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Abstract

Over 50 countries representing three quarters of global CO_2 emissions have pledged to achieve a net-zero carbon economy by 2050, and energy efficiency improvements are a primary contributor in policy scenarios that attain this goal. However, uncertainties remain about the realized effectiveness of energy efficiency programs. This paper provides evidence on the realized savings from Canada's largest residential energy retrofit program. We use utility data from all single-family homes in a mid-sized Canadian city and detailed energy audit records from the EnerGuide for Homes database, which includes modeled predictions of energy savings from retrofit adoptions. The retrofit program reduces natural gas consumption in the average participating home by about 21%, representing 60% of predicted natural gas savings. Whole-envelope retrofits are predicted to reduce natural gas consumption by 67%, but in practice only half of these savings are realized. This underscores the importance of developing new modeling approaches that incorporate house-level utility data, which reflect the outcome of realized rather than predicted occupant behavior, to increase retrofit energy savings and return per subsidy dollar spent.

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1 Introduction

Climate policy scenarios that meet net-zero carbon emission targets consistently emphasize the need for significant reductions in building energy consumption (IEA, 2021; IPCC, 2018). Since over two-thirds of the current building stock will still be operational in 2050, finding effective ways to dramatically reduce emissions in existing buildings is an urgent policy goal among many governments. This urgency 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, 2021). Recognizing this imperative, policymakers worldwide have enacted numerous programs and policies aimed at the building sector, including increasingly stringent energy codes, tax rebates and subsidies for home retrofits such as air sealing, insulation and energy-efficient heating and cooling equipment.

Building engineering models are widely used in these programs to identify the most cost-effective and impactful retrofits to undertake. However, by construction these models embed a number of assumptions about retrofit installation quality and occupant behavior, and recent studies using house-level utility data have identified that modeled predictions of retrofit energy savings fall significantly short of observed reductions (Fowlie et al., 2018; Christensen et al., 2021; Burlig et al., 2020; Chuang et al., 2022). On average, recent U.S. studies suggest that realized improvements in building energy performance are only approximately 60% as large as predicted. This brings up serious concerns from a climate policy perspective, particularly if these shortfalls are also prevalent in programs outside of the U.S., since they imply building retrofit program savings need to nearly double to align with planned energy and GHG reductions.

Despite these concerning outcomes, gaps still remain in our understanding of realized performance for home energy efficiency retrofit programs. This includes few studies evaluating the realized savings of residential energy efficiency investments from outside the U.S. (Giandomenico et al., 2022); a lack of evidence on the long-term persistence of retrofit savings; a dearth of realized savings results based on large-sample, comprehensive "whole envelope retrofit" data including multiple fuels such as electricity and natural gas consumption; and few studies from programs available to the general population rather than income-based or other similar eligibility criteria.

This paper contributes new evidence on each of these gaps. We combine house-level observations from the EnerGuide for Homes (EGH) program and match them to a 10-year history of monthly electricity and natural gas data from all single-family households served by a utility in the Canadian province of Alberta. The utility's population heats their homes almost exclusively with natural gas so that our combined data represent whole-house consumption for a large share of these homes. The EGH database has existed since 1998 and includes detailed house-level data derived from home energy audits, including predicted energy savings for potential energy efficiency investments. It has ratings for approximately 1 million houses, which represents 7% of the current housing stock in Canada. Federal home energy audits and retrofit rebate programs in place today and historically have been available to any Canadian house that submits an application, so that houses across the income spectrum are eligible to participate.

Our data are from the ecoEnergy rebate initiative, a program that was in place in Canada between 2008 and 2011, to assess the electricity and natural gas savings from adopted retrofits and their realization rate compared to engineering predictions. 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 robust to alternative choices of control group, including a control group restricted to homes that are eventually treated, as well as a control group formed by matching on pre-treatment observed variables. 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 retrofits take 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 energy efficiency retrofit program. Most of the energy savings occurred in natural gas consumption, which declined by 21%, whereas electricity use declined by 0%-4%.[1] The individual retrofits generating the largest savings were new furnace adoption and wall insulation, which each reduced natural gas consumption by about 25%. An event study analysis indicates that savings following a retrofit persist for at least a decade.

While these post-retrofit energy savings are considerable, particularly for natural gas, we find that pre-retrofit modeled savings predictions were almost two times higher in most cases. The average realization rate for total energy savings, representing the share of model-predicted savings that actually occurred after a retrofit, was 55%. Realization rates for individual retrofits vary widely: the realization rate for attic insulation, wall insulation and natural gas furnaces is 75%, 35% and 48% respectively, whereas they are statistically insignificant for basement insulation, central air conditioners and new windows and doors. The only measure with higher than predicted energy savings is air sealing, with a natural gas savings realization rate of 164%. However, while air sealing is a popular measure that was undertaken by a majority of houses, both the predicted and realized air sealing savings are very modest with less than a 5% reduction in natural gas and total energy use.

Taken together our results are consistent with evidence that has emerged from the U.S. Home energy retrofits save energy, and these savings persist over the long-term, but they fall significantly short of expected savings. A further cause for concern from a climate policy perspective is that a significant share of the energy savings from retrofits in the ecoEnergy program 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.[2]

This increases the importance of developing new pre-retrofit empirical approaches that improve upon the current status quo and help guide households to adopt retrofits that result in significantly higher energy savings (Christensen et al., 2022). Such an approach will require the development of data-sharing frameworks for utility data, which reflect the outcome of human behavior and occupant decision-making after a retrofit has been adopted. This is a key methodological improvement that can be made to avoid having to incorporate "best guess" assumptions about behavioral parameters 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 structure; Section 3 describes the data we make use of in our analysis; Section 4 presents our empirical approach and robustness checks; and Sections 5 and 6 include our results discussion and conclusion, respectively.

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

[2] Furnaces with efficiencies below 80% have also been phased out since the 1990s.

2 Program description

The ecoEnergy Retrofit Homes (ecoEnergy) program was announced by the Canadian federal government in 2007 and in place until 2011. 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 residential construction in the wake of the 2008 financial crisis (Department of Finance Canada, 2009).[3] It ran until March 2011, 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).[4] Most recently in 2021 Canada launched the Greener Homes program, which has a budget of $2.6 billion and is expected to run until 2028.

Each of these programs has largely followed the same model. To qualify for a grant a homeowner must complete a pre-retrofit audit by a qualified energy auditor. An audit consists of a detailed home inventory that includes house dimensions, orientation, number of windows and doors, furnace, air conditioner and water heater type and model, as well as the results of a blower door test, which measures the air leakage rate of the home envelope. Information from the audit is then entered into modeling software developed and maintained by Natural Resources Canada to support the EnerGuide initiative, which provides an estimate of building energy consumption. Based on the results of the pre-retrofit audit, houses are provided with a list of suggested grant-eligible retrofit options. 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 reimbursements 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 regulations for which upgrades qualify for a grant. In the ecoEnergy program grants were available for heating and cooling system upgrades (e.g., purchasing a more efficient natural gas furnace or air conditioner), building envelope upgrades (e.g., wall insulation, attic insulation, basement insulation), air sealing, and door/window upgrades (Government of Canada, 2009).[5] While retrofit grants were offered for 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 could also decide which upgrades (if any) to undertake.

3 Data

Our analysis is focused on Medicine Hat, a Canadian city in the province of Alberta with approximately 65,000 residents. We combine data from three distinct sources to conduct our analysis. First, house characteristics, recommended retrofits, retrofits undertaken, and predicted consumption savings collected during the first and second energy audits during the ecoEnergy timeframe are from the federal

[3] 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).

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

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

government's EGH database. Some of these variables, such as predicted consumption savings before and after a retrofit, are generated from a simulated building energy consumption software used by federal departments and agencies in Canada (the HOT2000 model).[6] We observe data for 1,729 houses that completed an energy efficiency audit through the EGH program in Medicine Hat between 2008 and 2019.

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

Out of the 1,729 EGH database observations from the Medicine Hat area we were able to match 1,486 to the property assessment data.[7] This data set was then merged with the energy consumption data based on a unique house ID variable, which resulted in a total of 1,475 homes with matched data on retrofits and home assessments, energy consumption, and property information.[8] We also retain energy consumption and property assessment information from houses that are non-participants in the retrofit program. For these non-participant households, we do not observe energy efficiency audit variables. We successfully match property assessment and energy consumption data for 18,460 non-participating homes.

Summary statistics for the data are provided in Table 1. The table shows that the data contain observations from 1,475 houses that participated in the retrofit program, along with 18,460 houses that did not participate. Participant houses undertook a number of energy efficiency retrofits, the most popular of which were air sealing, natural gas furnace upgrades, and attic/ceiling insulation upgrades. Gas, electricity, and total energy consumption are presented in this table as an annual average over the 13 year period we have data, and include both pre- and post-retrofit observations. The table shows that program participants have smaller lot sizes, slightly smaller building sizes, and lower assessment values. As expected, program participants live in homes that are on average a decade older than non-participants' homes. Table 1 also shows that over this period, there is little difference in energy consumption between participating and non-participating houses.

The EnerGuide for houses program undertakes detailed engineering calculations to estimate energy consumption both before and following retrofits. Table 1 shows that both pre- and post-retrofit predictions of energy consumption are higher than actual energy consumption, indicating a potential bias in the engineering models used to predict energy consumption. Comparing pre- and post-retrofit predictions of energy consumption, we can see that the typical participating house was projected to reduce natural gas consumption by about 28% and reduce electricity consumption by about 1.3%. Our analysis is focused on using post-retrofit billing data to determine whether these savings materialized.

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

[7] Failure to match may be due to: (1) incorrectly recorded addresses, (2) missing tax assessment data, and/or (3) some addresses in the EGH database are not within Medicine Hat city boundaries, such that we do not observe utility data for these houses.

[8] Unmatched observations are due to missing energy consumption data.

Table 1: Summary statistics

	Program participants		Non-program participants	
	Mean	SD	Mean	SD
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	147	48
Property Assessment Data				
Total assessed value ($)	277,613	87,795	289,233	123,794
Lot size (square feet)	6,916	3,160	8,925	20,412
Building size (square feet)	1,270	421	1,302	465
Effective year build	1971	18	1981	23
Program Participation Data				
Air sealing	0.82	0.38		
Attic insulation	0.64	0.48		
Walls insulation	0.04	0.20		
Basement insulation	0.13	0.33		
Foundation Header insulation	0.09	0.28		
Windows and Doors upgrades	0.18	0.39		
Central AC	0.13	0.34		
Natural Gas furnace	0.68	0.47		
Predicted pre-retrofit gas consumption (GJ/year)	161	60		
Predicted pre-retrofit electricity consumption (GJ/year)	33.6	1.0		
Predicted pre-retrofit energy consumption (GJ/year)	194	60.2		
Predicted post-retrofit gas consumption (GJ/year)	116	40		
Predicted post-retrofit electricity consumption (GJ/year)	33.1	1.4		
Predicted post-retrofit energy consumption (GJ/year)	149	40		
Total observations	1,475		18,460	

4 Empirical approach

4.1 Panel fixed effects analysis

To estimate the overall impact of participation in the energy efficiency retrofit program, we regress the natural logarithm of monthly energy consumption ($log(e_{iym})$) on an indicator (retrofit_{iym}) that takes on a value of 1 if a house has completed an energy efficiency retrofit under the ecoEnergy program, and zero otherwise. Our main specification includes house fixed effects as well as month-of-sample fixed effects (e.g., February 2017), and takes the following form:

$$log(e_{iym}) = \beta \text{retrofit}_{iym} + \alpha_i + \gamma_{ym} + \epsilon_{iym}, \tag{1}$$

where i indexes houses, y indexes year, and m indexes month. In all cases, we two-way cluster standard errors on house as well as month-of-sample.[9]

In this approach, house fixed effects control for time-invariant characteristics of homes, such as size or orientation, as well as fixed occupant characteristics, such as family size, political views, or environmental attitudes. Year-month fixed effects control for time-variant conditions that affect all houses equivalently in a given 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 quasi-experimental estimates in Fowlie et al. (2018), who evaluate a low-income home retrofit program in Michigan.[10]

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 participation in the energy efficiency retrofit program is not systematically related to other drivers of home energy consumption (conditional on observable covariates). 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.[11] 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 (e.g., environmental attitudes) using house fixed effects, 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). Furnace vintage may also interact with time-varying house or local characteristics that are correlated with program participation (e.g. cold snaps in old homes or a negative income shock). Another possibility is that houses who intend to sell their

[9] In all our specifications we drop data for dates between the pre- and post-retrofit audit for each house.

[10] Chuang et al. (2022) and Fowlie et al. (2018) include house-by-month fixed effects. Using house by month fixed effects does not affect our estimates, as shown in Appendix Table ??.

[11] 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.

homes in the near future might take advantage of the this 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 any energy efficient 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). As described in more detail in Section 4.2, we leverage our highly detailed house-level data, including furnace model and type, to address this self-selection by constructing five different matched control groups from different subsamples of houses who either never participated or have yet to participate in the program.

4.1.1 Event study and staggered adoption

Another feature of our data is the timeframe over which we observe houses following a retrofit: up to 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. To determine the persistence of energy efficiency retrofits, we use an event study approach, in which we interact the retrofit dummy variable in Equation (1) with a time-to-treatment variable:

$$log(e_{iy}) = \sum_{\substack{h=-5 \\ h\neq -1}}^{h=11} \beta_h \text{retrofit}_{iym} \mathbf{1}[y - D_i = h] + \alpha_i + \gamma_y + \epsilon_{iy}. \tag{2}$$

In the event study specification, we aggregate aggregate the monthly energy consumption data to calendar year and estimate a separate coefficient associated with leads and lags of a retrofit (the index h), from up to five years before and 11 years following a retrofit.[12]. The variable D_i in Equation (2) is the year of retrofit for house i, so that h measures number of years before or after a retrofit occurred in a given house i. 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 treatment effects, can lead to bias in the standard two-way fixed effects estimator (such as Equation (1)). This bias derives from comparing newly-treated units with previously-treated units. Sun and Abraham (2021) propose an alternative estimator for this setting, which avoids comparing units treated at different times. To account for this we augment our event study specification with this approach to estimate the treatment effect of residential energy retrofits, and compare the savings over time from this modified estimator to the standard two-way fixed effects estimator.

[12] These are the maximum window we observe in the data.

4.1.2 Measure-level savings estimates

In addition to estimating the overall savings from home retrofits as described above, we also use detailed program data to estimate measure-specific energy savings. The measure-specific 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. Measures are indexed by j and the complete set of measures is indicated by $\mathbb{J}$:

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

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 measures is not possible. However, past literature suggests interaction effects between retrofit measures are likely have second-order effects on energy consumption (Chidiac et al., 2011).

4.2 Matched sample analysis

To help address self-selection into the retrofit rebate program, we supplement the analysis described above using a matching approach. We construct several different matched control groups that serve as counterfactuals to the program participants. 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 five different approaches. First, we match on pre-treatment energy consumption.[13] 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.

Third, 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.[14] 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. Furnace type includes four categories: continuous

[13] 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.

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

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 in Canada 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 furnace type in the sub-sample of houses for which we observe furnace information (the 1,475 houses that completed a retrofit). 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.

In our fourth matched sample we identify a control group using both building characteristics and pre-treatment energy consumption variables to estimate propensity scores. Finally, we combine building characteristics, the pre-treatment energy consumption variables and furnace type to estimate propensity scores in the ever-treated sample of homes. We use nearest neighbour matching based on the propensity to create both of these samples.

In each case, we estimate Equation (1) 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 counterfactual 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.

4.3 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 actually occur following a retrofit. 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*$_j = \beta_j / \tau_j$.

5 Results

5.1 Graphical analysis

Figure 1 illustrates long run trends in electricity and natural gas consumption for treated and never-treated houses from before and after participation in the energy-efficiency retrofit program. The bottom panel shows that the years 2007 and most of 2008 were prior to program initiation.[15] The first retrofit occurred in late 2008, and these continued over the following three and a half years, with all participating houses completing retrofits by 2012. Prior to the beginning of the retrofit program (in 2007-08), electricity and gas exhibited similar (annual) trends. houses that would later participate in the retrofit program had higher natural gas consumption and slightly higher electricity consumption than non-participating houses. The figure suggests that electricity consumption declined slightly as a result of the retrofits, and that natural gas consumption in treated houses fell considerably relative to control houses. While the houses that chose to participate in retrofits were initially consuming about 5% more natural gas than non-participant houses, after the retrofits they consumed about 3-4% less natural gas than non-participating houses. The change occurred during the retrofit program roll-out (shown in the lower panel of Figure 1) and appears to be stable following completion of the roll-out.

[15] Less than 1% of participants had retrofitted by the end of 2008.

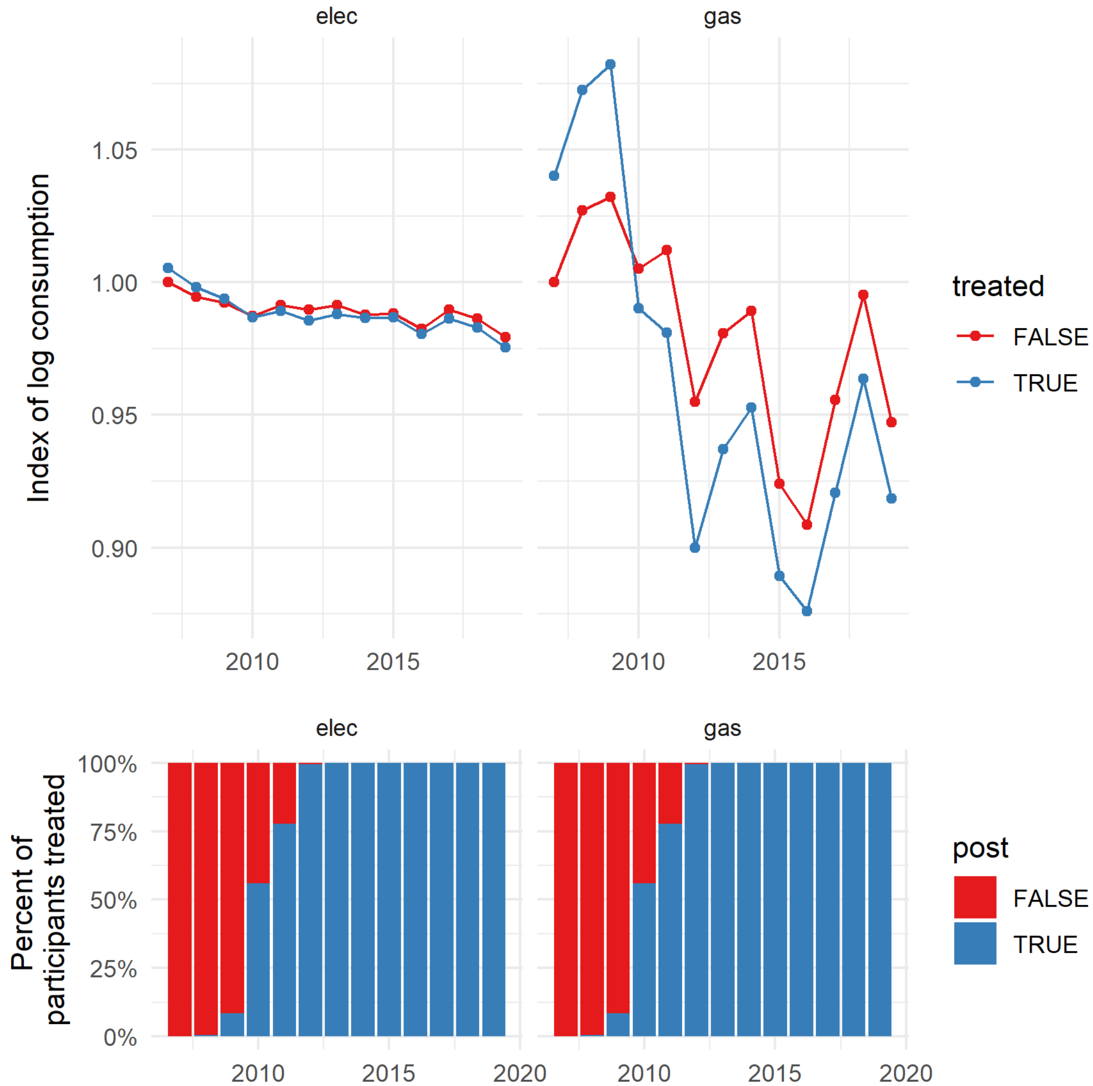

Figure 1: Long-run trends in electricity and natural gas consumption in treated and untreated houses.

Note: The data are raw and do not control for annual weather differences.

5.2 Panel fixed effects analysis

Table 2 shows estimates of $\hat{\beta}$ from Equation (1) as described above. Columns (1) to (3) show estimates of $\hat{\beta}$ using the larger sample that considers the never-treated houses in Medicine Hat as the control group while columns (4) to (6) reflect estimates of $\hat{\beta}$ using only houses who participated in the ecoEnergy program (hereafter the ever-treated sample). This sample keeps treated homes until 2011. Houses that renovate in 2012 are the implicit control group (they are eventually treated, but never treated within our window). The results from both samples show that participation in an energy efficiency retrofit reduced house energy consumption by 16%. Natural gas consumption fell by 21% and 22% in the never-treated and ever-treated samples, respectively. While the all-energy and natural gas estimates are robust and highly statistically significant across both samples, the electricity estimates are more variable. Electricity consumption fell by a statistically significant 4% in the never-treated sample and by a statistically insignificant 2% in the ever-treated sample.

The estimates provide strong evidence that natural gas consumption fell by a considerable amount following energy efficiency retrofits. The fact that natural gas consumption fell by a much 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.

Table 2: Main panel regression

	Including never treated houses			Only treated houses		
	log(gas) (1)	log(elec) (2)	log(energy) (3)	log(gas) (4)	log(elec) (5)	log(energy) (6)
Program participation	-0.21***	-0.04***	-0.16***	-0.22***	0.02	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Fixed-effects						
Household	Yes	Yes	Yes	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,917,877	2,953,814	2,926,831	77,732	78,521	77,488
R^2	0.85	0.47	0.79	0.84	0.54	0.81
Within R^2	0.00	8.68×10^{-5}	0.00	0.02	0.00	0.01

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Measure-level savings estimates from Equation (3) are presented in Figure 2. In the right panel, we show the number of energy efficiency measures adopted in the data set, and highlight that 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 available upgrades could increase furnace efficiency by over 30 percentage points.[16] 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 and basement insulation had no impact on natural gas consumption. This finding is similar to other studies, and suggests that window and door upgrades are ineffective at reducing energy consumption (Giandomenico et al., 2022). For electricity, we find no measures that substantially reduce consumption. We do find a statistically significant reduction in electricity consumption associated with air sealing, but the measure only results in savings of about 4%. 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 2, with most households selecting one or two upgrades out of the eight measures considered. Because of recent 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 households undertaking complete envelope retrofits in our data, and project the effect of complete envelope retrofits as the sum of coefficients on all of these measures.[17]

5.3 Event study and staggered adoption

Prior results on the savings from retrofit programs are estimated using a standard two-way fixed effects (TWFE) estimator, similar to Liang et al. (2018); Chuang et al. (2022); Fowlie et al. (2018), and others. Recent literature points to bias in the TWFE estimator in contexts where treatment effects are dynamic and adoption is staggered, which plausibly applies to our context. We thus use the Sun and Abraham (2021) estimator to estimate treatment effects as a complement to our main analysis. We show results for both the Sun and Abraham (2021) and the typical TWFE estimator in the never-treated sample after estimating Equation (2), the event study specification. The results are shown in Figure 3.[18]

[16] 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

[17] Specifically, $\hat{\beta}_{completeenvelope} = \hat{\beta}_{atticinsulation} + \hat{\beta}_{window/doorupgrade} + \hat{\beta}_{basementinsulation} + \hat{\beta}_{foundationinsulation} + \hat{\beta}_{wallinsulation} + \hat{\beta}_{airsealing}$.

[18] We also estimate equation (1) for the ever-treated sample of houses that completed a retrofit using the Sun and Abraham (2021) estimator. Results for total energy use slightly increased by 1 percentage point compared to the TWFE estimator. We further match houses from the treatment group with the control group using propensity scores on pre-treatment energy consumption, building characteristics, and an exact match on pre-treatment furnace type. The results in these specifications do not change meaningfully compared to those reported in Figure 3.

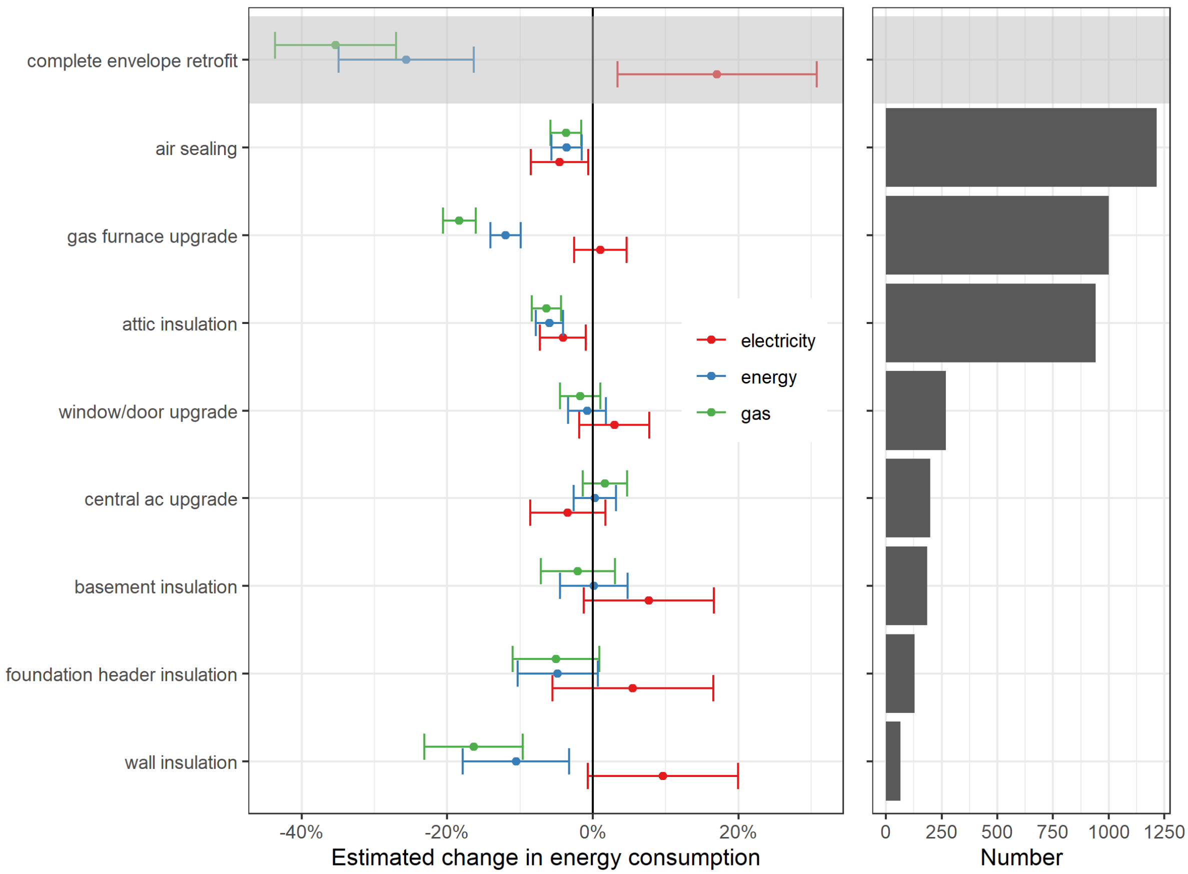

Figure 2: Estimated energy savings

Notes: The left panel shows point estimates and 95% confidence intervals for estimates of energy savings from energy efficiency retrofit measures, based on estimation of Equation (3). The right panel shows the number of each type of retrofit measure observed in our data. Complete envelope retrofits are shaded grey, as they are imputed from envelope measures undertaken by adding coefficients associated with air sealing, window/door upgrades, and attic, basement, foundation header, and wall insulation.

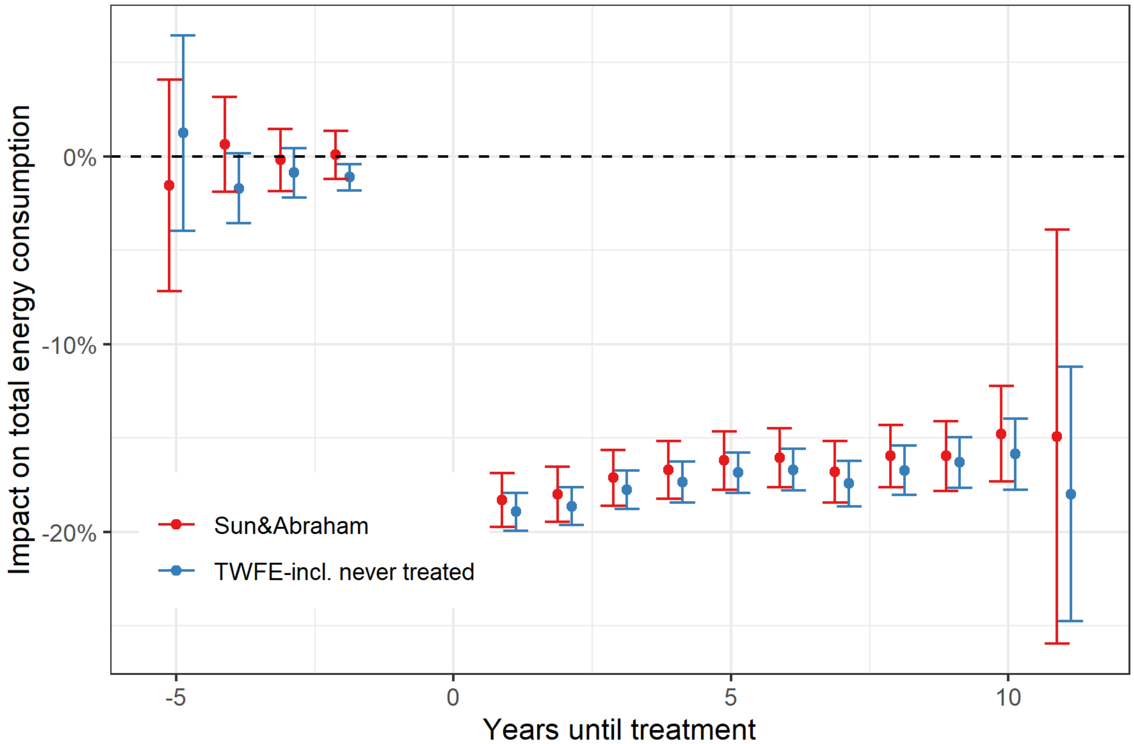

Figure 3: Event study plot

Several findings emerge from the event study plot. First, there are no obvious pre-trends in energy consumption. This indicates that the control houses are following the treated house energy consumption patterns prior to the retrofit, and suggests that they may serve as an appropriate control unit for treated houses. Second, energy consumption falls substantially, by between 15 and 20%, following the retrofit, confirming analysis above suggesting a large impact of retrofits on energy consumption. Third, the savings in home energy consumption following a retrofit persist for at least a decade following the retrofit. We observe some attenuation in the effect of retrofits on energy consumption over time, 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 Sun and Abraham (2021) estimator are very similar, 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 *are* 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.

5.4 Matching analysis and implications for selection into treatment

Table 3 reports estimates of $\hat{\beta}$ from estimating Equation (1) while restricting observations to treated and matched control units as described in Section 4.2. The table reports results for total energy consumption, though the patterns are very similar when we disaggregate between natural gas and electricity. For comparison column (1) replicates the estimates reported in column (3) of Table 2, in which all treated and control observations are included, and finds that participation in the retrofit program caused a reduction in energy consumption of 16%. In column (2), the sample is restricted to include treated houses that are matched on pre-treatment energy consumption to houses in the never-treated sample. The estimate of $\hat{\beta}$ decreases slightly to 15%. The estimate in column (3) is based on matching treated houses with control houses in the never-treated sample based on building characteristics and the estimated $\hat{\beta}$ remains at 15%. In column (4) we match houses from the treatment group with the ever-treated control group based on furnace type using an exact match with replacement, and the results are the same as the main analysis (column (1)). In column (5) we match treatment houses based on both building characteristics and pre-treatment energy consumption to controls in the never-treated sample. The point estimate falls slightly to 14%. Finally, in column (6) we match houses from the treatment group with the ever-treated control group using propensity scores on pre-treatment energy consumption and building characteristics, with an exact match on pre-treatment furnace. The estimated savings increase slightly to 17%.

Table 3: Panel data analysis with matching

	log(energy)					
	(1)	(2)	(3)	(4)	(5)	(6)
Program participation	-0.16***	-0.15***	-0.15***	-0.16***	-0.14***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed-effects						
Household	Yes	Yes	Yes	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes	Yes	Yes	Yes
Matching variables						
Pre-treatment consumption	No	Yes	No	No	Yes	Yes
Building characteristics	No	No	Yes	No	Yes	Yes
Furnace type	No	No	No	Yes	No	Yes
Fit statistics						
Observations	2,926,831	449,898	450,240	76,795	445,506	65,913
R^2	0.79	0.81	0.81	0.81	0.81	0.82
Within R^2	0.00	0.01	0.01	0.01	0.01	0.01

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Two facts are notable from the matching analysis. First, estimates of $\hat{\beta}$ using a number of different control groups matched-on-observables with the treated group result in very similar energy savings estimates compared to the analysis using the full set of never-treated observations. While we can't completely eliminate "free-riders" concerns due to other potential selection channels, our matching approach suggests that accounting for several plausible channels of selection into treatment negligibly changes the estimated savings results.[19]

Second, the treatment effect is slightly larger using the matched control group based on building characteristics, pre-treatment energy consumption and furnace type. This suggests that some of the houses that participated in the retrofit program may be infra-marginal and would have conducted the retrofit even without the program. However, our estimates are qualitatively similar and statistically indistinguishable to the unmatched analysis (17% energy savings in the analysis with a matched sample compared to 16% using the full control group). While our matching-on-observables approach is not able to perfectly control for self-selection into participation, this suggests that infra-marginal participation in the retrofit program may not be as large as in other contexts (Grosche and Vance, 2009; Boomhower and Davis, 2014). Given that our matching analysis indicates the estimates for total energy and natural gas savings are highly stable across all control groups, including our original never-treated estimates, we use specification (1) in our analysis going forward.

5.5 Realization rates

5.5.1 Overall realization rates

We estimate an aggregate realization rate by regressing energy consumption on a treatment dummy interacted with projected energy savings, as in Equation (4). As shown in Table 4, we find a realization rate for natural gas of 61%. Our realization rate for electricity is around 56%, 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.[20]

5.5.2 Measure-specific realization rates

Our procedure to estimate measure-specific realization rates occurs in two steps, as described in Section 4.3. 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). Figure 4 plots 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 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 2 by the measure-specific projected energy savings. The results are presented in Figure 5 with separate panels for natural gas, electricity and all-energy savings. We indicate measure-specific realization rates in percentage form above each measure in the Figure. For natural gas the highest realization rates are observed for air sealing (86% realization rate), furnaces (67% realization rate), and attic insulation (76% realization rate). Window and door upgrades and basement insulation have the

[19]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.

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

Table 4: Realization rates

	log(gas)	log(elec)	log(energy)
	(1)	(2)	(3)
Gas realization rate	0.61***		
	(0.02)		
Electricity realization rate		0.56	
		(0.47)	
Total energy realization rate			0.56***
			(0.03)
Fixed-effects			
Household	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes
Fit statistics			
Observations	2,915,228	2,951,064	2,924,122
R^2	0.85	0.47	0.8
Within R^2	0.00	1.05×10^{-5}	0.00

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

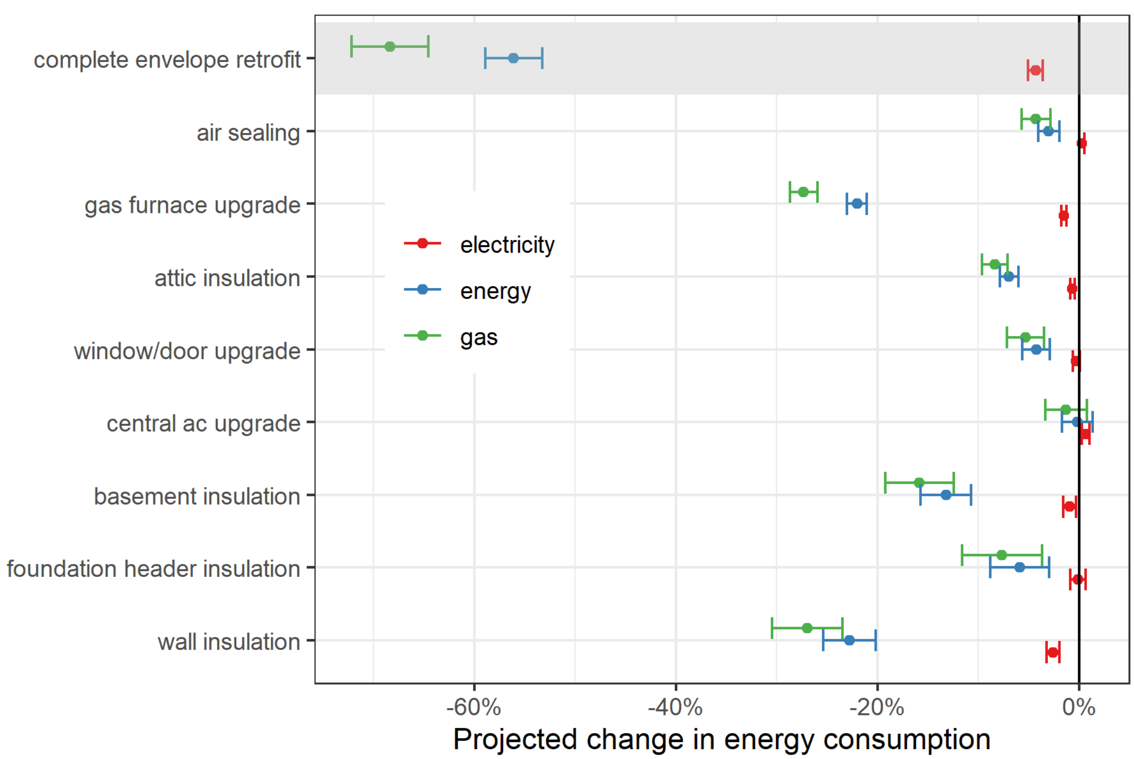

Figure 4: Measure-specific energy saving projections

lowest natural gas realization rates (33% and 13%, respectively). Most of the electricity realization rates are statistically insignificant with the exception of attic insulation. Although the realized electricity use reduction is less than 5%, this is more than double the model-predicted savings. The total energy use realization rates follow a similar pattern as those observed for natural gas. We find a realization rate of above 100% for air sealing measures (suggesting air sealing saves more energy than predicted), 86% for attic insulation, and 55% for new furnaces.

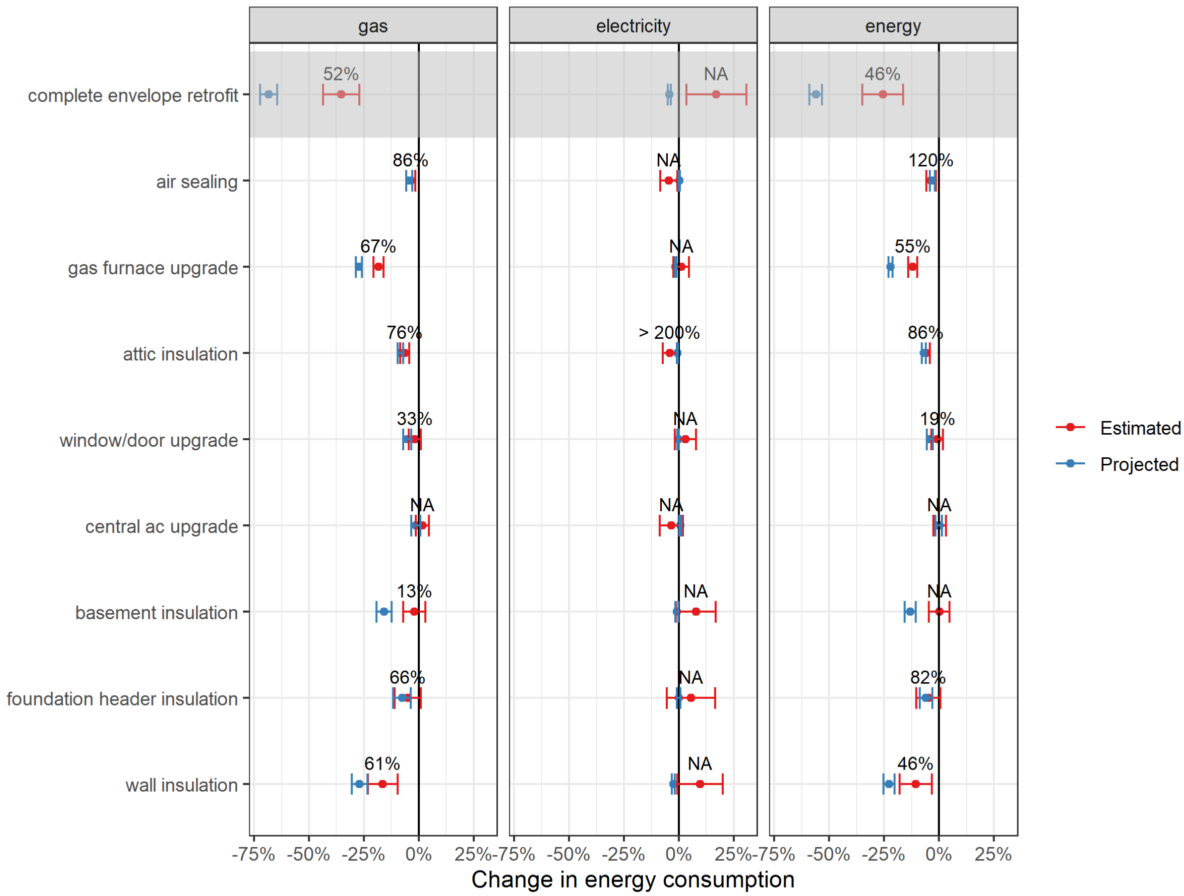

Figure 5: Measure specific realization rates

6 Conclusion

In this paper we use energy consumption data from all single family homes in a mid-sized Canadian city spanning 10 years to examine the energy savings and realization rates from Canada's largest energy efficiency retrofit program. We observe all homes in the city that participated in the ecoEnergy retrofit program that was in place between 2008 and 2011. On average, the program reduced participants' total energy consumption by about 15%. These savings persist throughout the timeframe we observe these homes, that is up to a decade after a home is retrofit. We find that the majority of this reduction is driven by natural gas, where consumption fell by 21%, compared to a 0%-4% for electricity. The average realization rate for total energy savings is 56%. In contrast to the natural gas and all-energy estimates, the electricity savings are not robust and become insignificant across different matching specifications.

Our rich data enable us to estimate measure-by-measure realization rates, including for specific HVAC equipment types, namely natural gas furnaces and Energy Star air-conditioners. We find that all measures, except for air sealing, deliver lower than predicted energy savings. In particular, 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 only declined by about 33%. At the measure-level we find that rebate programs for natural gas furnaces upgrades and wall insulation are the most promising renovations when it comes to energy savings and realization rates, on average.

These results are timely and important because analyzing utility consumption data is the only way to reliably assess the realized impact of residential energy efficiency programs, and thereby gauge progress towards net zero goals. Meeting mid-century climate targets will require most existing homes to be net-zero consumer of fossil fuels, whereas much of the current literature evaluating home retrofit performance focuses on programs available to low-income houses (Fowlie et al., 2018; Christensen et al., 2021; Hancevic and Sandoval, 2022). Our findings that most program savings arise from natural gas furnace upgrades are therefore concerning, since combustion technology is likely to play an increasingly limited role in the coming decades. Implementing new empirical methods and data-sharing partnerships incorporating utility data to accurately predict and magnify energy savings from home energy efficiency are essential next steps in the goal of meeting building-sector climate targets.

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Appendix

Additional results, ever-treated sample

Dependent Variables:	log(gas)	log(elec)	log(energy)
Model:	(1)	(2)	(3)
Variables			
ATT	-0.2071***	0.0068	-0.1759***
	(0.0233)	(0.0432)	(0.0223)
Fixed-effects			
id	Yes	Yes	Yes
consyear	Yes	Yes	Yes
Fit statistics			
Observations	5,135	5,135	5,135
R^2	0.89748	0.85984	0.90203
Within R^2	0.13934	0.00078	0.11731

Clustered (id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Additional results, matched samples

Dependent Variables:	log(gas)	log(elec)	log(energy)
Model:	(1)	(2)	(3)
Variables			
treated_postTRUE	-0.2326***	0.0088	-0.1649***
	(0.0132)	(0.0180)	(0.0137)
Fixed-effects			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
Fit statistics			
Observations	66,058	66,789	65,865
R^2	0.84239	0.54977	0.81794
Within R^2	0.01584	2.1×10^{-5}	0.01244

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Regression with house-month fixed effects

Dependent Variable:	log(energy)	
Model:	(1)	(2)
Variables		
treated_postTRUE	-0.1577***	-0.1579***
	(0.0063)	(0.0063)
Fixed-effects		
id	Yes	
cons_date	Yes	Yes
id-consmonth		Yes
Fit statistics		
Observations	2,926,828	2,926,828
R^2	0.79168	0.84947
Within R^2	0.00269	0.00371

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Regression results in levels

Dependent Variables:	gas	elec	energy
Model:	(1)	(2)	(3)
Variables			
as.numeric(treated_post) × delta_gas_lev	0.6308***		
	(0.0627)		
as.numeric(treated_post) × delta_elec_lev		0.2011	
		(0.4944)	
as.numeric(treated_post) × delta_energy_lev			0.5045***
			(0.0528)
Fixed-effects			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
Fit statistics			
Observations	2,938,572	2,952,422	2,924,674
R^2	0.75884	0.53795	0.75339
Within R^2	0.00381	2.37×10^{-6}	0.00348

Clustered (id & cons_date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*