

Summary statistics

I have regenerated the summary statistics. There is a small change, and it should be reflected in the paper. This table is not formatted as well as the one in the paper, but the layout is exactly the same, so it should be quick to cut and paste into the paper.

Table: Summary statistics

non_participant Variable	N	No Mean	SD	N	Yes Mean	SD
Energy consumption data	0			0		
Actual gas consumption (GJ/year)	1453	113	38	18284	116	41
Actual electricity consumption (GJ/year)	1453	31	12	18284	31	13
Actual energy consumption (GJ/year)	1453	144	45	18284	148	48
Property assessment data	0			0		
Total assessed value (\$)	1453	276665	87090	18284	289405	123025
Lot size (square metres)	1453	642	294	18284	816	1875
Building size (square metres)	1453	118	39	18284	121	43
Year built	1453	1971	18	18284	1981	23
Program participation data	0			0		
Air sealing	1453	0.82	0.38	18284	0	0
Attic insulation	1453	0.64	0.48	18284	0	0
Wall insulation	1453	0.044	0.21	18284	0	0
Basement insulation	1453	0.13	0.33	18284	0	0
Foundation header insulation	1453	0.087	0.28	18284	0	0
Window or door upgrade	1453	0.18	0.39	18284	0	0
Central A/C upgrade	1453	0.13	0.34	18284	0	0
Natural gas furnace upgrade	1453	0.68	0.47	18284	0	0
Predicted pre-retrofit gas consumption (GJ/year)	1453	161	60	0		
Predicted pre-retrofit electricity consumption (GJ/year)	1453	34	1	0		
Predicted pre-retrofit energy consumption (GJ/year)	1453	195	60	0		
Predicted post-retrofit gas consumption (GJ/year)	1453	116	40	0		
Predicted post-retrofit electricity consumption (GJ/year)	1453	33	1.1	0		

Introduction

The first results section should discuss research design, with a focus on sample selection. Do we want the *full sample*? A *matched sample* consisting of the treated group and matched controls? The *treated group only*? Each of these different approaches has been used in prior research (cite). Each has different things to recommend and detract. With untreated controls, we can estimate the treatment effect over a longer window. We also can be less worried about “forbidden regressions” that compare later treated with earlier treated units. However, with untreated units as controls, we may be more concerned about selection. The first section should elaborate on this discussion, with citations, and produce results. I present results in the following tables.

Unless otherwise stated, column definitions are as follows

1. Treated + all available controls
2. Treated + 1:1 matched controls based on pre-treatment consumption
3. Treated + 1:1 matched controls based on building characteristics
4. Treated + 1:1 matched controls based on pre-treatment consumption and building characteristics
5. Treated only

Note that in the ‘Treated only’ samples, I only follow units until 2011. After 2012, all units are treated.

Note that we do not need all of the tables that follow. I put them here for completeness (some may be dropped or go in appendix).

TWFE estimates for total energy; monthly data

Dependent Variable: Model:	(1)	(2)	log(energy) (3)	(4)	(5)
<i>Variables</i>					
treated_postTRUE	-0.1571*** (0.0063)	-0.1453*** (0.0072)	-0.1512*** (0.0070)	-0.1396*** (0.0074)	-0.1573*** (0.0107)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
cons_date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	2,882,662	429,578	429,833	429,866	75,461
R ²	0.79219	0.80557	0.81004	0.81181	0.81352
Within R ²	0.00267	0.01011	0.01134	0.00962	0.01377

Clustered (id & cons_date) standard-errors in parentheses

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

TWFE estimates for gas; monthly data

Dependent Variable: Model:	(1)	(2)	log(gas) (3)	(4)	(5)
<i>Variables</i>					
treated_postTRUE	-0.2081*** (0.0062)	-0.1944*** (0.0076)	-0.1993*** (0.0074)	-0.1901*** (0.0078)	-0.2196*** (0.0089)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
cons_date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	2,874,433	428,688	429,313	429,103	75,699
R ²	0.85408	0.85549	0.85894	0.86033	0.84099
Within R ²	0.00384	0.01381	0.01480	0.01352	0.01773

Clustered (id & cons_date) standard-errors in parentheses

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

TWFE estimates for electricity; monthly data

Dependent Variable: Model:	(1)	(2)	log(elec) (3)	(4)	(5)
<i>Variables</i>					
treated_postTRUE	-0.0387*** (0.0099)	-0.0138 (0.0121)	-0.0084 (0.0123)	0.0015 (0.0117)	0.0207 (0.0155)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
cons_date	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	2,908,550	432,238	432,263	432,424	76,430
R ²	0.46709	0.50410	0.49463	0.49444	0.5445
Within R ²	8.72×10^{-5}	5.66×10^{-5}	2.07×10^{-5}	7.29×10^{-7}	0.0001

Clustered (id & cons_date) standard-errors in parentheses

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

Sun + Abraham estimates

The Sun and Abraham correction (like the Callaway and Sant'Anna correction) is estimated by interacting a cohort dummy with a time-to-treatment dummy. In our monthly data, we observe 49 different “cohorts” (i.e., households retrofit in 49 different months). Our data has 200 different “time to treatments” (i.e., months before and after retrofit). This implies estimating a model with about 10,000 dummy variables. This is not feasible. Instead, to estimate the Sun and Abraham model, I convert to annual data first. The results first show the TWFE estimates based on annual data, to confirm that this does not meaningfully disturb the results.

TWFE estimates for energy; annual data

Dependent Variable: Model:	(1)	(2)	log(energy) (3)	(4)	(5)
<i>Variables</i>					
treated_postTRUE	-0.1682*** (0.0060)	-0.1573*** (0.0079)	-0.1605*** (0.0077)	-0.1489*** (0.0090)	-0.1870*** (0.0114)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
conyear	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	246,541	35,175	35,165	35,178	5,071
R ²	0.80826	0.84582	0.85472	0.85053	0.90145
Within R ²	0.01388	0.06664	0.07291	0.06048	0.11563

Clustered (id & consyear) standard-errors in parentheses

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

Sun+Abraham estimates for energy; annual data

Dependent Variable: Model:	(1)	(2)	log(energy) (3)	(4)	(5)
<i>Variables</i>					
ATT	-0.1668*** (0.0037)	-0.1544*** (0.0049)	-0.1577*** (0.0047)	-0.1468*** (0.0048)	-0.1725*** (0.0155)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
conyear	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	246,541	35,175	35,165	35,178	5,071
R ²	0.80831	0.84640	0.85521	0.85139	0.90159
Within R ²	0.01414	0.07016	0.07603	0.06588	0.11683

Clustered (id & consyear) standard-errors in parentheses

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

Sun+Abraham estimates for gas; annual data

Dependent Variable: Model:	(1)	(2)	log(gas) (3)	(4)	(5)
<i>Variables</i>					
ATT	-0.1958*** (0.0042)	-0.1848*** (0.0055)	-0.1890*** (0.0053)	-0.1781*** (0.0054)	-0.2028*** (0.0165)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
conyear	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	247,154	35,234	35,244	35,248	5,071
R ²	0.82162	0.84958	0.86034	0.85334	0.89767
Within R ²	0.01857	0.08732	0.09513	0.08423	0.14043

Clustered (id & consyear) standard-errors in parentheses

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

Sun+Abraham estimates for electricity; annual data

Dependent Variable: Model:	(1)	(2)	log(elec) (3)	(4)	(5)
<i>Variables</i>					
ATT	-0.0495*** (0.0071)	-0.0265** (0.0093)	-0.0195* (0.0101)	-0.0146 (0.0093)	0.0068 (0.0310)
<i>Fixed-effects</i>					
id	Yes	Yes	Yes	Yes	Yes
conyear	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>					
Observations	246,819	35,183	35,170	35,180	5,071
R ²	0.64327	0.70877	0.70024	0.70385	0.86097
Within R ²	0.00060	0.00172	0.00150	0.00112	0.00091

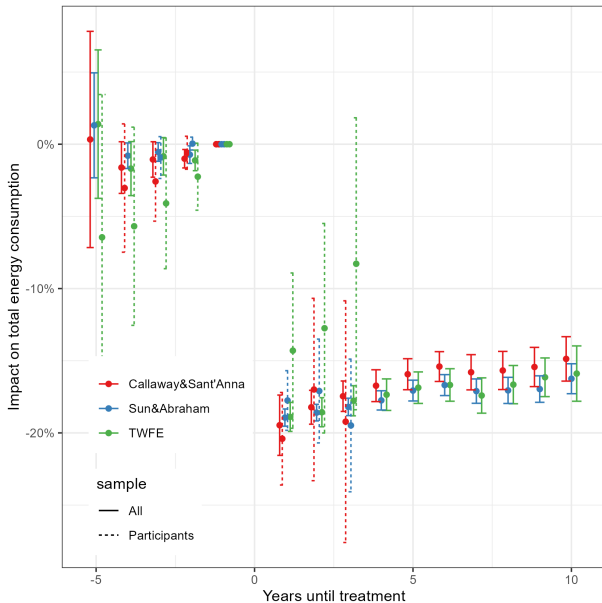
Clustered (id & consyear) standard-errors in parentheses

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

Event study plot

The next results section should be the event study plot. Here, we emphasize the new estimators, and the potential problems with TWFE. We can show that the TWFE estimator with participants only results in a very problematic estimate. We should explain that this is because it puts a lot of weight on comparisons between later-treated households and earlier-treated households – this is a problematic comparison. All other estimators deliver very similar estimates. The event study plot suggests that the effect of treatment is highly persistent. Even after 10 years, it looks like savings of about 15 percent are sustained.

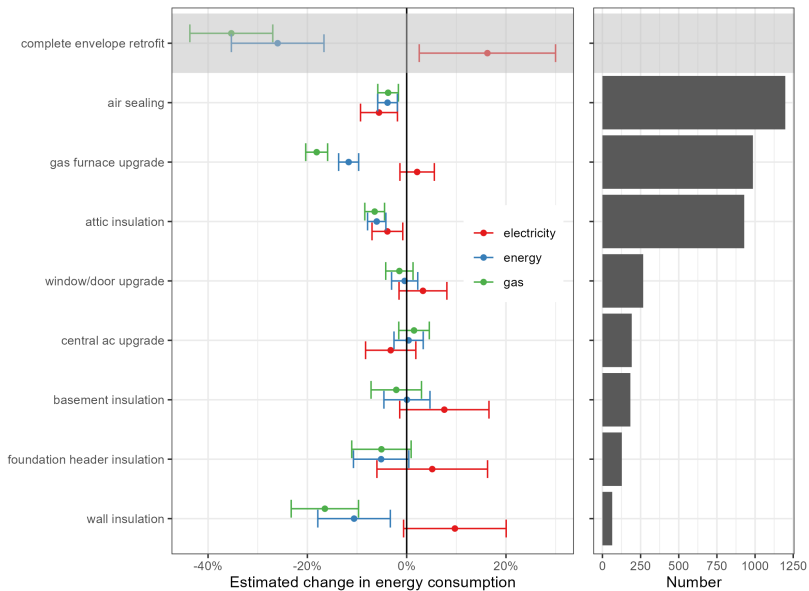
Event study plot



Measure by measure results

As before, we produce measure-by-measure estimates of savings.

Measure by measure results



Complete envelope retrofits

In the prior figure, we estimate complete energy retrofits using a linear combination of individual measures. Specific measures are listed in the current version of the paper. I have now added code to use the houses that actually undergo a complete energy retrofit in order to estimate savings from this combination of measures. Specifically, I define a complete energy retrofit as:

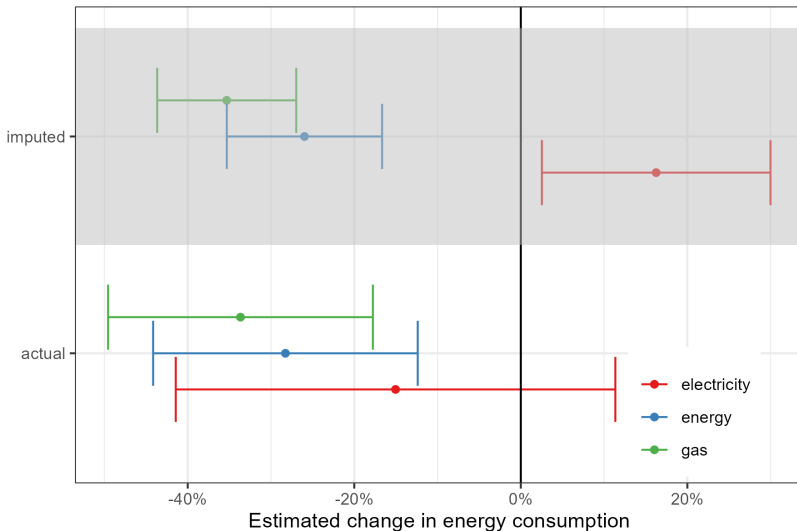
$$\begin{aligned} \text{complete envelope retrofit} = & \\ & \text{air sealing} + \text{attic insulation} + \\ & \text{window/door upgrade} + \text{wall insulation} + \\ & (\text{foundation header insulation OR basement insulation}) \end{aligned}$$

(Note that this is very slightly different from our imputed measure, which adds foundation header AND basement insulation to the other coefficients.)

There are a total of 15 homes that undergo this definition of a complete energy retrofit. To estimate the effect of this measure, I run a regression on a sample of these homes and untreated homes (and drop all homes that undergo some other retrofit). I control for gas furnace upgrades in this regression.

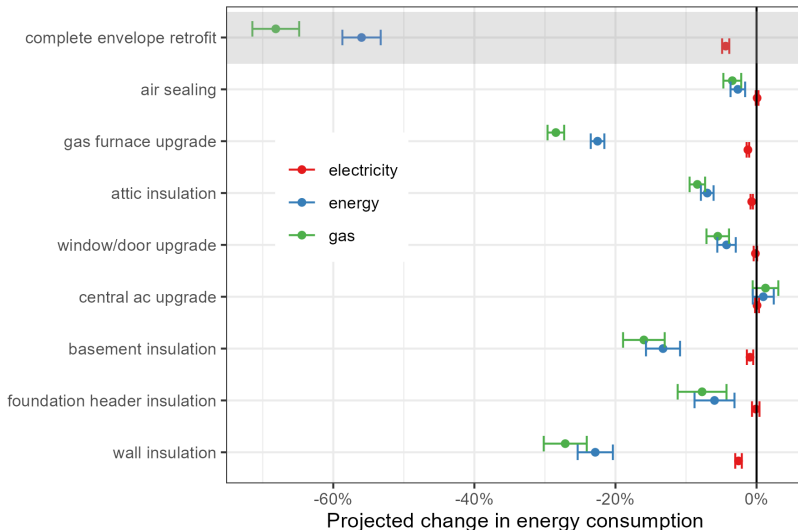
Complete envelope retrofits

Very similar estimates (except for electricity). Could either mention this, or insert the figure directly in the appendix.



Projected energy savings

We estimate *projected* energy savings using a cross-sectional regression of projected energy savings on recommended measures.



Realization rates

Overall realization rate table. This is based on estimation in logs. There is a table based on estimation in levels that can go in Appendix.

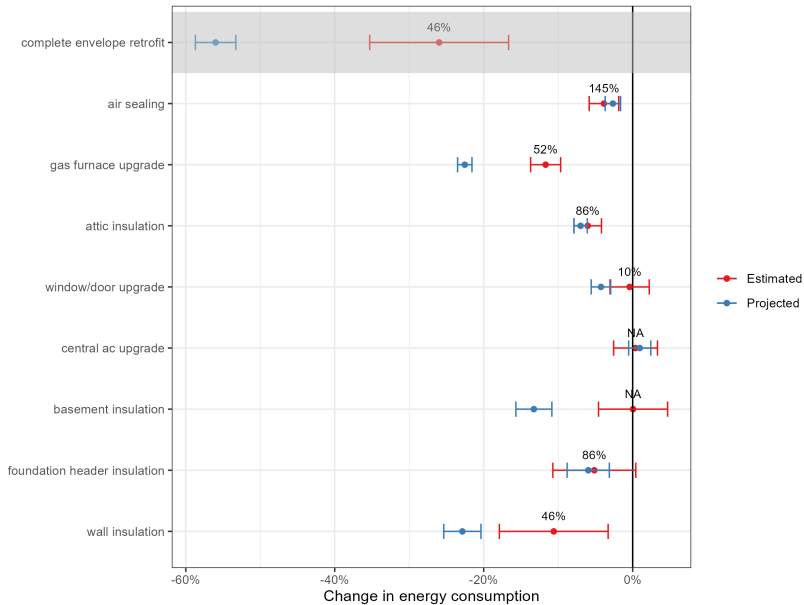
Dependent Variables: Model:	log(gas) (1)	log(elec) (2)	log(energy) (3)
<i>Variables</i>			
as.numeric(treated_post) × delta_gas	0.6072*** (0.0191)		
as.numeric(treated_post) × delta_elec		0.5160 (0.4724)	
as.numeric(treated_post) × delta_energy			0.5583*** (0.0270)
<i>Fixed-effects</i>			
id	Yes	Yes	Yes
cons_date	Yes	Yes	Yes
<i>Fit statistics</i>			
Observations	2,872,273	2,906,366	2,880,498
R ²	0.85417	0.46707	0.79226
Within R ²	0.00452	9.11×10^{-6}	0.00299

Clustered (id & cons_date) standard-errors in parentheses

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

Realization rates measure by measure

Here is the realization rate for energy only. The results directory also contains a figure separated by energy type.



Dollar savings

As we discussed, we calculate the average rebate in dollars. We calculate the *annual* projected savings and the *annual* realized savings. We divide the average rebate by the average annual savings (both realized and projected).

	average_rebate	dollar_per_annual_gj_realized	dollar_per_annual_gj_projected	dollar_bill_saving_projected	dollar_bill_saving_realized
1	1106.15	52.80	24.25	272.82	125.80

Dollar savings measure by measure

	measure	average_rebate	savings	projected_savings	dollar_per_annual_gj_realized	dollar_per_annual_gj_projected
1	air_sealing	87.62	6.69	4.57	13.09	19.11
2	bsmt_insulation	48.65		27.87		1.75
3	ceiling_insulation	646.25	7.61	13.11	84.90	49.30
4	fnd_header	7.38		8.80		0.80
5	natural_gas_furnace	489.53	15.32	37.16	31.95	13.11
6	walls_insulation	122.80	15.21	62.39	8.07	1.90
7	windowsand_doors	108.01		7.39		14.60