form:

$$log(e_{iym}) = \beta \text{retrofit}_{iym} + \alpha_i + \gamma_{ym} + \epsilon_{iym}. \tag{2}$$

In all cases, we two-way cluster standard errors by house and month-of-sample.[18]

In this approach, house fixed effects control for time-invariant characteristics of homes, such as size or orientation. Month-of-sample fixed effects control for time-variant conditions that affect all houses equivalently in a given year and month, such as weather (all houses are located in the same city, so experience similar weather) or energy prices. The approach is similar to Chuang et al. (2022), who evaluate electricity efficiency rebate programs in California, or to Liang et al. (2018), who evaluate electricity efficiency programs in Arizona. It is also similar to the experimental estimates in Fowlie et al. (2018), who evaluate a low-income home retrofit program in Michigan.

To account for treatment effect heterogeneity we also implement the Sun and Abraham (2021) estimator, which is estimated by interacting a cohort dummy with a time-to-treatment dummy. In our monthly data, we observe 49 different "cohorts" (i.e., households retrofit in 49 different months) and our data has 200 different "time to treatments" (i.e., months before and after retrofit). This implies estimating a model with close to 10,000 dummy variables, which is not feasible. Instead, to estimate the Sun and Abraham (2021) model, we convert to annual data. Therefore the specifications reported in Section 5.2, Table 2 include both the monthly data fixed effects model in equation (2) and the same model using annual data, the only difference being that the month-by-year fixed effect is replaced by a year fixed effect.[19]

4.2.1 Identification

The coefficient $\hat{\beta}$ is an estimate of the effect of retrofit program participation on energy consumption. The primary assumption required to identify $\hat{\beta}$ without bias is unconfoundedness, which implies that, conditional on observable covariates and fixed effects, participation in the energy efficiency retrofit program is not systematically related to other drivers of home energy consumption. An alternative way of expressing the unconfoundedness assumption is that the non-participant houses provide a good counterfactual for energy consumption of the participating houses had they not undergone the energy efficiency retrofit. In the differences-in-differences context, this assumption is satisfied if, in the absence of a house retrofit and conditional on covariates, the energy consumption of retrofitted and non-retrofitted

[18] In all our specifications we drop data for dates between the pre- and post-retrofit audit for each house. Our data identify the calendar day these audits occurred. In Table A3 in Appendix A we also report estimates with house-by-month fixed effects instead of separate house and month fixed effects. This does not substantively change our estimates.

[19] As indicated in Table 2, there is no appreciable difference in the estimates using monthly versus annual data.

houses would have followed parallel trends.[20] The key potential violation of this assumption occurs because, as in Liang et al. (2018) and Chuang et al. (2022) and other similar studies, houses self-select into program participation. While we control for time-invariant characteristics that are correlated with participation using house fixed effects (e.g., fixed environmental attitudes), there may be house-specific time-varying covariates that determine retrofit program participation which we cannot observe.

In the energy efficiency investment setting, including this program, selection may manifest through houses with an old furnace being more likely to participate, since the value of program participation is likely higher for these houses (Rivers and Shiell, 2016). Another possibility is that houses who intend to sell their homes in the near future might take advantage of the energy efficiency rebate program to undertake upgrades that might increase their home's market value. These "free-riders" or inframarginal houses would have been more likely to replace their furnace, upgrade their windows or undertake an energy efficiency renovation. In this case, the estimated $\hat{\beta}$ from the regression will be biased towards larger energy savings than actually occurred (Boomhower and Davis, 2014).

To assess whether possible self-selection may affect our results we leverage our highly detailed house-level data, including furnace model and type, by constructing four different matched control groups from different subsamples of houses who either never participated or have yet to participate in the program. We draw the matched control groups from different subsets of the approximately 20,000 houses that either never participated in the program or those that eventually did but had not yet done so, using four different approaches.[21]

First, we match on pre-treatment energy consumption.[22] For each house, we determine summer, winter, and shoulder season electricity consumption and natural gas consumption. We construct a matched control group by selecting the nearest neighbour for each participant house from the full control group of never-participants using propensity scores constructed from these six variables.

Second, we construct a control group using non-outcome variables that we observe in tax assessment data from the city of Medicine Hat. These variables include house size, house age, assessed value, neighbourhood, and house type. Using these variables, we again construct a control group using nearest-neighbour matching based on propensity scores. In a third matched sample we identify a control group using the same approach but include both building characteristics and pre-treatment energy consumption variables to estimate propensity scores.

Finally, since new furnace adoption was one of the most common retrofits undertaken, we use a matching approach to address a plausible selection channel, namely that houses with relatively older furnaces or boilers may be more likely to participate in the program and possess other unobserved characteristics correlated with consumption.[23] To do this, we exploit information on furnace type and furnace efficiency as measured by annual fuel utilization efficiency (AFUE) available in the EGH database, both of which are highly correlated with furnace age.

[20] Two other identifying assumptions in ex-post studies such as ours are overlap and no general equilibrium effects (SUTVA). Overlap assumes outcomes are observed for each treatment status at all values of the joint covariate distribution, and SUTVA assumes each house's potential outcomes are not affected by the treatment status of other houses.

[21] Since this matching approach is a selection-on-observables identification strategy, it still leaves open the possibility that time-varying unobserved variables could bias our results. However, our detailed matching variables and the stability of coefficients we observe in our reported results below are an indication that any remaining unobserved selection is likely minimal.

[22] The first house participates in the retrofit program in February 2008, so we use the full year of 2007 as the pre-treatment year for all houses.

[23] In the following discussion we refer only to furnaces, however 12 houses adopted energy efficient condensing natural gas boilers (compared to about 1000 furnaces), and our analysis matches on boilers as well.

Furnace type includes four categories: continuous pilot, spark ignition, induced draft (non-condensing), and condensing furnaces. Continuous pilot furnaces are considered a first-generation furnace technology and they are the oldest, lowest efficiency furnaces observed in our data. Their AFUE is typically less than 70%. Spark ignition furnaces are the next iteration in furnace technology with AFUEs in the mid- to high 70% range. Both continuous pilot and spark ignition furnaces were no longer available in the Canadian market after the mid-1990s due to federal regulations (Government of Canada, 2016). Induced draft furnaces with AFUEs above 78% up to about 90% became widely available in the 1980s. In 2009 a new set of federal regulations came into effect that phased out furnaces with efficiencies below 90%. Condensing furnaces are the most efficient furnace type, with efficiencies in the 92-95% range in our data. All furnaces (and boilers) adopted under the ecoEnergy program we study were condensing models.

Furnace type and furnace AFUE are almost perfectly correlated in our data. As a result we construct a control group using exact matching on pre-retrofit furnace type. The control group in this case is derived from what we term 'ever-treated' homes that eventually participated in the program but had not yet done so between 2007 and 2011.

We estimate Equation (2) using the samples of control and treated houses produced by the matching approaches described above. To the extent that our matching variables are correlated with unobserved time-varying predictors of energy consumption in the treated period, we expect the estimates of $\hat{\beta}$ from the matched sample to recover a less biased estimate of β than estimates with the full sample, as described above. However, it is important to point out that even our extensive building and pre-treatment energy consumption observations may not fully account for unobserved time-varying determinants of retrofit program participation. In that case our estimates of $\hat{\beta}$ would likely over-predict the energy savings from program participation and therefore also over-estimate the realization rate of predicted savings.

As reported in Section 5.2, we find that our estimates of overall energy savings are highly stable between the full and participant-only samples and across the different TWFE and matching estimators. As a result, we proceed with estimating energy savings for individual retrofit measures and realization rates using the full sample of participant and non-participant houses.

4.3 Measure-level savings estimates

Retrofit-specific energy saving estimates are generated in the same manner as the overall retrofit estimates, except we replace the dummy variable for retrofits with separate dummy variables for each type of upgrade. We refer to these as our measure-level estimates. Measures are indexed by j and the complete set of measures is indicated by $\mathbb{J}$:[24]

$$log(e_{iym}) = \sum_{j \in \mathbb{J}} \beta_j \text{measure}_{ijym} + \alpha_i + \gamma_{ym} + \epsilon_{iym}. \tag{3}$$

While this approach to estimating energy savings from specific energy efficiency measures is standard (e.g., Chuang et al., 2022; Liang et al., 2018), it is important to note that it treats energy savings from individual measures as additive, and ignores potential interactions between measures. Given our relatively small sample, running a specification that allows flexibly for interacting effects between

[24]The set $\mathbb{J}$ includes the following types of energy-efficiency upgrades: air sealing, gas furnace upgrade, attic insulation, window/door upgrade, central AC upgrade, basement insulation, foundation header insulation, and wall insulation.

measures is not possible. However, past literature suggests these interactions likely have second-order effects on energy consumption (Chidiac et al., 2011). As previously noted, given the stable estimates between the full sample and treated-only sample we proceed with using the full sample for all remaining analyses.

4.4 Realization rates

To compare model-predicted savings with the savings that actually occurred post-retrofit we use house-level energy audit data on predicted energy consumption before and after rebates, together with actual energy consumption, to measure *realization rates*. The realization rate is the proportion of projected savings (that are shown to prospective participants) that actually occur following a retrofit. While the realization rate is not observed by participants, it is an important determinant of the program's benefits for participants. We estimate realization rates with the following equation:

$$\log(e_{iym}) = \phi \text{retrofit}_{iym} \left(\log(\hat{e}_i^1) - \log(\hat{e}_i^0)\right) + \alpha_i + \gamma_{ym} + \epsilon_{iym}, \tag{4}$$

where $\hat{e}_i^1$ and $\hat{e}_i^0$ are predicted post- and pre-retrofit energy consumption from the HOT2000 engineering model, as described in Section 3. The coefficient ϕ that is recovered from estimating Equation (4) is the proportion of predicted energy savings that are realized.

We also aim to estimate measure-specific realization rates. Since the EGH database only includes predicted energy consumption following all retrofits that were undertaken by the home, but not predictions of energy savings from individual measures, we use a regression approach to obtain measure-specific projections of energy savings. We regress projected energy savings on the adopted energy efficiency measures as follows:

$$\left(\log(\hat{e}_i^1) - \log(\hat{e}_i^0)\right) = \sum_{j \in \mathbb{J}} \tau_j measure_{ij} + \epsilon_{ij}. \tag{5}$$

This is a cross-sectional regression that compares predicted energy savings associated with measure j across houses i. τ_j is an estimate of the predicted savings associated with the adoption of measure j. With an estimate of predicted savings associated with adoption of measure j in hand, we compute realization rates by comparing β_j, estimated from Equation (3), with τ_j so that $realization\ rate_j = \beta_j / \tau_j$.

4.5 Program benefits

Program benefits and their distribution across households are important determinants of the economic efficiency and equity of energy policies (Borenstein and Davis, 2016; Winter et al., 2023). They also play key roles in maintaining public support for the transition to a net-zero energy system (Romero-Lankao et al., 2023). In this section, we describe our methodology to calculate natural gas bill savings from program participation, both overall and from specific measures, and the distribution of bill savings and rebates disbursed across the distribution of property assessed value.[25] To do this, we leverage two additional data sources: historical monthly energy pricing data from 2007-2019 that we obtained from the municipal utility, and rebates paid to participating houses from federal government data.

[25] As explained further in Section 4.6, we use property assessed value as a proxy for wealth.

4.5.1 Total energy bill savings

Our bill savings analysis considers only gas bills given that the electricity savings from the program are statistically insignificant. We aggregate our monthly gas consumption to the annual level to obtain our benefit measures.[26]

To determine average program-induced gas bill savings, we multiply average annual variable gas costs (per gigajoule (GJ) charges) during the post-program period (2012-2019) by actual and predicted annual GJ of gas saved.[27] We proceed as follows. First, we calculate realized average annual gas consumption savings by re-estimating Equation (2) with annual consumption data in levels, as follows:

$$e_{iy} = \theta \text{retrofit}_{iy} + \alpha_i + \delta_y + \epsilon_{iy}, \tag{6}$$

Here, e_{iy}, represents annual gas consumption in GJ for household i in year y, and retrofit_{iy} is the retrofit indicator variable. The regression includes house fixed effects α_i and year fixed effects δ_y, with standard errors two-way clustered by house and year. The coefficient θ reflects the average annual impact of participating in the retrofit program on gas consumption in GJ.

Second, we calculate average annual GJ of gas saved predicted by the HOT2000 model, denoted as s_p, as follows:

$$s_p = \frac{\sum (\text{Pre-retrofit Cons}_{pred} - \text{Post-retrofit Cons}_{pred})}{n}, \tag{7}$$

where Pre-retrofit Cons_{pred} and Post-retrofit Cons_{pred} denote annual predicted pre-retrofit and post-retrofit consumption in GJ, and n is the number of retrofitted houses.

Third, we calculate average annual variable gas charges across all households in the post-program period (P_V); these averaged 5.98 per GJ.[28]

Finally, we multiply these gas prices with our estimates derived from Equations (6) and (7). We calculate BS_r, overall average annual realized bill savings, and BS_p, overall average annual projected bill savings:

$$BS_r = (\hat{\theta} * P_V) \tag{8}$$

$$BS_p = (s_p * P_V) \tag{9}$$

[26] This is for computational purposes and has no substantive effect on our results.

[27] We use only variable or per GJ cost savings since the program did not affect fixed costs. In our distributional analysis described below we report percent bill savings inclusive of fixed costs.

[28] Gas prices did not vary by much from year to year in the post-sample period, such that the choice of which period to average prices over makes little difference for the average cost we obtain.

4.5.2 Measure-level bill savings

Retrofit-specific bills saving are derived the same way as overall retrofit savings. However, instead of employing a single indicator variable for retrofits, we employ distinct indicator variables for each specific retrofit measure. Individual measures are denoted by the index j, and the full set of upgrades is represented by $\mathbb{J}$.

We re-estimate Equation (3) with levels and annual consumption data:

$$e_{iy} = \sum_{j \in \mathbb{J}} \theta_j \text{measure}_{ijy} + \alpha_i + \delta_y + \epsilon_{iy}. \tag{10}$$

Next, we estimate measure-specific projected annual gas savings predicted by the HOT2000 model, for each measure, in GJ. Since the HOT2000 does not provide measure-specific predicted savings, we regress projected gas savings on the adopted efficiency measures, similar to Equation (5), as follows:

$$\left(\hat{e}_i^1 - \hat{e}_i^0\right) = \sum_{j \in \mathbb{J}} \lambda_j measure_{ij} + \epsilon_{ij}. \tag{11}$$

This cross-sectional regression compares predicted gas savings associated with each measure j across houses i, where λ_j is the predicted savings estimate from the adoption of measure j in GJ.

Lastly, we use the previously derived average annual variable gas charge to calculate BS_{rj}, measure-specific annual realized bill savings, and BS_{pj}, measure-specific annual projected bill savings:

$$BS_{rj} = (\hat{\theta}_j * P_V) \tag{12}$$

$$BS_{pj} = (\left(\hat{e}_i^1 - \hat{e}_i^0\right) * P_V) \tag{13}$$

4.6 Distributional Analysis

In our final set of analyses we identify program participation rates, bill savings and rebates received across the distribution of assessed property value. We use house assessed value for the 2015 assessment year, which is available for each property in our data from municipal property tax records. Following the hedonic pricing literature, we use assessed value as a proxy for property value and therefore real estate wealth (Clapp and Giaccotto, 1992; Janssen and Soderberg, 1999). Real estate accounts for over half of total wealth in Canada, and over two thirds of total wealth among the bottom four quintiles of the wealth distribution (Statistics Canada, 2023).[29] In addition, real estate wealth is closely linked to indicators of the real economy, such as consumer spending and household welfare (Bostic et al., 2009; Kiyotaki et al., 2011; Aladangady, 2017). This implies energy policies delivering benefits among lower wealth households may be key to maintain public support for net zero targets. Bill savings and rebate

[29] Even more starkly, real estate wealth makes up over 80% of total wealth in the bottom half of the wealth distribution.

payments are two quantifiable benefits accruing to households from retrofit programs, and can offer suggestive evidence as to whether program benefits are distributed progressively, regressively or equally among participating houses.[30]

Our estimates for percent program participation, bill savings and rebates received are shown graphically and calculated by interacting dummy variables for houses in 14 assessed value bins with the variable of interest in the post treatment period (participation, percent bill savings and rebate amount).[31] Percent bill savings in the distributional analysis are obtained by dividing bill savings calculated using equation (8) by total monthly charges including fixed and variable (or per GJ) charges.[32]

5 Results

5.1 Graphical evidence: event study

We begin by graphically depicting evidence on the energy savings from participating in the Energy program. We estimate Equation (1) using the TWFE panel estimator in addition to the dynamic TWFE adjustments by Sun and Abraham (Sun and Abraham, 2021) and Callaway and Sant'Anna (Callaway and Sant'Anna, 2021) shown in Figure 2. We apply these estimators to both the full sample of all houses and the participants-only sample.

Estimates obtained using the participants-only sample without adjustments compare retrofit savings from earlier-treated houses to later-treated houses, which will result in biases in the presence of heterogeneous treatment effects. The unadjusted participants-only estimates are depicted by green dotted lines in Figure 2. A downward bias in energy savings is evident by comparing the unadjusted participants-only estimates to the Sun and Abraham or Callaway and Sant'Anna estimates, shown in the blue and red dotted lines, respectively.[33]

Several other findings emerge from the event study plot. First, there are no obvious pre-trends in energy consumption. The control houses are following the treated houses' energy consumption patterns prior to retrofitting, which suggests that they may serve as an appropriate control unit for treated houses. The only exception is observed for the participant-only sample before applying the Sun & Abraham or Callaway & Sant'Anna estimators. In the year before the retrofit occurs there is a borderline 10% significant in this sample. However, since this uncorrected estimator includes comparisons of early- and later-retrofitted houses as control and treated observations respectively, the comparison is likely biased due to heterogeneous treatment effects. This likelihood is corroborated by comparing the TWFE estimator in the participant-only sample with the participants-only corrected estimates, as illustrated by the blue (Sun & Abraham) and red (Callaway & Sant'Anna) dashed lines.

Second, energy consumption falls substantially by between 15 and 20%, following the retrofit. Third, the savings in home energy consumption following a retrofit persist for at least a decade following the

[30]Other benefits from adopted retrofits under the program may include home comfort or reduced hassle from operating heating or cooling equipment. Both of these elements of household welfare are difficult to measure without conducting a field experiment; as a result they are outside the scope of this paper.

[31]House assessed value ranges from \$25,000 to \$800,000, with a mean of approximately \$285,000.

[32]This contrasts with the bill savings in Sections 4.5.1 and 4.5.2. We use this additional measure in the distributional analysis because gas bill savings relative to the total gas bill may be more salient to households given that the quantity paid for gas on a monthly basis includes both fixed and variables charges.

[33]Estimates for only three years post-retrofit can be obtained for results using the participants-only sample because most houses have completed their retrofit by year four, resulting in insufficient unretrofitted homes to form a comparison group.

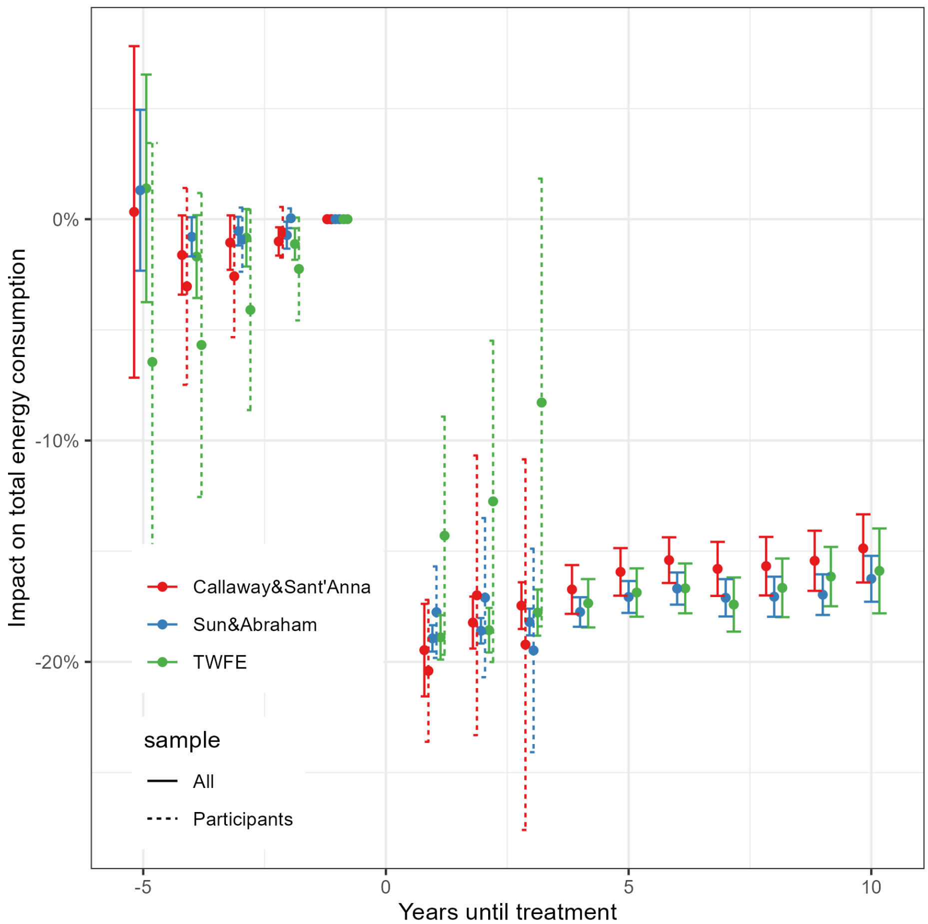


Figure 2: Event study plot

Notes: This figure overlays the event-study plots constructed using three different estimators: a dynamic version of the TWFE model, equation (1), estimated using OLS (in green); Sun and Abraham (2021) (in blue); Callaway and Sant'Anna (2021) (in red) for two different samples; full sample of all houses in the city (solid lines), and for participants-only sample (dotted lines). The outcome variable is total energy consumption. The time variable is years to being treated and the treatment group variable is given by the year in which the household joined the program. The figure displays five preperiods and eleven postperiod. The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and year.

retrofit. We observe a small degree of attenuation in the effect of retrofits on energy consumption over time after about three or four years following a retrofit, but the effect remains large for all years that we are able to follow houses. This suggests that the efficacy of home energy retrofits does not decay quickly following adoption. Fourth, the estimates from the standard TWFE model and the adjusted TWFE estimators are very similar in both the full and participant-only samples, suggesting that in our context the TWFE estimator is not significantly biased. Why is this? For one, the treatment effect in our context do not appear to change significantly over time (as noted above – they are persistent). Since retrofits deliver basically a one-time change in house energy consumption in our context, already-treated houses provide a good control group for newly-treated houses. In addition, our sample includes a large control group of never-treated houses. The presence of these never-treated houses reduces weight on already-treated houses in the regression, and thus helps to avoid potential bias.

5.2 Two-way fixed effects analysis

Table 2 shows estimates of $\hat{\beta}$ from Equation (2) as described above. Panel A reports results for total energy savings (natural gas + electricity) and Panel B reports natural gas savings.[34] Column (1) of Table 2 shows results including the full sample of all houses, columns (2)-(4) show the different matched observations described in Section 4.2, column (5) shows the participant-only sample, and column (6) shows the participant-only sample matched on the furnace type.

Panels A and B present results using the traditional TWFE estimator and the Sun & Abraham correction (hereafter S&A). The S&A estimator is obtained by interacting a cohort dummy with a time-to-treatment dummy. In our monthly data, we observe 49 different "cohorts" (i.e., households retrofit in 49 different months). Our data has 200 different "time to treatments" (i.e., months before and after retrofit). This implies estimating a model with about 10,000 dummy variables, which is not computationally feasible. Instead, to estimate the S&A model we convert to annual data first. Estimating the empirical model on monthly versus annual data does not substantively change the results. This can be seen by comparing the 'TWFE, Monthly' and 'TWFE, Annual' results in Panel A.

The results from both samples show that participation in the retrofit program reduced house energy consumption by about 16% on average. Natural gas consumption fell by about 20%. The estimates provide strong evidence that natural gas consumption fell by a considerable amount following energy efficiency retrofits. The results are consistent across the different samples we estimate in columns (1)-(6) and between the TWFE and S&A estimators. While we can't completely eliminate "free-riders" concerns due to potential selection channels that are not captured by our matching analysis, our approach using the detailed variables we do observe suggests that accounting for several plausible channels of selection into treatment negligibly changes the estimated savings.[35]

Given the highly stable coefficient estimates and statistically insignificant differences between estimated savings across each estimated specification, and our goal of assessing the long-term persistence of retrofit savings, we employ the full sample specification from column (1) in our results presented in the following sections.

5.3 Measure-level results

Measure-level savings from estimating Equation (3) using the full sample of participant and non-participant houses are presented in Figure 3. In the right panel, we show the number of energy efficiency measures adopted by participating houses. The most popular measures were air sealing, upgrading a natural gas furnace with a more efficient model, and adding ceiling/attic insulation. In the left panel, we show coefficient estimates and standard errors associated with each measure for each fuel type. Natural gas furnace upgrades are estimated to result in the largest natural gas savings, at around 18%. Furnaces are typically the largest sources of natural gas consumption in a house, and rebate-eligible upgrades

[34] Electricity savings results are reported in Appendix Table A1. As shown, the electricity savings are small and statistically insignificant across most specifications. The fact that natural gas consumption fell by a larger amount than electricity consumption is not surprising since the ecoEnergy program principally targeted space heating and thermal envelope efficiency, and space heating is provided predominantly by natural gas in the setting studied (Medicine Hat is known as 'The Gas City' due to its relatively cheap natural gas prices).

[35] For example, matching on pre-treatment consumption will mitigate selection bias from households that may have faced a positive consumption shock and therefore be more likely to choose an energy efficiency retrofit, and matching on pre-existing furnace type addresses selection caused by participation from houses with relatively older furnace models.

Table 2: Two-Way Fixed Effects Estimators with Matching

Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Total Energy Savings					
	TWFE, Monthly					
Program participation	-0.16***	-0.15***	-0.15***	-0.14***	-0.16***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,882,662	429,578	429,833	429,866	75,461	74,842
R^2	0.79	0.81	0.81	0.81	0.81	0.81
	TWFE, Annual					
Program participation	-0.17***	-0.16***	-0.16***	-0.15***	-0.19***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	246,541	35,175	35,165	35,178	5,071	5,029
R^2	0.81	0.85	0.85	0.85	0.90	0.90
	S &A , Annual					
Program participation	-0.17***	-0.15***	-0.16***	-0.15***	-0.17***	-0.17***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.02)	(0.02)
Observations	246,541	35,175	35,165	35,178	5,071	5,029
R^2	0.81	0.85	0.85	0.85	0.90	0.90
	Panel B: Natural Gas Savings					
	TWFE, Monthly					
Program participation	-0.21***	-0.19***	-0.19***	-0.19***	-0.22***	-0.22***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,874,433	428,688	429,313	429,103	75,699	75,078
R^2	0.85	0.86	0.86	0.86	0.84	0.84
	S &A , Annual					
Program participation	-0.20***	-0.18***	-0.19***	-0.18***	-0.20***	-0.20***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.02)	(0.03)
Observations	247,154	35,234	35,244	35,248	5,071	5,029
R^2	0.82	0.85	0.86	0.85	0.90	0.90
Matching variables						
Pre-treatment consumption		✓		✓		
Building characteristics			✓	✓		
Furnace type						✓
Sample	T + AC	T+ MC	T+ MC	T+MC	T-Only	T-Only

*Notes: This table explores the effect of participating in a residential retrofit program on the natural logarithm of total energy savings and on gas savings. Specifically, it presents estimates of coefficient $\hat{\beta}$ from Equation (2). Panel A reports results for total energy savings (natural gas + electricity) and Panel B reports natural gas savings. Column 1 estimates Equation (2) for the full sample of all houses in the city. column (2) , (3), and (4) estimates Equation (2) for matched observations on pre-treatment energy consumption, building characteristics, and matching both; pre-treatment energy consumption and building characteristics, receptively. Column (5) estimates Equation (2) using participant-only sample, and column (6) estimates Equation (2) for the matched observations on furnace- type using participants-only sample. These specifications include house and month-of-sample fixed effects. Standard errors are two-way clustered by house and month-of-sample. ***: 0.01, **: 0.05, *: 0.1.*

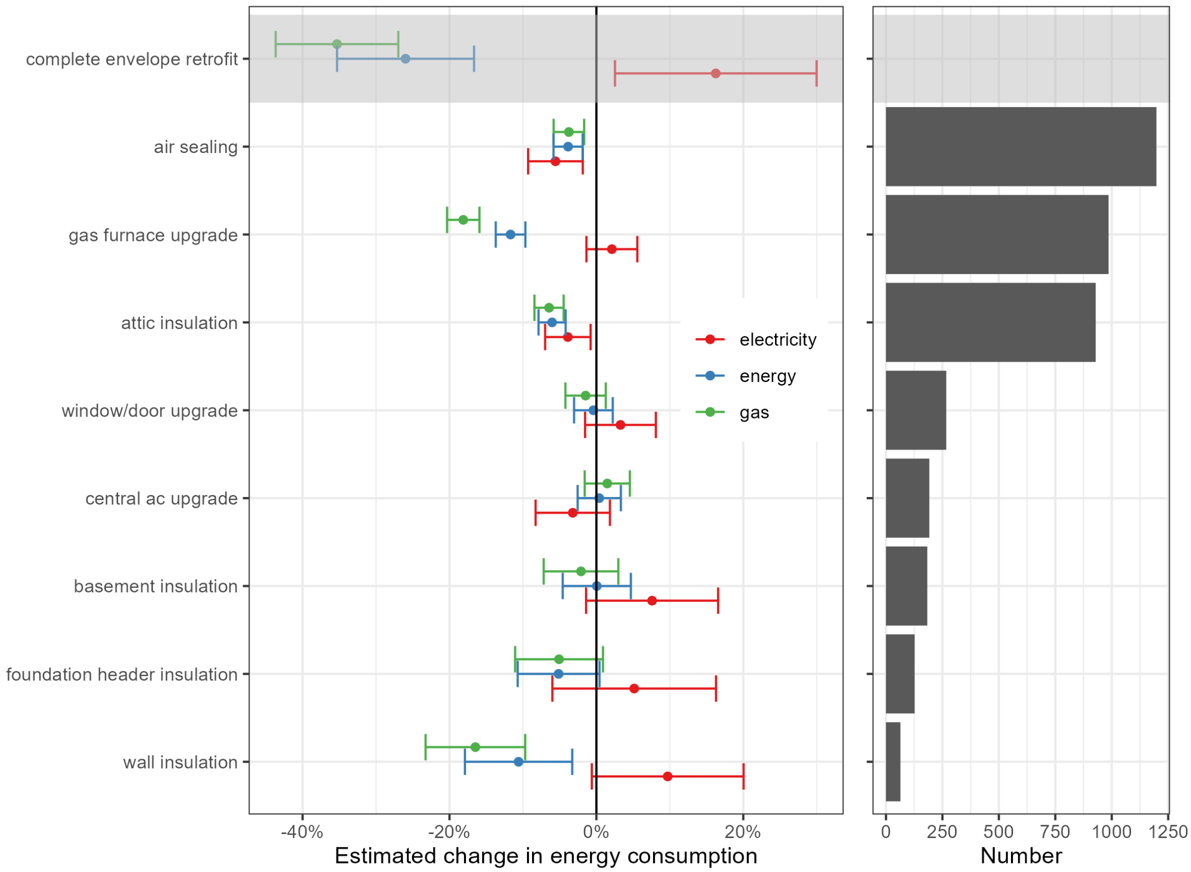


Figure 3: Measure-level realized energy savings

Notes: This figure explores the measure-level savings from estimating Equation (3) using the full sample of participant and non-participant houses. The left panel shows point estimates and 95% confidence intervals for estimates of energy savings from energy efficiency retrofit measures. The right panel shows the number of each type of retrofit measure observed in our data. Complete envelope retrofits are shaded in grey and are imputed from envelope measures. This imputation involves adding coefficients associated with air sealing, window/door upgrades, and insulation in the attic, basement, foundation header, and walls. The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and month-of-sample.

could increase furnace efficiency by over 30 percentage points.[36] Wall insulation also significantly reduced natural gas consumption, although the estimates are much less precise than for natural gas furnaces, likely because fewer houses undertook this measure (which is much more intrusive than a furnace upgrade). Attic insulation and air sealing reduce natural gas consumption by 6% and 3%, respectively. Other measures such as window and door upgrades had no impact on natural gas or total energy consumption. These finding are similar to other studies, and suggests that window and door upgrades are ineffective at reducing energy consumption (Giandomenico et al., 2022). Basement insulation and foundation header insulation also had no effect on energy consumption.

For electricity, we find no measures that substantially reduce consumption. We do find a statistically significant reduction in electricity consumption associated with air sealing and attic insulation, but

[36] The ecoEnergy program required a new furnace efficiency of at least 92% to qualify for rebates, while existing furnaces typically ranged between 60% to 80% efficient

these measures only save about 4-5%. Upgrading to an energy efficient air conditioner does not change electricity consumption on average.

Our data includes households engaging in a variety of energy efficiency upgrades as shown in Figure 3, with most households selecting one or two upgrades out of the eight measures considered. Because of recent policy interest in "deep" energy efficiency retrofits, we use our data to predict energy savings from a complete envelope retrofit. A complete home envelope retrofit consists of air sealing, window/door upgrades, as well as the addition of insulation in the attic, basement, walls, and foundation header. We do not observe many households undertaking complete envelope retrofits in our data, but we impute the effect of complete envelope retrofits as the sum of coefficients on all of these measures.[37] These projected values are shown in grey shading at the top of Figure 3. They suggest that a whole envelope retrofit reduces natural gas and total energy consumption by about 35% and 25%, respectively.

As an additional robustness check for these whole envelope retrofit results, we use data on 15 houses that undertook a close to complete envelope retrofit, defined as air sealing, attic insulation, window and/or door upgrades, wall insulation, and either foundation header or basement insulation, and estimate Equation (3). We show results that compare the imputed estimates with the estimated effect in the 15 houses in Appendix Figure A1. The imputed versus actual estimates are remarkably consistent for natural gas and total energy consumption, with a difference of less than 5% between the two estimation approaches (imputation versus observed whole envelope retrofits). These differences are statistically insignificant from each other.

5.4 Realization rates

5.4.1 Overall realization rates

We now turn to estimating the aggregate realization rate by regressing energy consumption on a treatment dummy interacted with projected energy savings, as in Equation (4). As shown in Table 3, we find a realization rate for natural gas of 61%. Our realization rate for electricity is around 52%, and not significantly different than zero. For all energy, we find a realization rate of 56%. The natural gas and energy realization rates are highly statistically significant.[38]

5.4.2 Measure-specific realization rates

Our procedure to estimate measure-specific realization rates occurs in two steps, as described in Section 4.4. First, we estimate *projected* energy savings by measure, using a cross-sectional regression of projected total savings regressed on a vector of dummy variables indicating which measures were adopted, as in Equation (5). Appendix Figure A2 plots the coefficients recovered from this regression. Large natural gas savings are projected for furnace upgrades as well as wall insulation. Basement insulation, ceiling/attic insulation, window and door upgrades, and air sealing are also all projected to deliver natural gas savings by the engineering model. Projected electricity savings are much smaller than natural gas savings, with

[37] Specifically, for each fuel type we calculate $\hat{\beta}_{completeenvelope} = \hat{\beta}_{atticinsulation} + \hat{\beta}_{window/doorupgrade} + \hat{\beta}_{basementinsulation} + \hat{\beta}_{foundationinsulation} + \hat{\beta}_{wallinsulation} + \hat{\beta}_{airsealing}$.

[38] We also conduct our analysis in levels rather than logs. Results are shown in the Appendix Table A4, and are similar to the main results in logs.

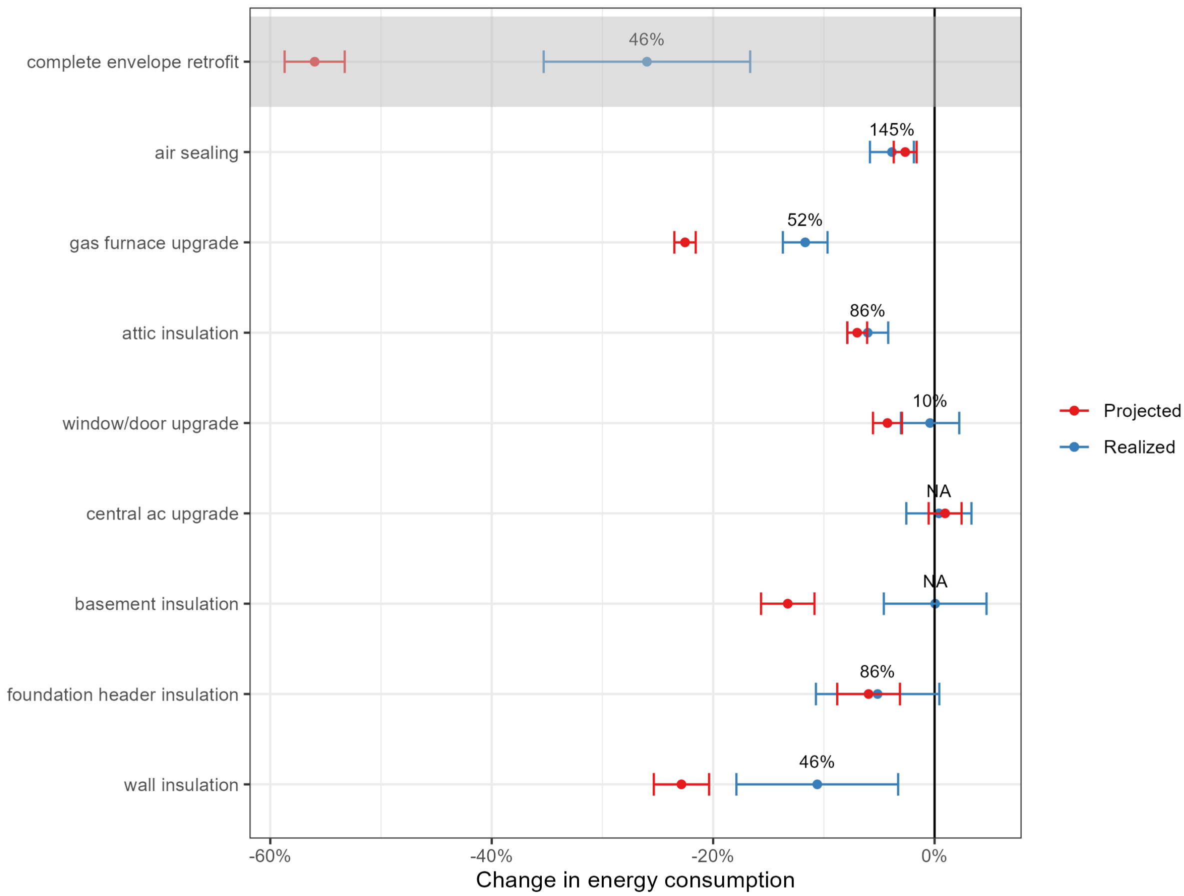


Figure 4: Measure specific realization rates

Notes: This figure examines measure-level realization rates by dividing the realized gas savings estimated in Equation 3 and depicted in Figure 3 by the measure-specific projected energy savings obtained from estimating Equation (5). Complete envelope retrofits are shaded in grey and are imputed from envelope measures. This imputation involves adding coefficients associated with air sealing, window/door upgrades, and insulation in the attic, basement, foundation header, and walls. The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and month-of-sample. Measures with positive point estimates for realized energy savings have realization rates denoted as N/A.

Table 3: Realization rates

	Gas (1)	Electricity (2)	Energy (3)
Gas realization rate	0.61***		
	(0.02)		
Electricity realization rate		0.52	
		(0.47)	
Total energy realization rate			0.56***
			(0.03)
Household	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes
Observations	2,872,273	2,906,366	2,880,498
R^2	0.85	0.47	0.79

*Notes: This table examines the overall realization rate of energy savings by comparing the predicted and actual energy savings post-retrofit. Specifically, it provides estimates of the coefficient ϕ obtained by estimating Equation (4), representing the proportion of predicted energy savings that are realized. The dependent variable in columns (1)-(3) corresponds to the logarithm of gas, electricity, and total energy, respectively. Standard errors are two-way clustered by house and month-of-sample. ***: 0.01, **: 0.05, *: 0.1.*

the largest reductions projected for wall insulation as well as natural gas furnace upgrades (due to lower electrical consumption by the furnace fan).

Finally, we estimate measure-specific realization rates by dividing the realized rates illustrated in Figure 3 by the measure-specific projected energy savings. The results are presented in Figure 4 for total energy savings.[39] We indicate measure-specific realization rates in percentage form above each measure in the Figure. The highest realization rates are observed for air sealing (145% realization rate), furnaces (52% realization rate), and attic insulation (86% realization rate). The air sealing realization rate above 100% indicates this measure saves more energy than predicted, whereas all other measures save less than predictions. Window and door upgrades, basement insulation, energy efficient air conditioners and foundation header insulation each have statistically insignificant savings.[40]

5.5 Program benefits and distributional analysis

In this section we report total and measure-level bill savings from retrofit program participation, then illustrate the realized distribution of bill savings and rebate payments across house property values among program participants.[41] We then investigate to what extent specific retrofit measures may contribute to the distribution of bill savings we observe.

[39] Appendix Figure A3 shows measure-level realization rates for natural gas, electricity and all-energy. The natural gas savings closely mirror the total energy savings in Figure 4, and the electricity savings are statistically insignificant across all measures, which is consistent with Table 3.

[40] Air conditioner upgrades and new basement insulation have very small *positive* coefficient estimates and as a result these realization rates are denoted as N/A in Figure 4.

[41] We also present the unconditional distribution of house assessed values for all single-family houses, though this is not our main variable of interest.

Table 4: Gas bill savings for projected vs. realized energy savings

	Annual gas bill savings in dollars (projected)	Annual gas bill savings in dollars (realized)
Retrofit Measure:	(1)	(2)
Air sealing	27	40
Attic insulation	78	46
Basement insulation	167	0
Foundation insulation	53	0
Natural gas furnace	222	92
Wall insulation	373	91
Window/door upgrade	44	0
Total savings for average participant	274	128

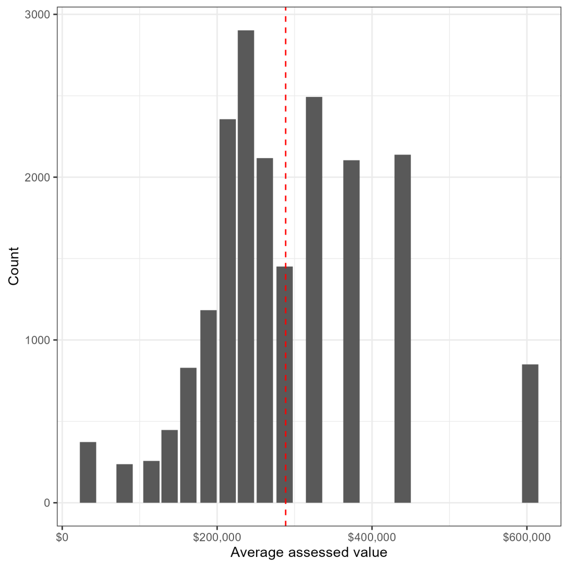
Notes: Projected and realized gas bill savings for each retrofit measure and gas bill savings for the average program participant. The measure-level projected and realized savings are obtained from estimating Equations 13 and 12, respectively. Total projected and realized bill savings for an average participant is shown in the last row and comes from estimating Equations 9 and 8, respectively.

Table 4 shows average natural gas bill savings for each adopted retrofit measure, and total gas bill savings for the average program participant, for both model-projected and realized energy savings.[42] Annual realized gas bill savings for the measure generating the largest program savings, natural gas furnaces, were $92 per year for the average participating house. Total realized bill savings are $128, less than half of projected bill savings.

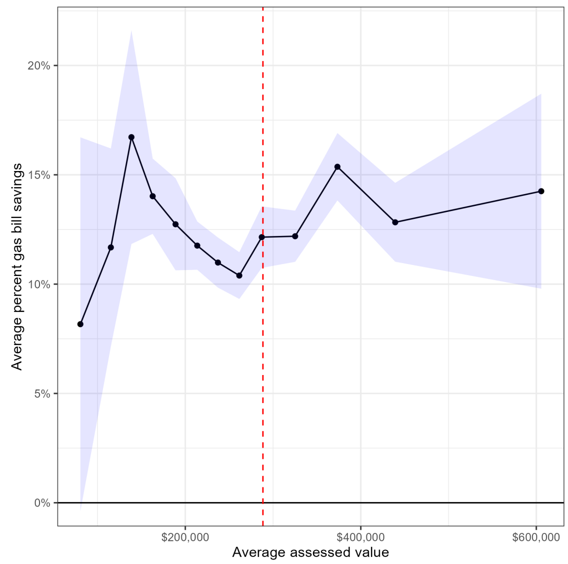
To put these gas bill savings in perspective, consider that among all the participant houses we observe, the average total gas bill is $843 per year. This implies that, all else equal, a natural gas furnace replacement was projected to reduce average natural gas bills by $222 (a 26% bill saving), whereas the actual annual bill reduction was $92, or 11%. Air sealing, the most popular measure undertaken and the only measure with higher than predicted savings, was projected to reduce bills by 3%, and actually saved 5%. Basement and foundation insulation additions and window and door upgrades did not generate any bill savings.

These results are unsurprising given the results discussed in the previous sections, but they further underscore that energy bill savings arising from retrofits, which are an important determinant of the private returns from energy efficiency retrofits, fall significantly short of delivering savings to households. Most starkly, 417 houses, close to a third of total participants, adopted new windows, doors, basement insulation or foundation insulation and obtained zero bill savings from these measures despite likely paying significant sums out of pocket for these measures net of the rebates they received.

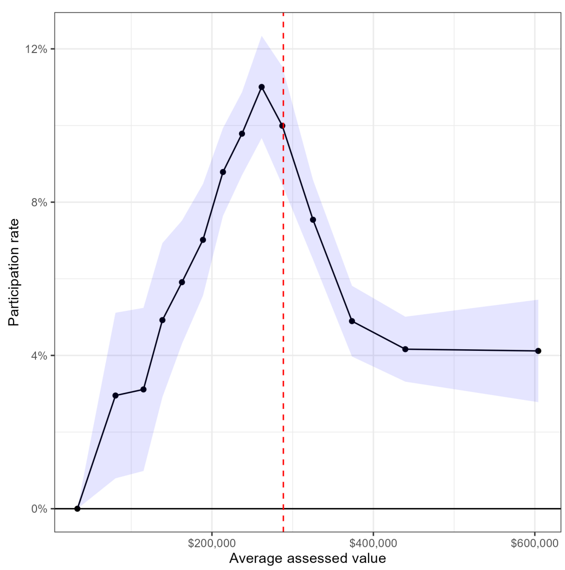
[42] As noted in Section 4.5.1 we do not include electricity bill savings since these are statistically insignificant.



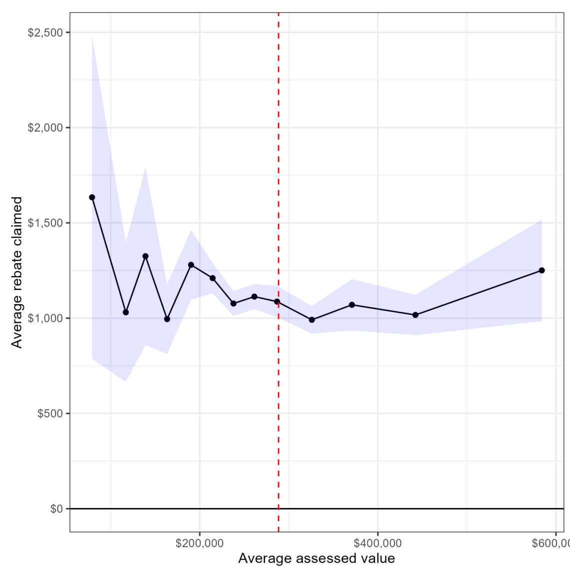
Panel A



Panel C



Panel B



Panel D

Figure 5: Distribution of program participation and benefits

The distribution of program participation, average participant bill savings and household rebates across bins of the house assessed value distribution. The red dotted line indicates the overall mean of house assessed value in 2015, approximately $285,000. Panel A displays the distribution of assessed values for all single-family houses in the city, based on total houses in each assessed value bin. Panel B shows the share of houses participating in the ecoEnergy program in each assessed value bin. Panel C presents the percentage reduction in total gas bills among ecoEnergy participants (standard errors are estimated using 100 bootstrapped samples), and panel D shows average rebates received among ecoEnergy participants. The purple shaded area in each Panel shows the estimates' 95 percent confidence intervals.

Program participation, bill savings and rebates received across the distribution of assessed property value are shown in Figure 5. The mean assessed value is approximately $285,000, as indicated by the red dashed line in each Panel. Panel A of Figure 5 presents a histogram of house assessed value across all 19,737 single-family houses in our sample. Panel B shows the ecoEnergy program participation rate for houses in each bin of the assessed value distribution. Participation peaks among houses just below mean assessed value, at 11% of houses in that bin, and then declines quite steeply before tapering off at 4% for houses assessed at approximately $400,000 or more.[43]

Panel C presents the distribution of percentage reduction in total gas bills (including fixed and variable charges).[44] Percent total bill savings range between 8%-17%. Peak savings of 17% are realized among houses with relatively low assessed values of $100,000, though bill savings taper off rapidly for houses assessed at values above and below the peak. On the other hand, bill savings approach their lowest values among houses with the highest retrofit program participant rate; this group had average gas bill reductions of approximately 10.5%.

Panel D shows the distribution of average rebate disbursements in each bin of the assessed value distribution. While total potential rebates available from the program were $5,000 in the ecoEnergy program, most houses received substantially less than this. The average payout was $1,100 and there is low variability in the average reimbursement amount across participating houses. While the confidence intervals for rebate payments are wide below the mean assessed value, the point estimates provide some suggestive evidence that houses with lower assessed values received slightly higher rebate payments than houses with higher than average assessed values.

Another take-away from Figure 5 is that gas bill savings exhibit a slight peak among lower wealth houses, as proxied by assessed value. This could be due to some combination of these houses adopting relatively higher return retrofits, or from selection, whereby houses with both poor energy performance and low assessed values are more likely to participate in the program.[45] While we are not able to determine the extent of selection, given unobserved house quality, our data do enable us to identify if lower-valued houses adopt retrofits with higher realized energy savings. These results are reported in Figure 6.

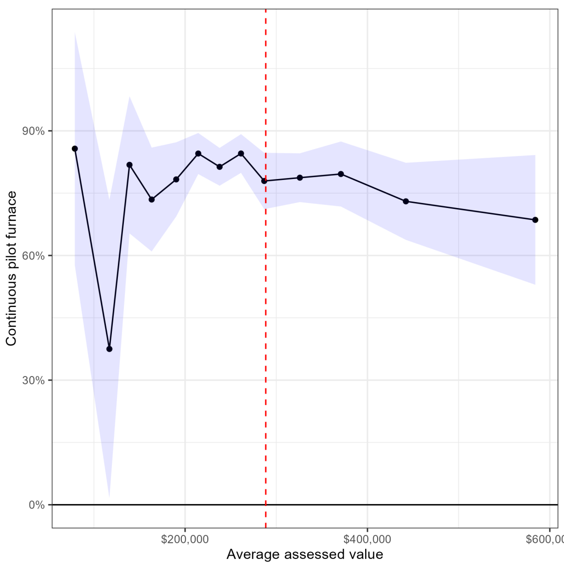
We focus on adoption patterns for the three most widely adopted retrofits: air sealing, gas furnaces, and attic insulation. These three retrofits account for the majority of the energy savings from the program, and with the exception of wall insulation, they also have the highest realization rates among the measures with statistically significant energy savings.[46]

[43]The participation rate overall among single family houses was about 7%.

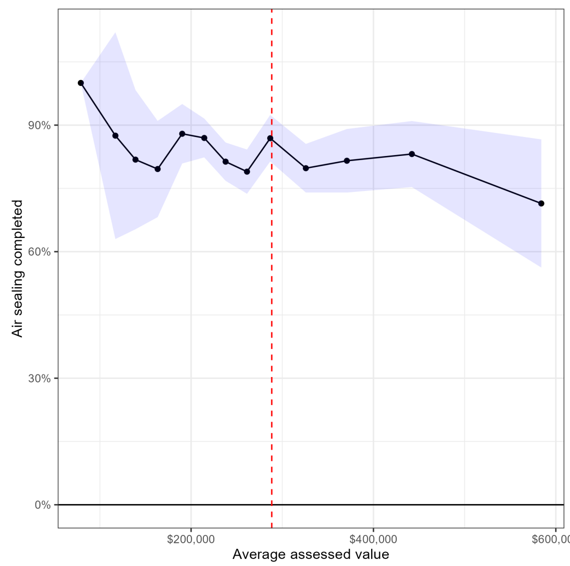
[44]Again, we only report gas savings since electricity savings are not statistically significant.

[45]It's possible low assessed value and poor energy efficiency are endogenous. For example, a house may have a lower assessed value due to it being poorly maintained, including having old energy-using equipment or envelope-related features such as single-pane windows. The low assessed value may then raise barriers to obtaining loans for house upgrades, and the program may have helped these houses afford these investments.

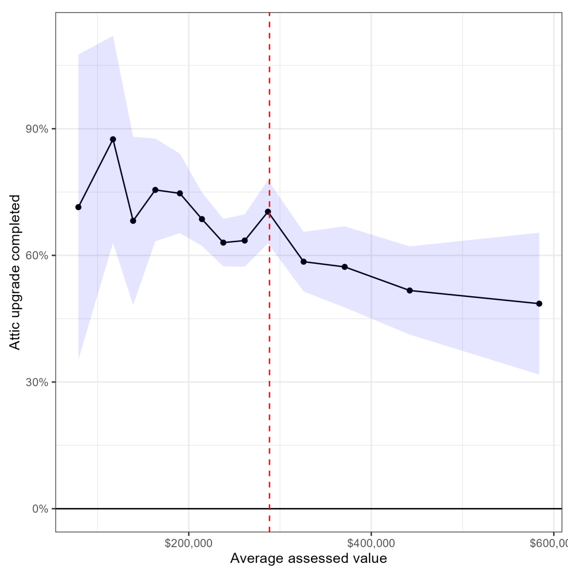
[46]While wall insulation significantly reduced energy consumption, it was adopted by fewer than 70 houses (see Figure 3), which precludes identifying a precise statistical signal for our distributional metrics, due to low statistical power. Part of the reason for the low adoption rate may be related to the high costs of adopting wall insulation, as it is a relatively invasive procedure that may require removing or replacing large wall sections and replacing them with new drywall or outdoor siding.



Panel A



Panel B



Panel C

Figure 6: Distribution of adopted retrofits

The share of participating houses adopting a given retrofit in each assessed value bin. Panel A shows continuous pilot furnaces, Panel B shows air sealing, and Panel C shows attic insulation. The red dotted line in the four figures reflects the mean assessed value of approximately $285,000. The purple shaded area in each Panel shows the 95 percent confidence intervals for the estimates.

Panel A of Figure 6 shows the share of program participants with continuous pilot furnaces before they retrofit. Continuous pilot furnaces are the least energy efficient furnace models due to an ignition mechanism relying on continuous combustion of natural gas. Houses with continuous pilot furnaces that adopted an energy efficient furnace would have benefited from large energy savings. Over 85% of houses that adopted a new energy efficient furnace did so by replacing a continuous pilot furnace. As illustrated in the Figure, there is little variation in the pre-retrofit share of houses with a continuous pilot furnace across the assessed value distribution. While the second assessed value bin estimate exhibits a significantly lower point estimate, the confidence interval around this value is very wide and we can't rule out close to a 75% share of continuous pilot furnaces.

Panels B and C of Figure 6 show the rate of air sealing and attic insulation adoption among program participants. Like the furnace results, the rate of air sealing adoption exhibits only small differences across house assessed values. The rate of attic insulation adoption is slightly higher among houses with assessed values lower than $200,000, but the confidence intervals are relatively large and indicate that at most the difference in the adoption rate compared to houses at or above mean assessed values is approximately 5%-10%.

Taken together the results in Figure 6 do not provide strong evidence that the slightly higher gas bill savings in houses valued in the range of $100,000-$125,000 are driven by greater adoption rates for the highest energy-saving retrofits. Rather, these results are consistent with some form of selection driving higher bill savings. Houses with lower property values exhibit a lower than average ecoEnergy program participation rate of about 5% yet attain the highest share of bill savings. Factors related to energy performance that are observable to participant homeowners may enable them to benefit from higher energy savings from their retrofits. In contrast, in the property value segment with the highest participation rates of 11%, near the mean of the property value distribution, bill savings reach a local minimum of 10%. This is suggestive that factors other than energy performance may be guiding retrofit program participation and retrofit measures chosen, such as taking advantage of the program as part of a larger set of cosmetic home retrofits to improve re-sale value.

6 Conclusion

Despite being primarily designed and communicated as an energy efficiency program that would lower energy bills and help offset the up-front costs of home retrofits (Natural Resources Canada, 2009), there is mixed evidence that houses who participated in Canada's ecoENERGY program derived significant benefits from adopted retrofits. The program participation rate was low, averaging about 7% of all single-family houses in the city, and while participating houses near the mean of the house wealth distribution exhibited the largest participation rates, program benefits were relatively modest in this group, with average natural gas bill savings of 10% and average rebates received valued at $1,100 despite total potential program rebates available being up to $5,000. Peak gas bill savings of approximately 17% occurred among some lower wealth houses, but the confidence interval around the estimate is relatively wide and the savings are not attributable to the adoption of higher energy-saving retrofits. Rebates were disbursed at roughly the same level for participants across the house wealth distribution, and the adoption rate of the most popular and high-saving measures did not vary appreciably between low and high assessed value homes.

Our results provide strong suggestive evidence that 1. unobserved selection on some combination of house quality, energy performance and preferences for cosmetic retrofits/renovations are drivers of the realized distribution of bill savings for participating households; and 2. the program resulted in regressive outcomes whereby lower property wealth houses invested in popular and high-saving measures at rates at or above higher property wealth houses but derived similar bill savings and received the same subsidy payments on average.

We also find that all eligible investment measures, except for air sealing, delivered lower than predicted energy savings, with several measures saving zero energy. Complete envelope retrofits, a type of "deep energy retrofit" that has recently gained prominence in the policy community as a strategy to help meet climate targets for existing buildings (Zhivov and Lohse, 2021), exhibit realization rates of 52% and 46% for natural gas and all-energy, respectively. Houses that completed these retrofits were predicted to reduce their natural gas consumption by 66%, but usage actually declined by approximately 33%.

The combination of low realized savings from complete envelope retrofits, zero bill savings for several individual program-recommended measures, and low participation rates among eligible homes demonstrates the significant challenges that remain in identifying effective, scalable policies that meet both climate goals and deliver welfare-promoting net zero technology investments in housing.

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A Appendix

A.1 Rebate calculations

Participant households who completed one or more retrofits through the ecoEnergy program obtained rebates that varied based on the retrofit. We use these rebate data in our distributional analysis. The rebate dataset was obtained as follows. First, we use a household-level variable obtained from Natural Resources Canada that denotes whether a household received a rebate for each retrofit undertaken. This variables does not include the incentive amount, it only indicates whether an incentive was disbursed to the household.[47]

Second, to identify rebate amounts, we use ecoEnergy grant tables that were also provided to us by Natural Resources Canada, and delineate eligible retrofits under the ecoEnergyRetrofit – Homes program, along with their corresponding rebate amounts. The maximum rebate or grant per household for home upgrades is capped at $5,000. The initial grant table was introduced in 2007 and underwent four revisions during the program's duration on March 30th, 2009; July 1, 2009; November 30, 2009; and June 6, 2011. The rebate payments are based on the date the first energy audit was completed, and the EGH database includes the exact day this occurred. We use this date together with the grant tables to identify total rebates paid. Examples of rebate payments are described below to illustrate how we derive incentives paid.

Throughout the program, air sealing rebates ranged from CA$150 to CA$190, contingent upon homeowners reaching the air sealing target specified in their pre-retrofit audit report (which we also observe). Gas furnace rebates varied based on the type and efficiency of the newly adopted system, as well as the existing heating system pre-retrofit. For instance, the minimum amount was CA$300 if a household upgraded the existing furnace with an ENERGY STAR gas furnace of 90% AFUE or better, according to the 2007 grant tables. The maximum amount was CA$790 if a household adopted an ENERGY STAR gas furnace with 94% AFUE or better when installing a condensing furnace for the first time, according to the grant tables effective from March 30, 2009.

Rebate amounts for ceiling/attic insulation varied based on the starting point and the achieved insulation value, in RSI. A lower the starting RSI value, coupled with a higher achieved RSI value, resulted in larger rebate amounts. For instance, in the 2009 grant tables, starting with an RSI value of 2 and a final RSI of 8.8 guaranteed a rebate of CA$750. For basement insulation rebates, a minimum of 20% of the basement's total wall surface was required to be insulated. Additionally, rebate amounts varied based on the percentage of surface area insulated above 20% and the RSI value achieved post-renovation. For example, the maximum rebate of CA$1,250 was assured if 100% of the basement surface area was insulated with at least 4 RSI, as per the March 30, 2009 grant tables.

Similarly for exterior walls insulation, the maximum rebate of CA$1,875 was achieved when 100% of the surface area was insulated with at least 1.6 RSI, according to the March 30, 2009 grant tables. Header insulation rebates, obtained by sealing and insulating the entire basement header area to achieve a minimum of 3.5 RSI, ranged from CA$100 to CA$125 depending on the time of the rebate application. Finally, replacing existing windows or doors with ENERGY STAR qualified models granted applicants an amount ranging from CA$30 to CA$40 per item.

[47] We use the terms rebate and incentive interchangeably.

Average rebate amount paid per participant was CA$1,100, with only two individuals receiving the maximum rebate amount of CA$5,000.

A.2 Tables and Figures

Table A1: Summary statistics

	Program participants		Non-program participants	
	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Property Assessment Data				
Total assessed value ($)	276,665	87,090	289,405	123,025
Lot size (square feet)	6,910	3,165	8,783	20,182
Building size (square feet)	1,270	420	1,302	463
Effective year built	1971	18	1981	23
Energy Consumption Data				
Actual gas consumption (GJ/year)	113	38	116	41
Actual electricity consumption (GJ/year)	31	12	31	13
Actual energy consumption (GJ/year)	144	45	148	48
Actual pre-retrofit gas consumption	145	50		
Actual pre-retrofit electricity consumption (GJ/year)	33	15		
Actual pre-retrofit energy consumption (GJ/year)	178	57		
Actual post-retrofit gas consumption	103	37		
Actual post-retrofit electricity consumption (GJ/year)	30	12		
Actual post-retrofit energy consumption (GJ/year)	133	44		
EnerGuide for Homes Data				
Predicted pre-retrofit gas consumption (GJ/year)	161	60		
Predicted pre-retrofit electricity consumption (GJ/year)	34	1.0		
Predicted pre-retrofit energy consumption (GJ/year)	195	60		
Predicted post-retrofit gas consumption (GJ/year)	116	40		
Predicted post-retrofit electricity consumption (GJ/year)	33	1.1		
Predicted post-retrofit energy consumption (GJ/year)	149	40		
Air sealing	0.82	0.38		
Attic insulation	0.64	0.48		
Basement insulation	0.13	0.33		
Central AC	0.13	0.34		
Foundation Header insulation	0.09	0.28		
Natural Gas furnace	0.68	0.47		
Walls insulation	0.04	0.21		
Windows and Doors upgrades	0.18	0.39		
Total observations	1,453		18,284	

Notes: The table displays the means and standard deviations of the variables used in the analysis from three datasets: property assessment data, energy consumption data, and Energuide for homes data (audit data). Columns (1) and (2) present data for the 1,453 houses that participated in the program, while columns (3) and (4) provide data for the remaining single-family homes in the city—18,284 houses that did not participate in the program.

Table A2: Two-Way Fixed Effects Estimators with Matching: Electricity Savings

Model:	(1)	(2)	(3)	(4)	(5)
			TWFE, Monthly		
Program participation	-0.04***	-0.01	-0.01	0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	2,908,550	432,238	432,263	432,424	76,430
R^2	0.47	0.50	0.49	0.49	0.54
			S &A , Annual		
Program participation	-0.05***	-0.02**	-0.02*	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Observations	246,819	35,183	35,170	35,180	5,071
R^2	0.64	0.71	0.70	0.70	0.86
Matching variables					
Pre-treatment consumption		✓		✓	
Building characteristics			✓	✓	
Sample	T + AC	T+ MC	T+ MC	T+MC	T

*Notes: This table explores the effect of participating in a residential retrofit program on electricity savings. Specifically, it presents estimates of coefficient $\hat{\beta}$ from Equation (2) with electricity savings as the outcome variable. Column 1 estimates Equation (2) for the full sample of all houses in the city, column (2) , (3), and (4) estimates Equation (2) for matched observations on pre-treatment energy consumption, building characteristics, and matching both; pre-treatment energy consumption and building characteristics, receptively. Column (5) estimates Equation (2) using participant-only sample. These specifications include house and month-of-sample fixed effects. Standard errors are two-way clustered by house and month-of-sample. ***: 0.01, **: 0.05, *: 0.1.*

Table A3: Regression with house-by-month fixed effects

Dependent Variable:	log(energy)	
Model:	(1)	(2)
Variables		
Program participation	-0.16***	-0.16***
	(0.01)	(0.01)
Household	Yes	
Month of sample	Yes	Yes
House by month of sample		Yes
Observations	2,926,828	2,926,828
R^2	0.79	0.85

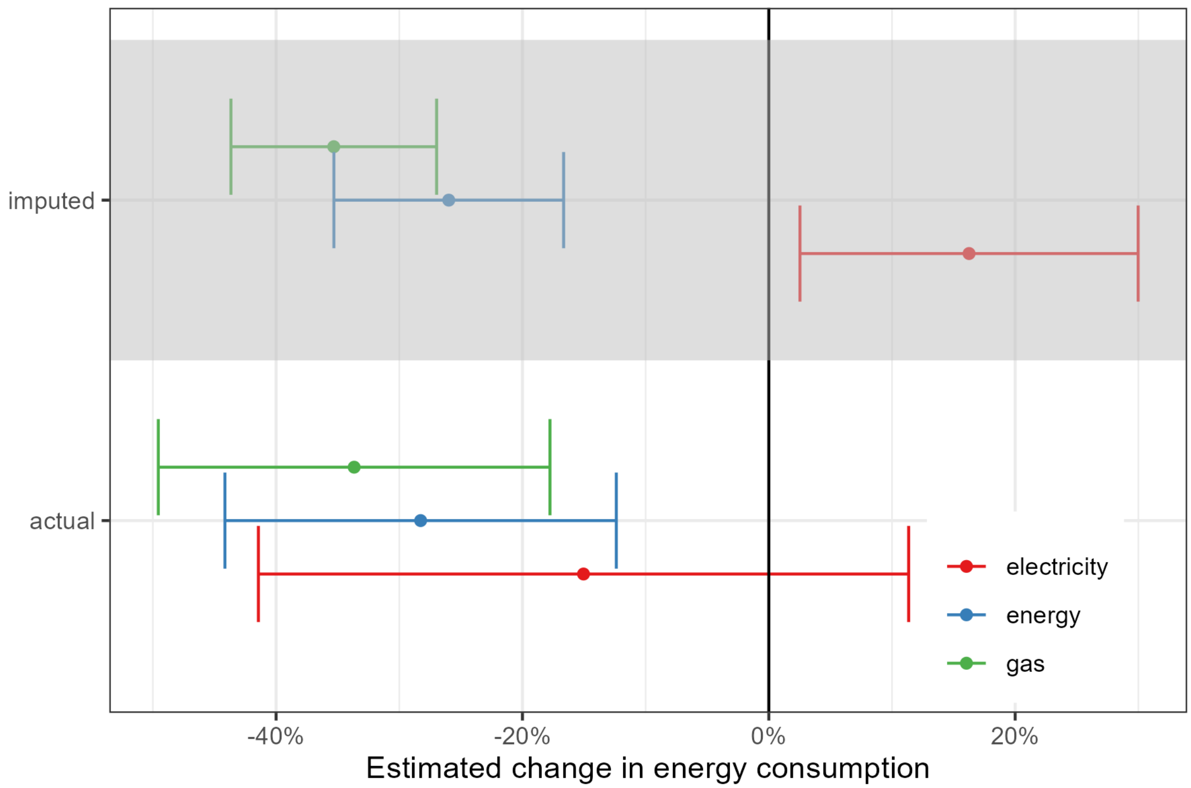
*Notes: This table explores the effect of participating in a residential retrofit program on total energy savings. Specifically, it presents estimates of coefficient $\hat{\beta}$ from Equation (2) with the natural logarithm of total energy consumption as the outcome variable . In Column (1), we include house and month-of-sample fixed effects, while in Column (2) we include house-by-month fixed effects .Standard errors are two-way clustered by house and month-of-sample. ***: 0.01, **: 0.05, *: 0.1.*

Table A4: Regression results in levels

Dependent Variables:	gas	elec	energy
Model:	(1)	(2)	(3)
Variables			
Program participation	0.63***		
	(0.06)		
Program participation		0.20	
		(0.49)	
Program participation			0.50***
			(0.05)
Household	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes
Observations	2,938,572	2,952,422	2,924,674
R^2	0.76	0.54	0.75

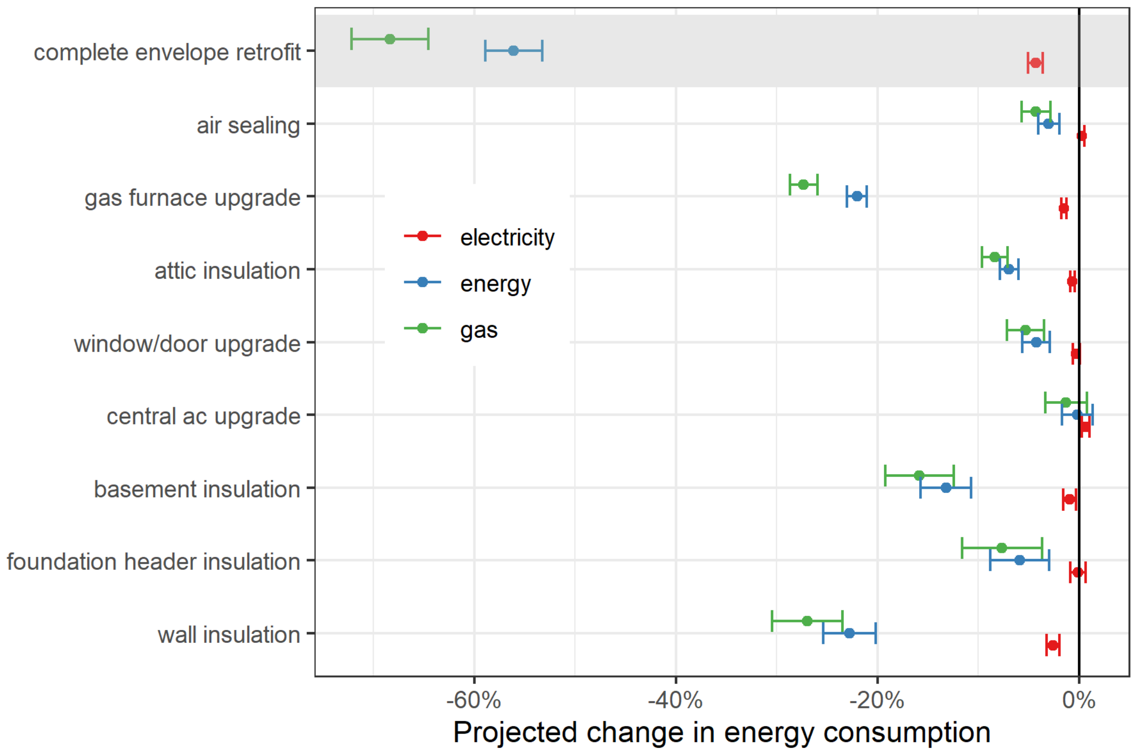
*Notes: This table examines the overall realization rate of energy savings by comparing the predicted and actual energy savings post-retrofit. Specifically, it provides estimates of the coefficient ϕ obtained by estimating Equation (4), representing the proportion of predicted energy savings that are realized. The dependent variable in columns (1)-(3) corresponds to gas, electricity, and total energy (in levels), respectively. Standard errors are two-way clustered by house and month-of-sample. ***: 0.01, **: 0.05, *: 0.1.*

Figure A1: Complete envelope retrofits



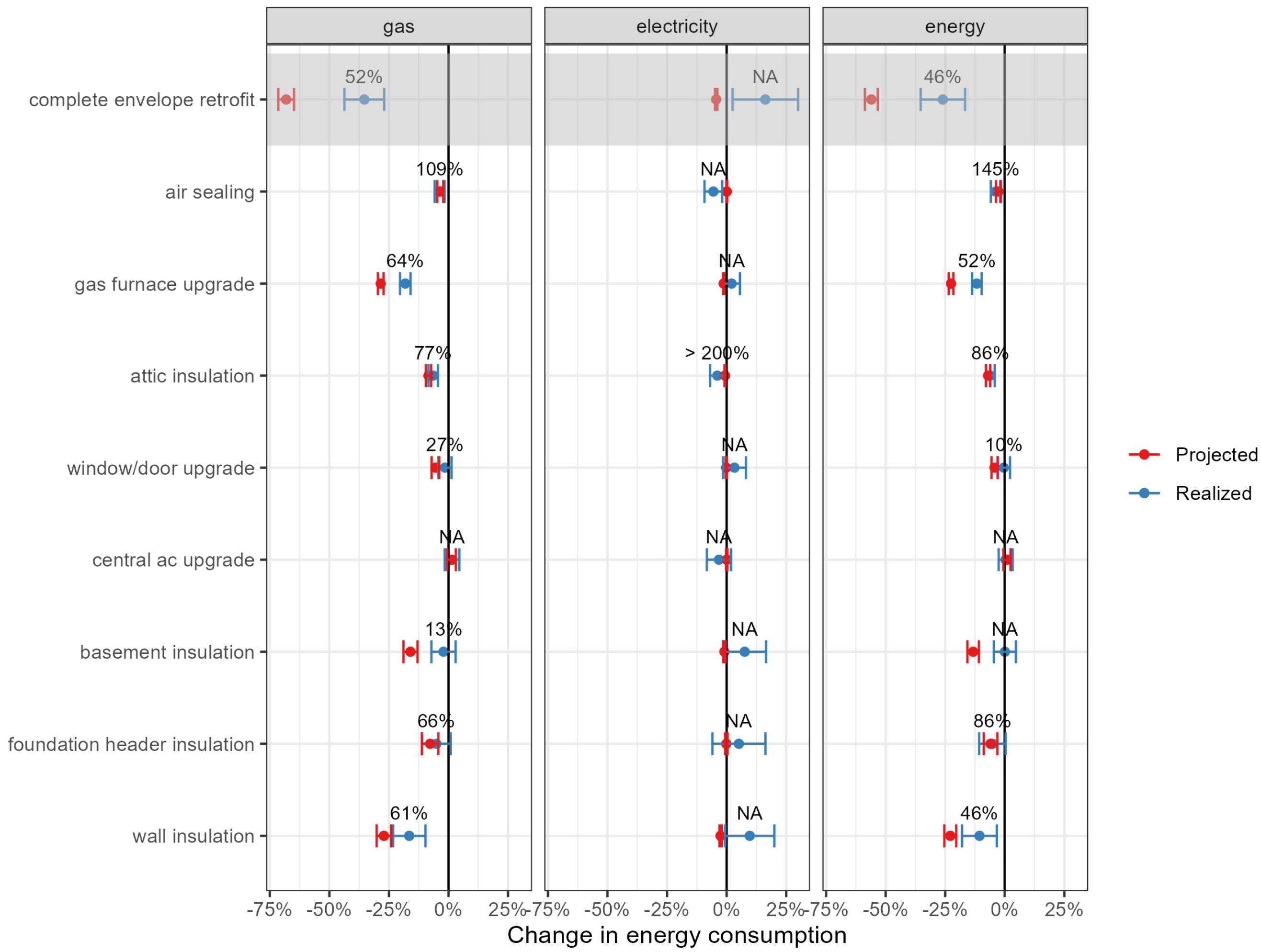
Notes: This figure explores the measure-level savings from estimating Equation (3) using 15 houses that undertook a close to complete envelope retrofit, defined as air sealing, attic insulation, window and/or door upgrades, wall insulation, and either foundation header or basement insulation.The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and month-of-sample.

Figure A2: Projected energy savings



Notes: This figure illustrates projected measure-level energy savings by plotting estimates derived from Equation (5). The estimation process involves a cross-sectional regression of projected total savings, regressed on a vector of dummy variables indicating the adopted measure. Complete envelope retrofits are shaded in grey and are imputed from envelope measures. This imputation involves adding coefficients associated with air sealing, window/door upgrades, and insulation in the attic, basement, foundation header, and walls. The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and month-of-sample.

Figure A3: Measure-specific realization rates for natural gas, electricity and energy



Notes: Notes: This figure examines measure-level realization rates for gas, electricity and total energy, by dividing the measure-specific realized savings estimated in Equation 3 by its projected savings obtained from estimating Equation (5) for gas, electricity and total energy, respectively. Complete envelope retrofits are shaded in grey and are imputed from envelope measures. This imputation involves adding coefficients associated with air sealing, window/door upgrades, and insulation in the attic, basement, foundation header, and walls. The bars represent 95 percent confidence intervals. Standard errors are two-way clustered by house and month-of-sample. Measures with positive realized energy saving point estimates have realization rates denoted as N/A.