Estimates of long-run energy savings and realization rates from a large household energy efficiency retrofit program

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July 4, 2022

Abstract

Abstract goes here.

1 Introduction

Introduction goes here.

2 Program description

This paper evaluates the EcoEnergy Retrofit Homes (EERH) program, which was announced in 2007 and was in place until 2011. EERH 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 face of the 2008-09 financial crisis (Department of Finance Canada, 2009).[1] It ran until March 2011, when its budget was exhausted.

EERH is one iteration in a line of similar residential retrofit programs in Canada. In 2003, the federal government launched the $73 million EnerGuide for Houses Retrofit Incentive, as part of the 2002 Climate Change Plan for Canada (Government of Canada, 2002).[2] This program was eliminated upon the change of federal government in 2006 and later replaced with the EcoEnergy Retrofit Homes program, which is the subject of this paper. In 2021, government launched the Greener Homes program, which has a budget of $2.6 billion and is expected to run until 2028.

While some details associated with the different iterations differ from one another, the programs largely follow the same model. In each case, to qualify for a grant, a homeowner is required to complete a pre-retrofit audit by a qualified auditor. Audits consist of a detailed home inventory, which measures home dimensions, orientation, windows and doors, and equipment, as well as a blower door test,

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[1]During part of this period, households 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).

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

which measures air leakage rates. Information from the audit is input into building simulation software developed by Natural Resources Canada called HOT2000[3], which estimates building energy consumption. Based on the results of the pre-retrofit audit, households are provided with a list of grant-qualifying retrofit options. Different iterations of the program have different rules for which upgrades qualify for a grant. In the EERH program under review, grants were available for heating and cooling system upgrades (e.g., purchasing a more efficient natural gas furnace), building envelope upgrades (e.g., adding wall insulation, adding attic insulation, basement insulation), air sealing, and door/window upgrades (Government of Canada, 2009).[4] While grants were offered for different upgrades in different iterations of the program, in each case, the total grant for an individual household was limited to $5,000 (although most households receive less than $5,000). Households decide which upgrades to make to their home based on the audit report, and undertake the upgrades. Within 18 months of the pre-retrofit audit, to qualify for the grant, households are required to undertake a post-retrofit audit, to confirm upgrades.

3 Data

We use data from three sources to conduct the analysis. First, we use program data for the EcoEnergy Homes program as well as energy assessment data from EnergyGuide for Homes. Second, we use energy billing data. Third, we use municipal tax assessment data.

The program data is provided by Natural Resources Canada. The data includes all households in Medicine Hat that obtained an energy efficiency audit through the EnerGuide for Homes program. The EnerGuide for homes program is designed to provide a detailed assessment of a home's current energy consumption and to model impacts of energy upgrades on potential energy consumption. Homes go through an in-person audit by an energy efficiency auditor, which includes a physical assessment of the home as well as a blower-door test. Our data includes home measurements and modeled energy consumption.

The program data also includes a record of energy efficiency upgrades that were performed by the household in response to the energy efficiency assessment. In addition, the program data includes a prospective assessment of ex ante expectations of energy savings associated with the suite of upgrades that were undertaken by the homeowner.

The energy consumption data was provided by the City of Medicine Hat, and includes monthly billing data for natural gas and electricity for all homes in the municipality from 2007 to 2019. The energy consumption data was merged with the program participation data based on address matching. For estimating the effect of participation in the EERH program on energy consumption, we drop observations of energy consumption in the period between the pre-retrofit and post-retrofit audit. We also drop households with zero recorded natural gas or electricity consumption.

Should explain how successful the matching was (how many observations were dropped because we could not address match).

The tax assessment data was provided by the City of Medicine Hat, and includes information on the

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

[4]In the 2006 version of the program, grants were performance-based, depending on the improvement in home rating achieved. In the 2021 version of the program, grants are reserved for certain specified upgrades, with natural gas furnace upgrades no longer qualifying for grants.

building type, size, and vintage as well as information on which neighbourhood the building is located in and an assessment of the building's value. The tax assessment data was merged with the program participation data based on address matching.

Summary statistics for the data are provided in Table 1. The table shows that the data contain observations of 1525 households that participated in the retrofit program, along with 20204 houses that did not participate. Participant households undertook a number of energy efficiency retrofits, the most popular of which were air sealing, natural gas furnace upgrades, and attic 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 over this period, there is little difference in energy consumption between participating and non-participating households. As described, 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 projections 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 household 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. The summary statistics can also be used to compare building characteristics of participating and non-participating houses. Participating households have lower assessed value, smaller lot sizes (and similar building structure size), and are built earlier compared to non-participating households.

Table 1: Summary statistics

participant		No			Yes	
Variable	N	Mean	SD	N	Mean	SD
air_sealing	20404	0	0	1525	0.824	0.381
ceiling_insulation	20404	0	0	1525	0.643	0.479
walls_insulation	20404	0	0	1525	0.045	0.206
bsmt_insulation	20404	0	0	1525	0.122	0.327
fnd_header	20404	0	0	1525	0.085	0.278
windowsand_doors	20404	0	0	1525	0.18	0.385
central_ac	20404	0	0	1525	0.132	0.339
natural_gas_furnace	20404	0	0	1525	0.674	0.469
actual_gas_gj_per_yr	20404	113.039	42.625	1525	113.158	37.558
actual_elec_gj_per_yr	20404	30.428	13.07	1525	30.872	12.126
actual_energy_gj_per_yr	20404	143.444	50.002	1525	144.123	44.766
predicted_preretrofit_gas_gj_per_yr	0	NaN		1525	161.003	60.61
predicted_preretrofit_elec_gj_per_yr	0	NaN		1525	33.614	1.143
predicted_preretrofit_energy_gj_per_yr	0	NaN		1525	194.617	61.223
predicted_postretrofit_gas_gj_per_yr	0	NaN		1525	116.048	40.281
predicted_postretrofit_elec_gj_per_yr	0	NaN		1525	33.158	1.429
predicted_postretrofit_energy_gj_per_yr	0	NaN		1525	149.206	40.537
TotalAssesmentValue	18460	289232.966	123794.04	1475	277612.814	87795.463
LotSize	18460	829.15	1896.374	1475	642.524	293.614
BuildingSize	18460	120.952	43.224	1475	118.009	39.125
EffectiveYearBuild	18460	1980.76	23.387	1475	1970.906	18.1

4 Empirical approach

4.1 Panel fixed effects analysis

To estimate the overall impact of participation in the energy efficiency retrofit program, we use a panel fixed effects approach and 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 household has completed an energy efficiency retrofit under the EcoEnergy Houses program, and zero otherwise. Our main specification includes household 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 households y indexes year, and m indexes month. In all cases, we cluster standard errors on both household as well as month-of-sample.

In this approach, household fixed effects control for time-invariant characteristics of homes in the data set, such as size or orientation, as well as fixed occupant characteristics, such as family size, political orientation, or environmental attitudes. Year-month fixed effects control for time-variant conditions that affect all households equivalently, such as weather (all households 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 Phoenix. It is also similar to the quasi-experimental estimates in Fowlie et al. (2018), who evaluate a low-income home retrofit program in Michigan.[5]

The coefficient $\hat{\beta}$ that is estimated in the regression analysis is an estimate of the effect of retrofit program participation on energy consumption. The coefficient will identify the true effect of program participation on energy consumption when the so-called "parallel trends" assumption holds; that is, when the non-participant households provide a good counterfactual for energy consumption of the participating households had they not undergone the energy efficiency retrofit. The key potential violation of this assumption occurs because, as in Liang et al. (2018) and Chuang et al. (2022) and other similar studies, households self-select into program participation. While we control for time-invariant characteristics that are correlated with participation, such as environmental attitudes, using household fixed effects, there may be house-specific time-varying covariates that determine retrofit program participation, which we cannot observe. For example, households with an old furnace may be more likely to participate in the program, since the value of program participation is likely higher for these households (Rivers and Shiell, 2016). However, these "inframarginal" households would have been more likely to replace their furnace anyway, given that it is old. In this case, the estimated $\hat{\beta}$ from the regression will be biased towards larger energy savings than actually occurred (Boomhower and Davis, 2014).

One of the features of the data we use in this study is that we have long-term observations of households following energy efficiency retrofits, allowing us to observe houses for over 10 years following retrofits. This enables us to determine whether the energy savings associated with home energy retrofits

[5] 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 A1.

are persistent, or if they decay after adoption, relative to the control group. Decay could result from physical degredation 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 the energy consumption data annually, 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 (these are the maximum window we observe in the data). The variable D_i in Equation (2) is the year of retrofit for household i. As is standard, we normalize the estimates by dropping the indicator variable for the year prior to retrofit.

Think about other potential issues related to identification. Is this infra-marginal issue explained well enough here?

In addition to estimating the overall savings from home retrofits, we also use the 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 in 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.

4.2 Matched sample analysis

To help address self-selection into participation, we supplement the analysis described above using a matching approach, as in Chuang et al. (2022). In this approach, we construct a matched control group that serves as a counterfactual to the program participants. We draw the matched control group from the full set of control households, using three approaches. First, we match on pre-treatment energy consumption.[6] For each household, 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 household from the full control group using propensity scores

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

constructed from these six variables. Second, we construct a control group using non-outcome variables, which we observe in the tax assessment data. These variables include building size, building age, building assessed value, neighbourhood, building type, and customer type. Using these variables, we again construct a control group using nearest-neighbour matching based on propensity scores. Third, we construct a matched control group using both building characteristics as well as pre-treatment energy consumption variables to estimate propensity scores, again using nearest neighbour marching.

In each case, we estimate Equation (1) using the samples of control and treated households produced by the matching approaches described above. To the extent that our matching variables are correlated with unobserved predictors of counterfactual energy consumption in the treated period (e.g., furnace age), 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 are unlikely to fully account for unobserved time-varying determinants of retrofit program participation, and so we expect our estimates of $\hat{\beta}$ to over-predict energy savings from program participation.

Should we perhaps use a theoretical model to explain better why we think that we will capture some infra-marginal households?

4.3 Accounting for staggered adoption

Adoption of retrofits occurs over a number of years in the data, and so reflects an example of a "staggered" difference-in-difference research design. 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)). 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 newly-treated units with previously-treated units. We use both of these approaches to estimate the treatment effect of residential energy retrofits using our data, and compare these modified estimators to the standard two-way fixed effects estimator.

4.4 Realization rates

We use data on predicted energy consumption before and after rebates, along with actual energy consumption, to measure *realization rates*. The realization rate is the proportion of projected savings that are realized following a retrofit. We estimate realization rates by estimating:

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

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 β 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. This is complicated because the data records only the predicted energy consumption following all retrofits that were undertaken by the home, and does not provide predictions of energy savings following individual measures. We thus first estimate measure-specific projections of energy savings, using a regression of projected energy savings on the adopted energy efficiency measures:

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

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: 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 non-treated households from before and after participation in the energy-efficiency retrofit program. The bottom panel shows that the years 2007 and 2008 were prior to program initiation. The retrofit program began in 2009, and rolled out over the following three years, with all participating households completing retrofits by 2012. Prior to the beginning of the retrofit program (in 2007-08), electricity and gas exhibited similar (annual) trends. Households that would later participate in the retrofit program had higher natural gas consumption and slightly higher electricity consumption than non-participating households. The figure suggests that electricity consumption declined slightly as a result of the retrofits, and that natural gas consumption in treated households fell considerably relative to control households. While the households that chose to participate in retrofits were initially consuming about 5% more natural gas than non-participant households, after the retrofits they consumed about 3-4% less natural gas than non-participating households. 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.

5.2 Panel fixed effects analysis

Table 2 shows estimates of $\hat{\beta}$ from estimating Equation (1) as described above. The results show that participation in an energy efficiency retrofit reduced household energy consumption by about 14%, with consumption of natural gas falling by 19% and consumption of electricity 2.5%. These estimates are highly statistically significant, providing strong evidence that energy consumption fell by a significant 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 Houses program principally targeted space heating and thermal envelope efficiency, and space heating is provided predominantly by natural gas in the setting studied.

In Figure 2, we present results from estimating Equation (3) separately for gas, electricity, and total energy consumption. 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

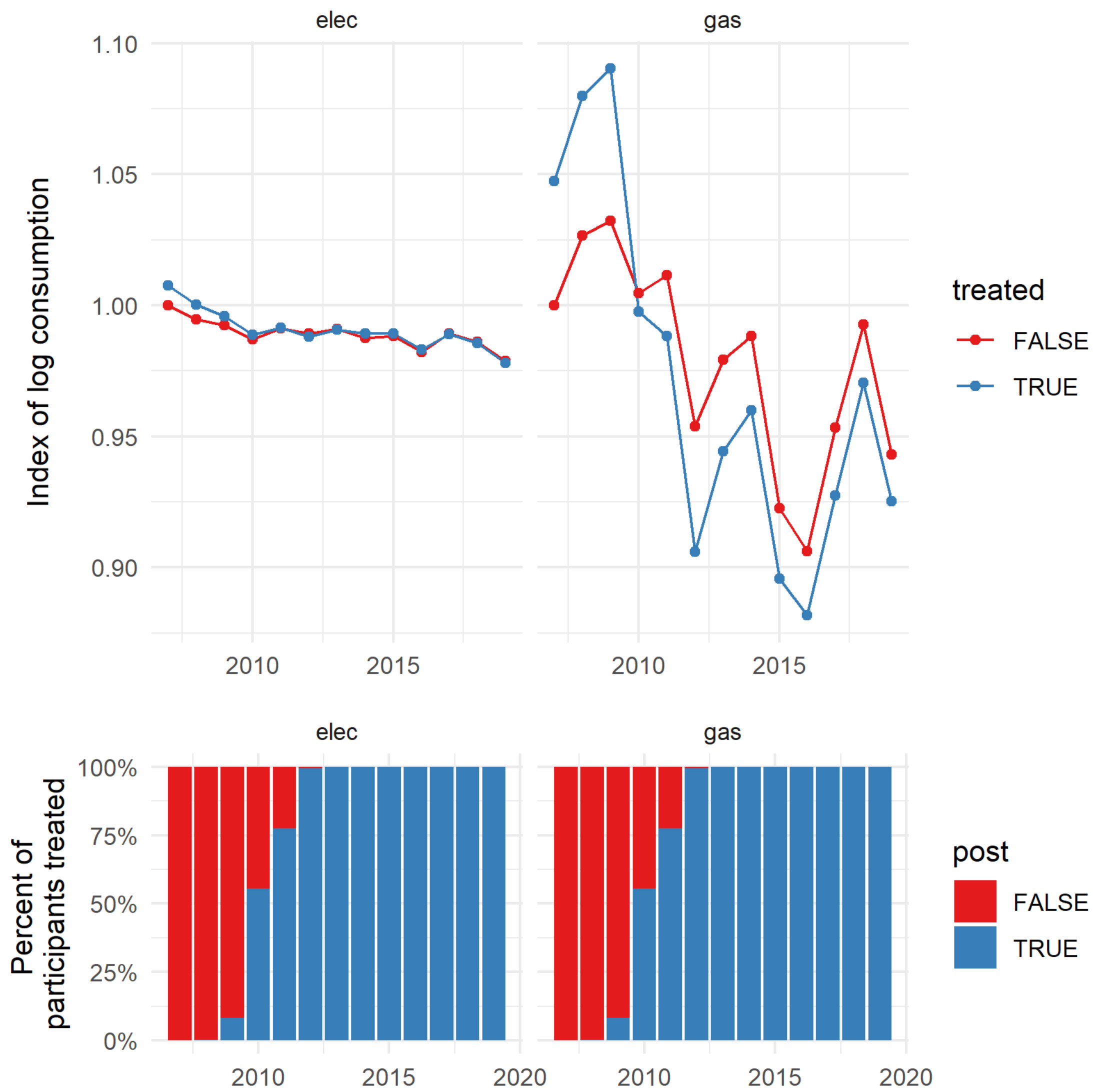

Figure 1: Long-run trends in electricity and natural gas consumption in treated and untreated households

Table 2: Main panel regression

Dependent Variables:	log(gas)	log(elec)	log(energy)
Model:	(1)	(2)	(3)
Variables			
treated_postTRUE	-0.2092***	-0.0279***	-0.1532***
	(0.0066)	(0.0099)	(0.0066)
Fixed-effects			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
Fit statistics			
Observations	3,168,052	3,211,074	3,178,905
R^2	0.84895	0.47321	0.78437
Within R^2	0.00361	4.11×10^{-5}	0.00228

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

upgrades are estimated to result in the largest natural gas savings, at around 17%. The furnace typically consumes the largest amount of natural gas in a house, and at the time upgrades could furnace efficiency by as much as 20% (the EERH program required a new furnace efficiency of at least 92% to qualify for rebates, while older furnaces typically were 60 to 80% efficient.) Wall insulation is also estimated to significantly reduce natural gas consumption, although estimates are much less precise than for natural gas furnaces because few houses undertook this measure (which is much more intrusive than a furnace upgrade). Attic insulation and air sealing are also estimated to reduce natural gas consumption, by 6% and 3%, respectively. Other measures, such as window and door upgrades and basement insulation, are found to have no impact on natural gas consumption. This finding is similar to other studies, which suggest that window and door upgrades are ineffective at reducing energy consumption (Giandomenico et al., 2020). For electricity, we find no measures that substantially reduce consumption on average. We do find a statistically significant reduction in electricity consumption associated with air sealing, but the measure only results in savings of about 4%. Our estimates suggest that wall insulation *increases* electricity demand, although again the estimate is fairly imprecise. Other energy efficiency measures are not associated with a statistically significant change in electricity consumption.

5.3 Matching analysis

Table 3 reports estimates of $\hat{\beta}$ from estimating Equation (1) while restricting observations to treated and matched control units. The table reports results for total energy consumption. In column (1), the table replicates the estimation reported in Table 2, in which all treated and control observations are included. As above, estimating this model suggests that participation in the retrofit program caused a reduction in energy consumption of 13.8%. In column (2), the sample is restricted to include treated households and control units that are matched on pre-treatment energy consumption, as described in Section 4.2. The estimate of $\hat{\beta}$ falls by about one percentage point to 12.6%. The estimate in column (3) is based on matching treated households with control households based on building characteristics. Again,

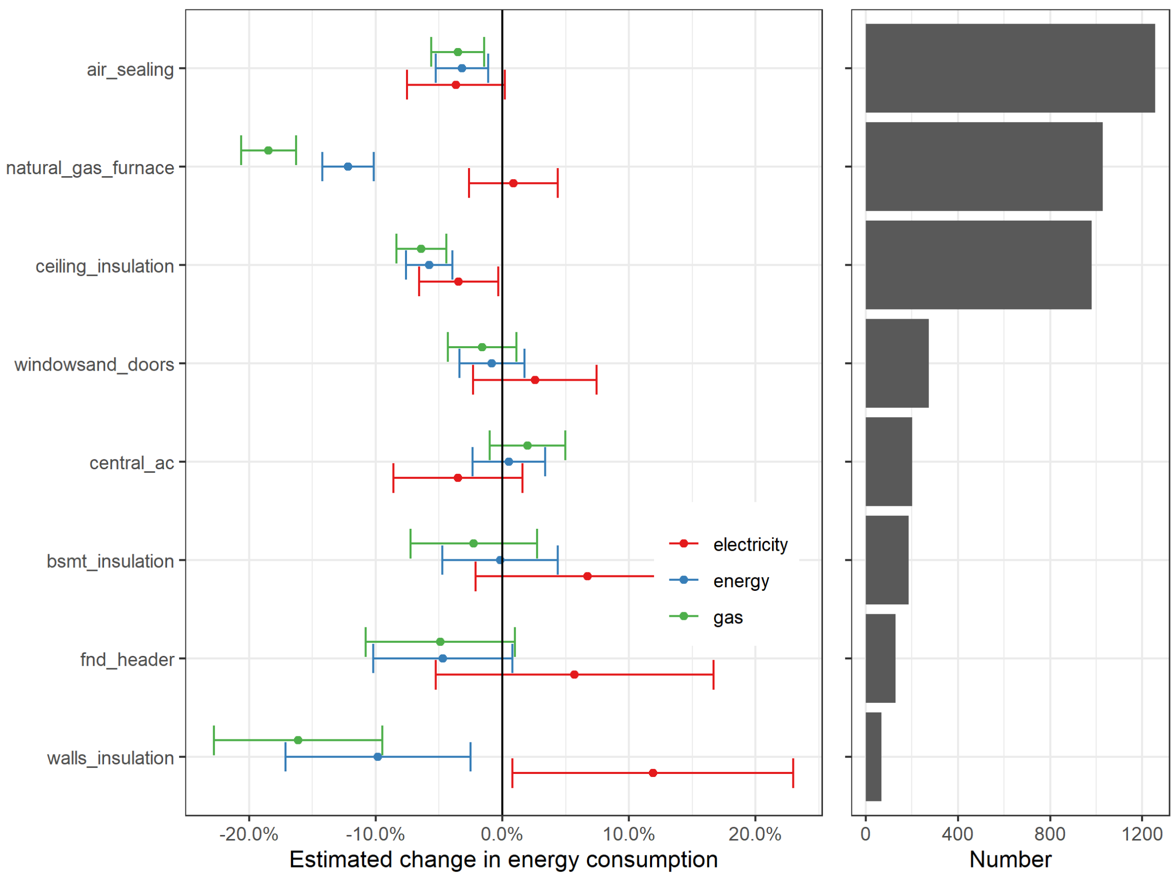

Figure 2: Estimated energy savings

the estimated $\hat{\beta}$ is smaller than in the unmatched analysis, suggesting some infra-marginal households participating in the retrofit program. Finally, in column (4), we match on both building characteristics and pre-treatment energy consumption. The point estimate suggests that participation in the retrofit program reduced energy consumption by 12.4%.

Two facts are notable from the matching analysis. First, estimates of $\hat{\beta}$ using a control group that is matched-on-observables with the treated group result in smaller estimates of energy savings compared to analysis using the full group of untreated observations. This suggests that some of the households that participated in the retrofit program are likely infra-marginal, and would have conducted the retrofit even without the program. By matching control households with treated households, we can to some degree account for this selection into treatment. This results in smaller estimates of the treatment effect. Second, while the treatment effect is smaller using the matched control group, our estimates are qualitatively similar to the unmatched analysis (12.4% energy savings in the analysis with a matched sample compared to 13.8% 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 for this program (Grosche and Vance, 2009; Boomhower and Davis, 2014). Given that the matching analysis can control in part for selection into treatment, we adopt column (4) of Table 3 as our preferred estimate of the effect of retrofit program participation on energy savings.

Should we run subsequent analysis using the matched sample?

Table 3: Panel data analysis with matching

Dependent Variable:	log(energy)			
Model:	(1)	(2)	(3)	(4)
Variables				
treated_postTRUE	-0.1376***	-0.1264***	-0.1285***	-0.1238***
	(0.0065)	(0.0069)	(0.0071)	(0.0068)
Fixed-effects				
id	Yes	Yes	Yes	Yes
cons_date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	3,172,442	452,464	453,094	448,518
R^2	0.78444	0.80537	0.80832	0.80819
Within R^2	0.00208	0.00850	0.00901	0.00837

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

5.4 Staggered adoption and event studies

Prior results 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 treatement 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

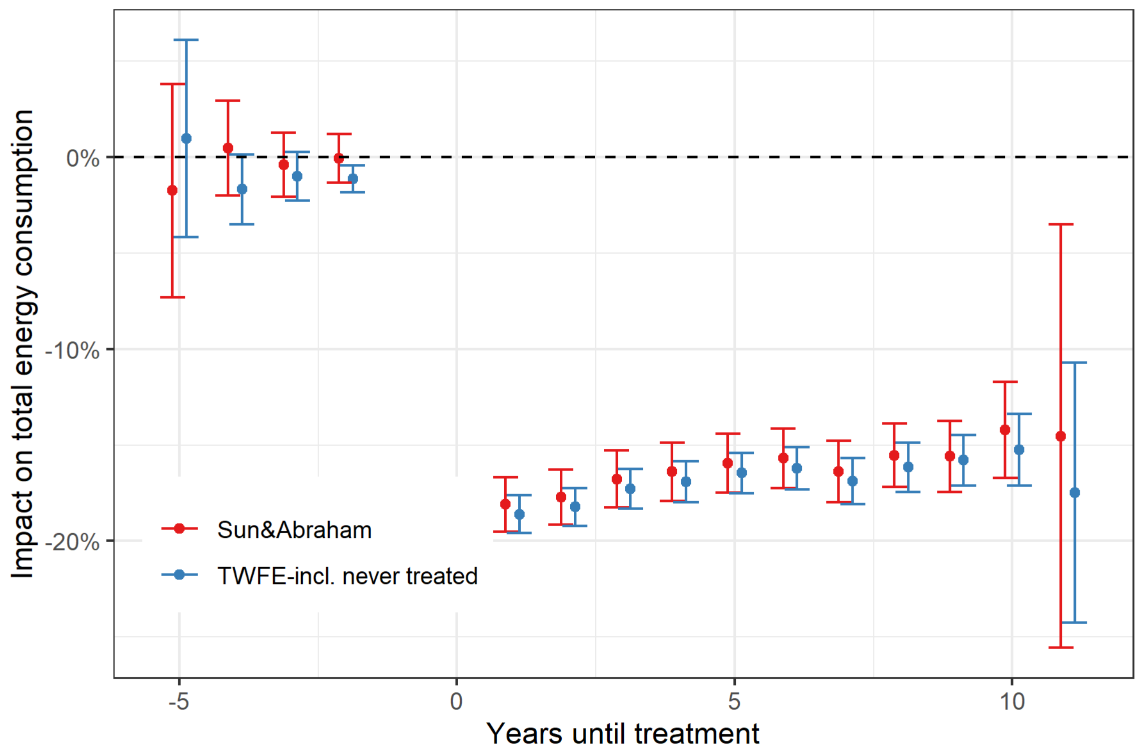

Figure 3: Event study plot

as a complement to our main analysis. We show results for both the Sun and Abraham (2021) and the typical TWFE estimator in the context of Equation (2), the event study specification. The results are shown in Figure 3.

Several findings emerge from the event study plot. First, there are no obvious pre-trends in energy consumption. This indicates that the control households are following the treated household energy consumption patterns prior to the retrofit, and suggests that they may serve as an appropriate control unit for treated households. 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 households. 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, 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 household energy consumption, in our context, already-treated households *are* a good control group for newly-treated households. In addition, our sample includes a large control group of never-treated households. The presence of these never-treated households reduces weight on already-treated households in the regression, and thus helps to avoid potential bias.

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 the table below, we find a realization rate for natural gas of 60%. Our realization rate for electricity is around 10%, and not significantly different than zero. For all energy, we find a realization rate of 55%.

Dependent Variables:	log(gas)	log(elec)	log(energy)
Model:	(1)	(2)	(3)
Variables			
as.numeric(treated_post) × delta_gas	0.6055***		
	(0.0195)		
as.numeric(treated_post) × delta_elec		0.1226	
		(0.5118)	
as.numeric(treated_post) × delta_energy			0.5464***
			(0.0276)
Fixed-effects			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
Fit statistics			
Observations	3,165,406	3,208,330	3,176,199
R^2	0.84913	0.47322	0.78446
Within R^2	0.00417	4.62×10^{-7}	0.00258

Clustered (id & cons_date) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

We also conduct our analysis in levels rather than logs. Results are shown in the Appendix (Need table number here), and are similar to the main results in logs.

5.5.2 Measure-specific realization rates

Estimating 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). Figure 4 plots coefficients recovered from this regression. Large savings in natural gas are projected for natural gas 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 largest reductions projected for wall insulation as well as natural gas furnace upgrades (because less electrical consumption by the furnace fan).

Finally, we estimate measure specific realization rates by dividing realized by projected energy

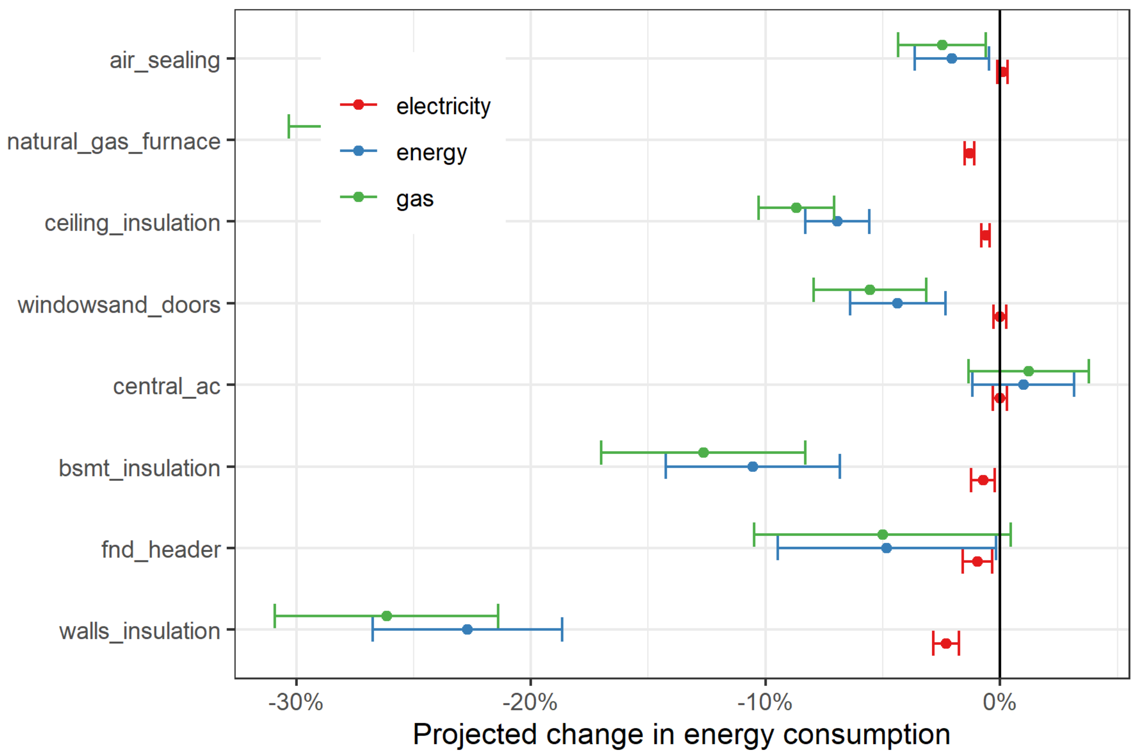

Figure 4: Measure-specific energy saving projections

savings by measure. Results are presented in Figure 5. We indicate measure-specific realization rates in percentage form above each measure. For natural gas, we find realization rates of 59% for furnace upgrades and 51% for walls insulation. We find a realization rate of above 100% for air sealing measures. For electricity, we find realization rates that are mostly negative, since most measures appear to be associated with an increase in electricity consumption.

6 Conclusion

Conclusion goes here.

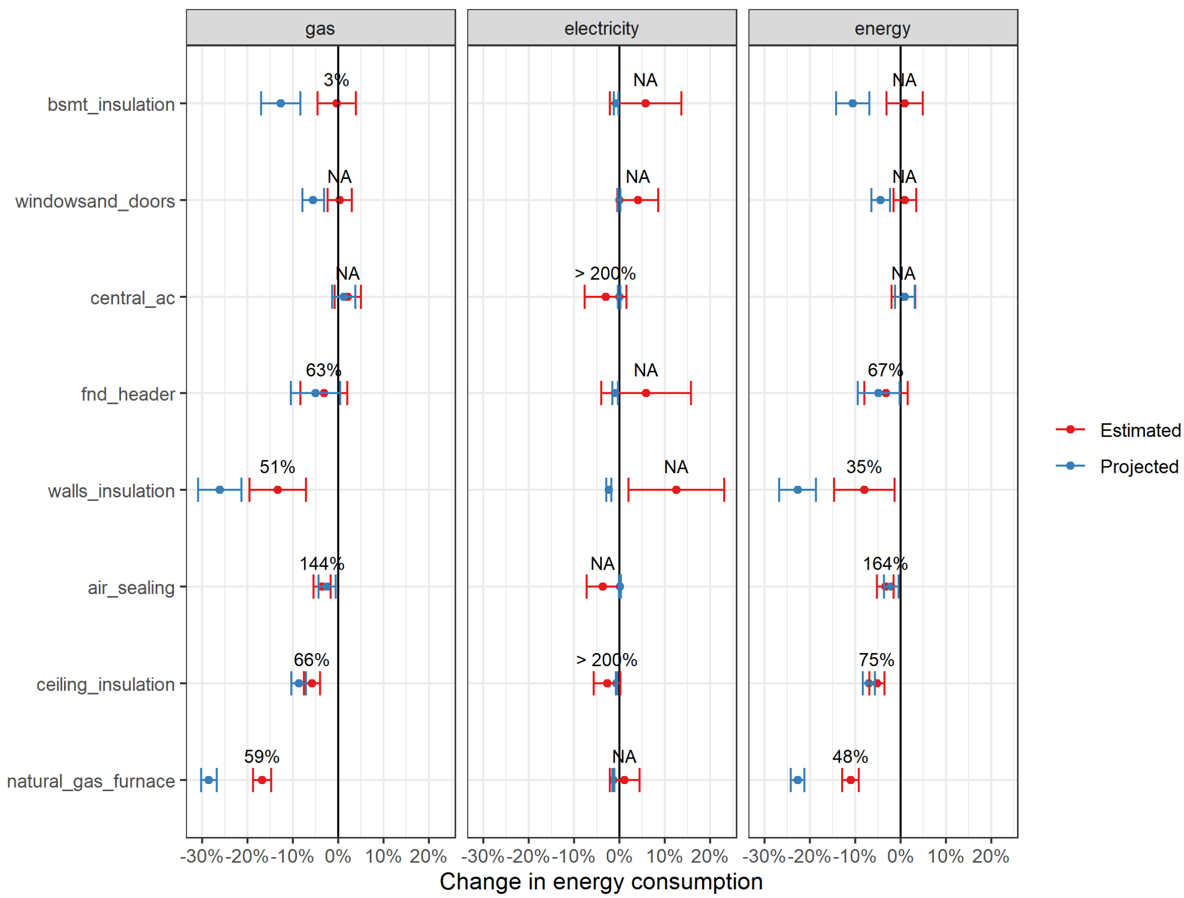

Figure 5: Measure specific realization rates

References

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A Additional results

Table A1: Regression with house-month fixed effects

Dependent Variable:	log(energy)	
Model:	(1)	(2)
Variables		
treated_postTRUE	-0.1532***	-0.1533***
	(0.0066)	(0.0063)
Fixed-effects		
id	Yes	
cons_date	Yes	Yes
id-consmonth		Yes
Fit statistics		
Observations	3,178,905	3,178,905
R^2	0.78437	0.84301
Within R^2	0.00228	0.00312

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

Dependent Variables:	gas	elec	energy
Model:	(1)	(2)	(3)
Variables			
as.numeric(treated_post) × delta_gas_lev	0.6245***		
	(0.0661)		
as.numeric(treated_post) × delta_elec_lev		0.0499	
		(0.4932)	
as.numeric(treated_post) × delta_energy_lev			0.4970***
			(0.0553)
Fixed-effects			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
Fit statistics			
Observations	3,192,857	3,210,277	3,176,946
R^2	0.75198	0.54135	0.74822
Within R^2	0.00360	1.43×10^{-7}	0.00327

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