Measuring the Accuracy of Engineering Models in Predicting Energy Savings from Home Retrofits: Evidence from Monthly Billing Data [1]

Joe Maher[2]

Buildings account for 42 percent of energy use and 38 percent of carbon dioxide emissions in the United States, making building energy efficiency a key component of broader energy and climate goals (US Green Building Council 2011). In recent years, state and federal governments have increased funding programs that subsidize energy-efficient retrofits to existing buildings. For example, the American Recovery and Reinvestment Act of 2009 included $17 billion for energy efficiency programs, which helped initiate $54 billion in energy-related home improvements in 2009 (von Schrader 2010). And in 2013, President Obama announced a new goal: "Let's cut in half the energy wasted by our homes and businesses over the next 20 years. We'll work with the states to do it."[3]

Despite the widespread implementation of retrofit rebate programs and calls for increased investment in demand-side management programs, surprisingly little is known about whether energy efficiency retrofits are an effective way to reduce energy consumption. Engineering simulations provide most of the evidence, but simulated predictions, even if based on sound models, do not account for installation quality or

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[1] This draft has been recently updated with new results for presentation at the 2016 ASSA meetings. I apologize for any inconsistences in referencing results that I may have missed. This paper draws upon the first chapter of my dissertation. I gratefully acknowledge funding for this work from a University of Maryland graduate fellowship and the Resources for the Future Postdoctoral Fellows Program.
[2] Postdoctoral Fellow, National Socio-Environmental Synthesis Center (SESYNC), University of Maryland.
[3] Statement delivered on February 12, 2013, in a State of the Union Speech. Obama continues to promise that "Those states with the best ideas to create jobs and lower energy bills by constructing more efficient buildings will receive federal support to help make that happen."

behavioral responses (Allcott and Greenstone 2012). Hence, there is an important and timely need for empirical research that uses field data to evaluate more fully the effects of energy efficiency retrofits on energy consumption.

This paper answers a basic question, How much do energy efficiency investments reduce energy use? Next, it compares the estimated energy savings with engineering models to answer the question, How do engineering model biases contribute to the energy efficiency gap?

EMPIRICAL SETTING AND DATA COLLECTION

A central barrier for research in this field is the difficulty of obtaining data to better understand energy efficiency investment behavior and its implications for energy use. Furthermore, empirical assessments are context specific. Generalizing the findings from one energy use and energy user context to other uses and users may have limited validity.

Yet empirical ex post assessments of energy savings from efficiency investments present a tremendous opportunity to improve demand-side management policies. Quantifying the size and nature of energy savings in different energy uses and user contexts is critical to understanding the social benefits of efficiency investments. Understanding the heterogeneity of such benefits helps reveal which policy interventions are effective in achieving program goals. Putting this information to action by targeting policies toward specific energy uses and energy users will improve policy effectiveness.

This paper develops empirical estimates of energy savings from a wide range of energy efficiency investments and housing contexts using data on household energy consumption and efficiency investments for Gainesville, Florida. The econometric approach uses a difference-in-difference method. The purpose is to evaluate retrofit-specific residential rebate programs based on observed household-level consumption data. Energy savings from nine retrofit rebate programs in Gainesville are detailed in a panel data set of electricity and natural gas consumption and building characteristics for 30,000 residences**.** The difference-in-difference method compares changes in energy use in a residence before and after an energy-saving retrofit intervention (treatment group) with changes in energy use in residences that will become program participants in the future. The monthly billing data are combined with time-variant and time-constant characteristics of each residence.

The paper tests two hypotheses to identify variations in energy savings. First, it examines seasonal variation in energy savings, testing whether energy savings for each technology vary across seasons. Second, it looks at the dynamics of energy use over time, testing whether the energy savings of a technology persist through time. Results suggest that ex post assessments provide rich and valuable information about the heterogeneity of size and timing of energy savings across different technologies and energy users.

This work makes general contributions to the literature assessing energy efficiency programs. First, this is among the first assessments of a retrofit rebate program to apply the difference-in-difference method to link billing data and housing characteristics. Second, by assessing ten retrofit programs, it explores heterogeneity across a diverse range of retrofit options using actual billing data.

The Energy Efficiency Rebate Programs

Gainesville Regional Utilities (GRU) is a municipal utility and exclusive supplier of electricity and natural gas for more than 30,000 households in Gainesville, Florida, and is the state's fifth-largest electric utility. GRU is responsible for almost all of the electricity generation for the city, as well as transmission and distribution. GRU is also an award-winning national leader in energy conservation with the ability to demonstrate the potential of well-designed retrofit rebate programs.[4]

GRU's Gainesville Residential Energy-Efficiency Incentives (GREEN) provided rebates and low-cost loans for the purchase of energy-efficient products. Established in 2008, GREEN was primarily a rate-payer funded utility program, that also received modest federal funding under the American Reinvestment and Recovery Act of 2008 (ARRA). In 2013, all GREEN subsidy programs were terminated after the expiration of ARRA funding coupled with GRU's decision to build new power plants. Despite this short life, shared by dozens of utility-run subsidy programs funded by ARRA, the GREEN program spurred investment across more than a dozen retrofit products, thus creating opportunity for quasi-experimental analysis of retrofit programs.

For a utility-level program, GREEN had a large number of participants. By December 2012, GREEN had provided subsidies for approximately 25,000 residential energy efficiency interventions. In total, more than 14,000 households participated in the program, many qualifying for subsidies for multiple retrofit products. Program take-up was unusually high, with approximately half of eligible GRU customers participating in GREEN over the five-year program lifetime. Most rebate programs were available to all GRU customers.

[4] Awards include the 2005 Green Power Beacon Award, presented by the U.S. Environmental Protection Agency, the U.S. Department of Energy, and the Center for Resource Solutions (http://www.epa.gov/greenpower/documents/2005awards.pdf; https://www.gru.com/AboutGRU/NewsReleases/Archives/Articles/news-2005-10-28.jsp).

GREEN reimbursement required submission of original billing receipts with rebate application forms. GRU recorded the exact date of installation, total project costs, company name, and details of equipment and materials. Participants were required to hire GRU-certified professional contractors to be eligible for rebates, ensuring a basic level of quality assurance and accurate reporting by reputable businesses. The precise and accurate treatment dates permit a clean timing for a difference-in-difference model.

Each rebate program issued rebates based on a formula that reflected treatment intensity and provided both fixed cash rebates and sliding, capped rebates. All programs had a maximum rebate level. Exact formulas, rebate rates, and maximum caps varied from year to year with each program. Program inception dates and program termination dates varied across retrofit types. Households could accept rebates as a cash subsidy or as a credit to future utility bills. Program participants were reimbursed for the subsidy about one month after the file was completed. Funding for specific programs varied from year to year, and rebates were issued on a first-come-first-served basis until annual funding was exhausted.

Data

The rebate programs collected unusually detailed information about program participants, linked to natural gas and electricity billing data, building characteristics, and home improvement permits. Monthly natural gas and electricity bills are available for all houses in the GRU service area between years 2000 and 2015. Program participant data include the date, rebate amount, company name, and technical details of retrofit intervention, in-house engineering estimates, and total cost of installation.

Table 1 provides descriptive statistics for 10 rebate programs that focus on 8 technologies: super-SEER (seasonal energy efficiency ratio) central air-conditioner replacement, SEER-15 central air-conditioner replacement, room air-conditioner replacement, pool pump replacement, refrigerator removal, attic insulation improvement, duct leakage repair, and air-conditioner maintenance. The final two programs – low-income grants and home performance – often involve the installation of multiple retrofits.

Table 1 includes summary statistics of ex-ante engineering estimates of energy savings, rebates paid to participants, and the project cost. Each retrofit includes energy-saving predictions based on GRU engineering simulations. These predictions, which were used for program evaluation purposes, allow comparisons between observed energy savings with engineering predictions.

Detailed technical specifications characterize each retrofit installation. For most retrofit programs, variables include continuous measures of the energy efficiency ratings, which approximate treatment intensity. For example, attic insulation includes the R-value of added insulation, square footage of coverage, and type of insulation material. For equipment replacements, such as air-conditioners, data include the brand, model number, capacity, certification number, and SEER rating of the installed equipment.[5]

Engineering estimates are specific to each technology. For example, different energy savings estimates are reported for a SEER-15 air-conditioner a SEER-16 air-conditioner. In some cases, engineering estimates are project-specific and based on house energy audits, particularly for low-income grants and whole home performance

[5] Data do not generally include information about the old equipment that is replaced. The refrigerator buyback program is an exception that includes data about removed equipment.

programs. For more straightforward retrofits, technology-specific ex-ante estimates based on engineering formulas are used in lieu of house energy audits.

Empirical Methods

A difference-in-difference model estimates the effect of retrofits on household energy consumption. To evaluate average energy savings of DSM programs using quasi-experimental techniques, I employ a two-way fixed effect model, where a panel of monthly energy bills is used to eliminate time-constant features of each residence. As a further innovation, I exploit differences in the timing of retrofit installation during the five-year rebate program. To identify treatment effects for early retrofits installed at time *t*, I use a control group made of future program participants that have not yet installed retrofits at time *t*. By using only treated households, I eliminate bias introduced from participant self-selection.

The simple case of a single retrofit per household would entail estimating the following two-way fixed effects model:

$$y_{it} = \lambda_t + c_{im} + W_{it}\tau + \varepsilon_{it} \qquad t = 1, \dots, T \tag{1}$$

where y_{it} is electricity consumption for house i in month t; λ_t is a month-specific effect for time t that is introduced with time-period indicator variables to capture city-wide trends that affect electricity consumption over time, such as weather fluctuations; c_{im} is a household-by-month-of-year fixed effect for house i and month-of-the-year *m*, where M=12, that is introduced with house indicator variables to capture all time-constant factors of a house that affect seasonal electricity consumption; $W_{it} = [w_{it1}, \dots, w_{itJ}]$ is a row vector of retrofit-specific treatment indicators variables associated with observation

y_{it}, where each element w_{itj} is equal to 1 for all months t after a retrofit of type j is installed in house i and equal to 0 otherwise; τ is a J-vector of retrofit-specific treatment effect coefficients that represent the average monthly energy savings from each retrofit type j, which is assumed to persist over time; T is a constant equal to the total number of billing months; J is a constant equal to the total number of rebate programs; and ε_{it} is an error term clustered by house and represents unmeasured time-variant factors affecting electricity consumption.

In addition, the sample of households is restricted in several ways. First, the analysis is restricted to single-family households that have a single customer account during the four-year period. Second, all treatment households have at least 24 months of billing data pre-retrofit and post-retrofit to ensure consistent estimation of treatment effects. Third, the treatment group includes only households that receive a single retrofit intervention; households that receive rebates from multiple retrofit programs are excluded from the analysis. This final restriction reduces the sample size substantially, to include a total of 5,165 participating households.

EMPIRICAL ANALYSIS OF ENERGY SAVINGS

Results confirm expectations: most retrofits reduce total combined energy use. At the upper extreme, a retrofit can save up to 223 kWh per month, or 13 percent of the average household energy consumption of 1,700 kWh per month.[6] Five programs have results significant at the 1 percent level (monthly combined energy savings reported in

[6] The average pre-treatment energy consumption for the houses with Super-SEER central air-conditioning replacements was ~1,700 kWh across all months. Energy consumption varies seasonally.

parentheses): super-SEER air-conditioner replacement (223 kWh), SEER-15 air-conditioner replacement (151 kWh), refrigerator removal (47 kWh), and attic insulation improvement (88 kWh). Monthly energy savings for pool pump replacement (99 kWh) and low-income grants (67 kWh) are significant at the 5 percent and 10 percent levels respectively.

Four programs yield coefficients that are not different from zero at any reasonable level of statistical significance using any energy consumption measure, including: room air-conditioner replacement, duct leakage repair, air conditioning maintenance, and whole home performance.

Comparison of results across panels in Table 2 shows that different technologies provide energy savings across different fuel types. For example, central air-conditioner replacement reduces both electricity and natural gas consumption. This may suggest that central systems have efficiency gains for summer cooling, which draws electricity, as well as winter heating, which can draw from either electricity or natural gas. In contrast, pool pump replacements and refrigerator removals only reduce electricity consumption, as these are appliances that never use natural gas. On the other hand, attic insulation seems to most strongly affect natural gas consumption, perhaps because insulation is most effective at containing heat during winter months. An alternative explanations might be that the effect of insulation on natural gas may be identified more easily than electricity, since natural gas is primarily used for heating homes while electricity is used or many purposes unrelated climate control.

Seasonal Variation in Energy Savings

Retrofit technologies offer varying energy services, and some services vary with weather but others do not. Retrofits related to climate control should yield seasonally variable energy savings, whereas retrofits related to all-season appliances should yield constant levels of energy savings throughout the year. Results in Table 3 test this hypothesis by including an interaction between posttreatment and a seasonal indicator variable equal to one for electricity bills in May through October. Seasonal interactions indicate the time of year that different retrofits provide energy savings, which is useful information for managing peak demand loads.

Energy savings are constant for products with year-round energy services, confirming that reductions in energy use are caused by retrofit installation. The seasonal interaction coefficient is not significant for refrigerator and pool pumps—products with year-round energy services—suggesting constant energy savings during warm and cool seasons.[8]

On the other hand, energy savings vary seasonally for products that provide climate control services. Efficient central air conditioners provide double the energy savings during warmer seasons, consistent with a humid tropical climate associated with extremely hot summers and mild winters. Seasonal results further suggest that attic insulation provides energy savings mostly in cooler months.

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[8] Pool pumps filter water to prevent algae growth and need to be operated more intensively during summer than in winter. So single-speed pumps have oversized motors that waste energy during winter months. In contrast, high-efficiency pool pump motors have variable speeds and programmable timers, features that save energy by reducing hours of operation and lowering motor speeds in winter.

Energy savings from climate control services shifts across fuel types based on seasons. For example, central air-conditioners provide nearly all of their electricity savings during summer months, and a majority of their natural gas savings during winter months. Similarly, attic insulation provides almost exclusively natural gas savings during winter months. In addition, duct leakage repair may provide some electricity savings, but only during summer months, suggesting the gains come from reduced air conditioning demand.

Inferring Causality via the Timing of Retrofit Installation

Panel data techniques inherently identify effects based on changes in treatment status over time. In the case of multiple experiments, where retrofits are installed at different points in time, panel analyses can also provide insights on whether retrofit effectiveness evolves over time.

The difference-in-difference estimates in equation (1) provide no sense of the dynamics of retrofit installation and energy savings: how quickly energy savings occur after a technology is installed and whether this effect accelerates, stabilizes, or reverts to a mean. If past reductions in energy consumption spurs a homeowner to invest in retrofits, rather than vice versa, the previous estimates would obscure this reverse causality. On the other hand, if a temporary surge in utility bills prompts homeowners to adopt energy efficiency measures, then previous estimates would obscure this reversion to the mean. To explore these dynamics, table 4 provides estimates a model with leads and lags of retrofit installations. Specifically, I add indicator variables for years 1, 2, and

3 before designation, years 0-3 after designation, and year 4 forward.[9] Of these eight indicator variables, the first seven are equal to one only for only 12-billing cycles, while the final variable is equal to one in each billing cycle starting beginning fourth years after the date of the retrofit installation.

Figure 4 (table 4, model 2) shows the change in treatment effects leading up to, and following the installation of Super-SEER air conditioner systems. The coefficients on the one, two, and three year lags are close to zero, showing little evidence of energy reducing trends leading up to a retrofit investment. In the year of retrofit installation, total energy consumption drops by an average of 200 kWh per month within the first 12-months, an effect that is significant at the 1-percent level. This considerable energy savings occurring precisely at the time of installation provides powerful causal evidence that the observed energy savings are, in fact, attributed to the new technology. Furthermore, the energy saving effects persist over time, showing no evidence of a rebound effect over time, or diminishing effectiveness in the years immediately following installation. Figure 4 (table 4, model 2) shows that SEER-15 air conditioner retrofits follows a similar pattern, albeit less pronounced and with weaker statistical significance.

Figures 5 and 6 (table 4, models 4 and 5) also show a strong decline in electricity consumption in the 12-month period immediately following a pool pump replacement and refrigerator removal, effects that are statistically significant at the 10-percent level in

[9] 1-year encompasses 12-monthly billing cycles. The first seven indicator variables equals 1 for 12-monthly electricity bills, either before the date of installation (leads) or after the date of installation (lags).
Additional models were estimated with additional leads and lags, including eleven indicator variables for 1, 2, 3, and 4 years before designation, years 0-5 after designation, and year 6 forward. Alternative estimates are similar in sign, significance, and magnitude to the estimates presented in the model with eight indicator variables representing leads and lags and so are not included here.

both models. Prior to removal energy consumption is very stable around zero, and the treatment effect stabilizes at a constant level for all years after the technology change.

Figure 2 (table 4, model 6) shows the effect of attic insulation on natural gas consumption, which follows a similar pattern, with a reduction of 2.5 therms in the year of installation that is significantly different from zero at the 5 percent level. Each of these technology changes follows a similar pattern using the total combined energy consumption as the dependent variable, although with some loss of statistical significance. The models presented in table 4 are recreated using each of the three energy consumption measures in Appendix 1.1, 1.2, and 1.3.

VALIDATION OF ENGINEERING ESTIMATES

A central debate in the energy efficiency literature concerns how energy savings should be measured. Most policies rely on engineering simulations. Homeowners rely on ex ante energy audits to guide investment decisions. Policymakers, in turn, apply the same engineering estimates to conduct ex ante program evaluations. As a result, policies continue to be justified based on engineering estimates of the savings that the technologies could deliver.

Such predictions may be prone to bias from several sources. Faulty assumptions create a gap between realized and predicted energy savings. For example, engineering simulations tend to assume perfect installation and maintenance of energy efficiency upgrades, thereby overstating the projected energy savings. Second, even if based on sound models, simulations fail to account for behavioral responses. In some cases, this can arise from failure to account for interactions between energy uses. For example, efficient light bulbs radiate less heat than incandescent bulbs, and as a result efficient lighting upgrades may increase use of heating systems.

Typical engineering models also assume constant use of energy services before and after efficiency investments. Higher efficiency reduces the marginal price of the energy services provided by a product and, consequently, may lead to increased consumption of these energy services, a response called the *rebound effect*. For example, a new, more efficient air-conditioner will lower the marginal price of cool air, possibly leading homeowners to set thermostats at a lower temperature. If so, model bias may have implications for an energy efficiency paradox and related cost-effectiveness.

More than 30 years of research finds that engineering simulations relying on faulty assumptions create a gap between realized and predicted energy savings. For example, Metcalf and Hassett (1999) find that engineering simulations overpredict the energy savings from attic insulation by more than 500 percent when compared with actual savings in household energy bills. More recently, Davis et al. (2014) find that aggregate engineering figures overestimate effects of refrigerator replacements by 250 percent or more.

The large magnitude of engineering bias for residential retrofits is surprising, especially considering that validations in similar settings, such as residential building codes and commercial lighting retrofits, find engineering estimates are quite accurate (Jacobsen and Kotchen 2013; Lang and Siler 2013).

One explanation may be that residential retrofit validation studies represent apples-to-oranges comparisons, whereby engineering bias may be exaggerated because of poorly defined retrofit parameters that differ from the retrofits actually installed. Metcalf and Hassett (1999) and Davis et al. (2014), both validation studies of residential retrofits, compare empirical estimates with a priori engineering estimates based on a hypothetical scenario of technology adoption; neither study compares ex ante engineering models calibrated to estimate energy savings from the actual sample of households and technologies used for empirical estimates. A priori engineering estimates have limited policy relevance; in fact, most ex ante program evaluations use predictions from engineering models parameterized according to the precise technology improvements and building characteristics as the true sample of adopters. Hence, a timely and policy-relevant need exists for empirical validations of technology-specific ex ante engineering estimates of energy savings from retrofits compared with ex post empirical estimates using billing data.

Empirical Comparison with Engineering Estimates

Figures 1 and 2 visually compares the empirical results with ex-ante engineering estimates of energy savings recorded by GRU. Red triangles denote average engineering estimates of energy savings (table 1, row 1). Black dots denote coefficients of energy savings from the difference-in-difference models (table 2). In Figure 1, coefficients correspond to total energy savings (table 2, panel A); while in Figure 2, coefficients correspond to electricity savings only (table 2, panel B). Vertical black bars represent 95-percent confidence intervals around point-estimates. When the engineering estimate of energy savings

If engineering estimates of energy savings fall within confidence intervals of empirical estimates, then the difference-in-difference models fail to reject equality among ex-ante and ex-post estimates. Based on prior literature, one might expect that most engineering estimates of energy savings fall well above the bounds of the confidence intervals, which would support the claim overestimation bias from engineering models.

Contrary to expectations, in figure 1, a large majority of engineering estimates fall within the confidence intervals of the difference-in-difference models. Engineering estimates are impressively accurate for retrofits novel to this study and, in some cases, too conservative. Engineering estimates for eight of the 10 programs fall within, or very nearly within, the 95 percent confidence surrounding difference-in-difference estimates derived from observational data. . Energy savings estimates for SEER-15 air-conditioner replacements are very conservative—underpredicting energy savings. Similarly, engineers also underpredict energy savings from Super-SEER central air conditioning systems. Ex ante engineering models must forecast future weather conditions, which are inherently unpredictable; thus it is surprising to find accurate modeling of climate-dependent energy systems, such as air cooling and pool circulation.

Figure 2, that reports difference-in-differenence estimates using only electricity, underscores the importance of considering both natural gas and electricity with validating engineering estimates. When only considering electricity, engineering energy simulations overestimate actual electricity savings about half of the time – in five out of 10 programs. However, it is important to recognize that this may be a poor validation for technologies, such as attic insulation, that derive most of their energy savings from natural gas.

Results confirm an upward bias in engineering estimates for three technologies previously studied in empirical literature: attic insulation, refrigerator replacement, and room air-conditioners. However, on average, the magnitude of engineering bias appears to be smaller than some prior studies suggest, at least after adjusting for confidence intervals. Engineers overestimate energy savings from attic insulation by 50 percent—a substantial bias. However, even this large bias appears modest compared with a bias of more than 500 percent reported in past literature (Metcalf and Hassett 1999). However, in the case of refrigerators, estimates are in line with recent studies. Engineers overestimate energy savings from refrigerator buybacks by 100 to 300 percent, which is comparable to the bias of 250 percent reported for a similar program in Mexico (Davis et al. 2014).[10] Although engineers estimate energy savings from room air-conditioners, estimates in this study find no statistically significant or economically important energy savings but do not suggest that room air-conditioner replacements increase energy consumption, as reported in Mexico (Davis et al. 2014). It is worth noting, however, that comparison of the magnitude of engineering bias across studies is difficult because of idiosyncratic differences in climate, program regulations, and other confounding factors that complicate generalizations about the accuracy of engineering models. Hence, when compared with previous literature, these estimates should be viewed as additional evidence rather than an improved assessment of engineering bias.

[10] Some of the difference in engineering overestimates for refrigerator programs may be due to differences in specific program requirements in Mexico and Gainesville. In particular, the Mexican refrigerator replacement program issues rebates at the time of a new refrigerator purchase, whereas the GRU refrigerator buyback program only required removal of an old refrigerator. Because of differences in refrigerator replacement requirements, and possibly in how engineering estimates are calculated, valid comparisons between these programs may be limited.

In sum, the accuracy of engineering models varies across retrofit programs, with a tendency to modestly overpredict energy savings. However, inasmuch as this study measures actual performance of retrofits as implemented by residential energy users, the results likely have more relevance for assessing the benefits of policies designed to foster residential energy retrofits than engineering studies.

CONCLUSIONS

Despite the many retrofit rebate programs and calls for increased investment in demand-side management programs, surprisingly little is known about whether energy efficiency retrofits are an effective way to reduce energy consumption. Engineering simulations provide most of the evidence, but simulated predictions, even if based on sound models, do not account for installation quality or behavioral responses. Empirical research that uses field data can evaluate more fully the effects of energy efficiency retrofits on energy consumption.

This paper has evaluated retrofit-specific residential rebate programs by using observed household-level consumption data. The results identify the energy savings from nine retrofit rebate programs in Gainesville, Florida, using a panel data set of electricity and natural gas consumption and building characteristics for **30,000 residences**. The difference-in-difference method compares changes in energy use by a residence before and after an energy-saving retrofit intervention (the treatment group) with changes in energy use by future participants that have not yet received improvements (the control group). The monthly billing data are linked to time-variant and time-constant characteristics of each residence.

This study makes three contributions to the literature assessing energy efficiency programs. First, it is the first assessment of a retrofit rebate program to apply a difference-in-difference method linking billing data and housing characteristics for every customer within a utility service area. Second, by assessing nine retrofit programs, it explores heterogeneity across a range of retrofit options. Third, it uses technology-specific data on engineering predictions and rebate levels to identify retrofit-specific estimates of simulation bias.

The primary contribution is the evaluation of retrofit-specific residential rebate programs based on actual billing data. Results show that engineering simulations are surprisingly accurate compared with empirical estimates, in stark contrast to previous studies. For a majority of retrofit programs, engineering models predicted energy savings within the 95 percent confidence interval of actual energy reductions. For the remaining programs, engineering biases are modest relative to previous studies. Beyond providing new confidence in technology-specific engineering models, the results also shed light on variation in engineering bias across retrofit types.

These findings provide new policy insights about the effectiveness and cost-effectiveness of specific retrofits. First, results inform policymakers about the relative efficacy of different retrofit rebates, allowing inefficient programs to be terminated and efficient programs to be expanded. Second, results provide new empirical evidence about the bias of engineering models, suggesting a need for future research to explain the cause of variation in model accuracy across retrofit types. Third, these evaluations empower homeowners to make informed decisions about energy efficiency investments, using credible information on the expected cost savings from various retrofit options

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Table 1 Descriptive Statistics for Gainesville Residential Energy Efficiency Incentives [mean, (standard deviation)]

Variable	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioning Maintenance	Low-Income Grants	Whole Home Performance
Ex-Ante Energy Savings	160.6	46.0	19.5	146.7	127.4	129.5	107.8	37.6	93.7	207.4
(kWh per month)	(44.0)	(9.7)	(0.0)	(13.0)	(33.1)	(3.7)	(7.0)	(2.9)	(68.1)	(83.3)
Project Cost	$7,291	$5,672	-	$1,452	-	$761	$863	$97	-	-
	($1,467)	($1,412)	-	($505)	-	($501)	($913)	($94)	-	-
Rebate	$555	$295	$162	$284	$72	$199	$359	$55	$2,138	$867
	($62)	($44)	($21)	($97)	($12)	($77)	($100)	($4)	($1,564)	($418)
Treated Houses	623	297	234	394	1,160	577	365	1,216	210	89

Descriptive statistics of rebate participants for each retrofit program. Average project costs, average rebate amounts, average engineering estimates of energy savings by rebate program are calculated from project-level cost and rebate data and technology-specific energy saving estimates. Numbers in parentheses report standard deviations. Sample includes houses participating in only a single rebate program during 2005-2012. Low-income and home performance rebate programs often involve installation of multiple retrofit measures.

Table 2 Estimates of the Electricity Savings from Energy Efficiency Investments

Variables	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioner Maintenance	Low-Income Grants	Whole Home
	A. Total energy consumption (kwh per month)									
Treatment Effect	-222.9***	-151.2***	-23.9	-98.7**	-46.6***	-87.6***	-39.5	1.2	-67.2*	-101.3
	(27.6)	(38.7)	(47.4)	(46.9)	(17.5)	(28.4)	(33.8)	(18.6)	(40.6)	(70.2)
Constant	1,677***	1,360***	1,267***	2,575***	1,479***	1,369***	1,444***	1,724***	1,281***	1,654***
	(48.2)	(26.9)	(31.7)	(37.9)	(12.3)	(23.8)	(30.3)	(13.6)	(42.6)	(59.4)
Observations	114,415	51,173	38,645	65,606	195,337	98,570	62,108	201,670	35,306	15,128
R-squared	0.72	0.72	0.58	0.65	0.66	0.65	0.68	0.67	0.558	0.677
	B. Electricity consumption (kWh per month)									
Treatment Effect	-138.9***	-81.0***	-26.5	-125.4***	-49.8***	-28.2	-14.9	5.0	-96.8***	-46.3
	(18.6)	(28.2)	(32.1)	(30.3)	(12.5)	(18.8)	(23.9)	(12.7)	(27.5)	(42.2)
Constant	1,262***	1,035***	961***	1,764***	1,106***	1,121***	1,194***	1,114***	935***	993***
	(34.1)	(17.1)	(30.3)	(24.8)	(8.4)	(11.8)	(18.6)	(9.3)	(38.5)	(34.2)
Observations	114,156	51,046	38,332	65,483	194,544	97,837	61,923	201,004	35,114	15,053
R-squared	0.77	0.74	0.59	0.71	0.67	0.68	0.69	0.68	0.608	0.666
	C. Natural gas consumption (therm per month)									
Treatment Effect	-4.0***	-3.5***	-1.0	0.7	-0.1	-2.8***	-1.3	-0.2	1.9	-2.5
	(0.8)	(1.1)	(1.6)	(1.1)	(0.5)	(0.8)	(0.9)	(0.5)	(1.5)	(1.9)
Constant	33.3***	23.3***	22.6***	30.5***	28.9***	23.4***	21.6***	25.4***	23.8***	28.3***
	(0.5)	(1.0)	(1.7)	(2.4)	(0.4)	(0.7)	(1.2)	(0.5)	(1.1)	(1.7)
Observations	75,974	26,677	19,583	44,584	126,233	59,913	38,886	128,741	19,907	11,248
R-squared	0.80	0.80	0.68	0.75	0.77	0.76	0.80	0.80	0.649	0.771

Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. In Panel A the dependent variable is total energy consumption (electricity and natural gas combined) measured in kilowatt hours per month. In Panel B the dependent variable is electricity consumption (kWh per month). In Panel C the dependent variable is natural gas consumption (therms per month). The variable *treatment effect* is a retrofit specific treatment indicator equal to 1 for billing months after retrofit installation for houses participating in that specific program and equal to 0 otherwise. Coefficients represent the monthly electricity use changes after retrofit installation. Numbers in parentheses report standard errors clustered by house. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *).

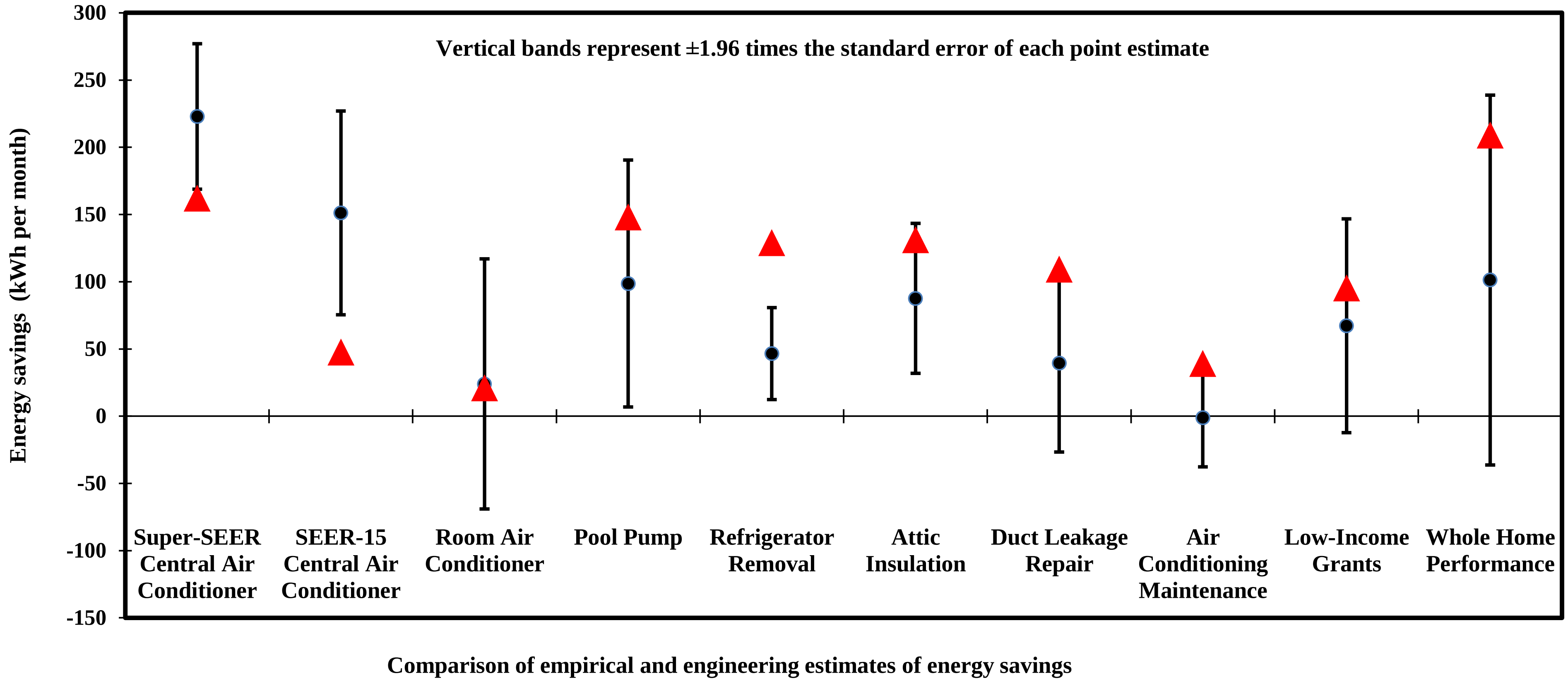

Figure 1 Comparison of empirical and engineering estimates of total energy savings. Red triangles denote average ex-ante engineering energy savings estimates (table 1, row 1). Black dots denote coefficients of total energy savings from both electricity and natural gas (table 2, panel A). Vertical black bars represent 95-percent confidence intervals around point-estimates.

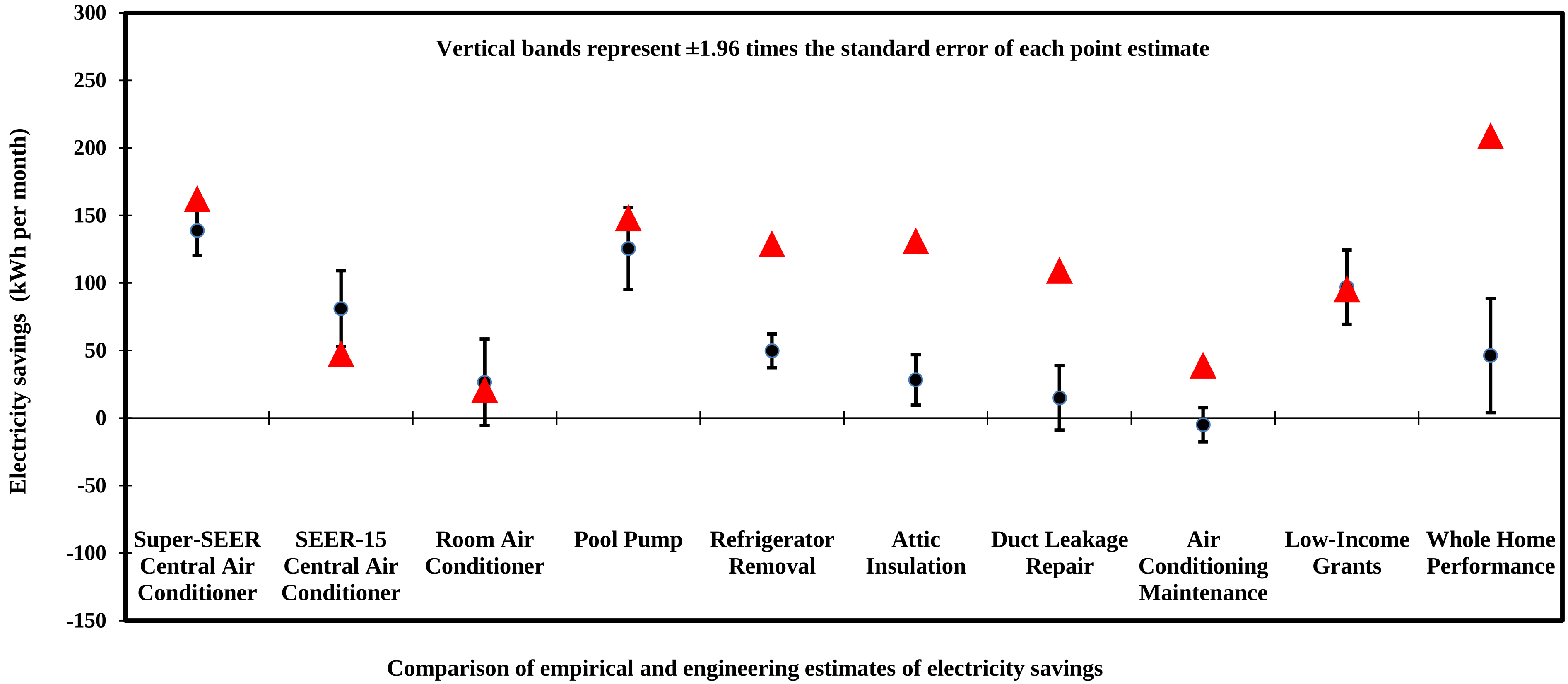

Figure 2 Comparison of empirical and engineering estimates of electricity savings. Red triangles denote average ex-ante engineering energy savings estimates (table 1, row 1). Black dots denote coefficients of energy savings from electricity (table 2, panel B). Vertical black bars represent 95-percent confidence intervals around point-estimates.

Table 3 Seasonal Estimates of the Electricity Savings from Energy Efficiency Investments

Variables	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioner Maintenance	Low-Income Grants	Whole Home
	A. Total energy consumption (kwh per month)									
Treatment Effect	-147.3***	-106.0**	-11.4	-100.1*	-23.3	-116.5***	-23.9	14.5	-21.8	-12.2
	(36.0)	(43.8)	(61.6)	(53.9)	(22.1)	(34.7)	(41.1)	(23.2)	(56.4)	(93.4)
Treatment Effect X May-October	-148.8***	-90.1**	-24.8	2.9	-46.2**	57.3*	-31.3	-29.5	-86.7	-168.5**
	(32.0)	(35.8)	(48.6)	(45.1)	(19.1)	(29.5)	(39.4)	(23.5)	(53.0)	(84.7)
Observations	114,415	51,173	38,645	65,606	195,337	98,570	62,108	201,670	35,306	15,128
R-squared	0.72	0.72	0.58	0.65	0.66	0.65	0.68	0.67	0.559	0.677
	B. Electricity consumption (kWh per month)									
Treatment Effect	-1.8	24.6	-28.3	-114.6***	-32.8***	-10.5	18.6	9.3	-106.4***	59.9
	(17.5)	(25.4)	(34.3)	(27.1)	(11.9)	(16.8)	(20.6)	(13.0)	(28.4)	(38.7)
Treatment Effect X May-October	-269.6***	-210.3***	3.6	-21.2	-33.6***	-35.2*	-67.6***	-9.6	18.2	-200.7***
	(17.3)	(26.7)	(30.8)	(25.8)	(11.2)	(18.3)	(23.8)	(14.0)	(31.3)	(55.7)
Observations	114,156	51,046	38,332	65,483	194,544	97,837	61,923	201,004	35,114	15,053
R-squared	0.77	0.74	0.59	0.71	0.67	0.68	0.69	0.68	0.608	0.667
	C. Natural gas consumption (therm per month)									
Treatment Effect	-6.6***	-6.4***	-1.2	-0.2	0.2	-5.3***	-2.4	-0.1	5.3**	-3.3
	(1.4)	(1.7)	(3.0)	(1.7)	(0.8)	(1.4)	(1.5)	(0.8)	(2.7)	(3.3)
Treatment Effect X May-October	5.2***	5.7***	0.3	1.7	-0.6	4.9***	2.2	-0.2	-6.5***	1.4
	(1.3)	(1.5)	(2.9)	(1.5)	(0.7)	(1.2)	(1.4)	(0.8)	(2.4)	(2.9)
Observations	75,974	26,677	19,583	44,584	126,233	59,913	38,886	128,741	19,907	11,248
R-squared	0.80	0.80	0.68	0.75	0.77	0.76	0.80	0.80	0.649	0.771

Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. In Panel A the dependent variable is total energy consumption (electricity and natural gas combined) measured in kilowatt hours per month. In Panel B the dependent variable is electricity consumption (kWh per month). In Panel C the dependent variable is natural gas consumption (therms per month). The variable *May to October* is an indicator variable equal to 1 for billing months during the warm season between May and October, and equal to zero otherwise; the interaction term *(treatment effect * May to October)* represents the additional treatment effect during warmer months. Coefficients represent the monthly electricity use changes after retrofit installation. Numbers in parentheses report standard errors clustered by house. Asterisks denote significance at levels of 1, 5, and 10 percent.

Table 4 Estimated Effects of Retrofit Installation on Energy Consumption: Temporal Dynamics Using Leads and Lags

	(1) Super-SEER Central Air Conditioner	(2) SEER-15 Central Air Conditioner	(3) Room Air Conditioner	(4) Pool Pump	(5) Refrigerator Removal	(6) Attic Insulation	(7) Duct Leakage Repair	(8) Air Conditioner Maintenance
Retrofit installation leads and lags:								
Technology change $_{t+3}$	-19.3	-20.4	19.2	7.8	4.5	-0.4	27.6	54.0*
	(23.3)	(31.4)	(40.2)	(26.3)	(13.2)	(0.7)	(28.6)	(28.8)
Technology change $_{t+2}$	-9.8	18.7	50.4	1.1	6.1	-0.9	49.1	61.1
	(30.8)	(45.3)	(59.6)	(40.2)	(17.7)	(0.9)	(41.4)	(46.0)
Technology change $_{t+1}$	-20.1	18.3	28.6	4.8	1.1	-1.0	49.4	106.0
	(39.9)	(64.7)	(72.7)	(54.0)	(22.0)	(1.3)	(54.2)	(65.5)
Technology change $_{t0}$	-204.7***	-126.0	29.8	-120.4*	-49.8*	-3.5**	-1.6	100.9
	(49.4)	(80.5)	(90.1)	(69.9)	(25.8)	(1.7)	(61.4)	(75.7)
Technology change $_{t-1}$	-257.5***	-131.4	-37.1	-135.2	-52.1*	-3.6*	12.3	100.4
	(63.2)	(96.2)	(115.1)	(86.8)	(29.7)	(2.0)	(74.8)	(83.0)
Technology change $_{t-2}$	-288.5***	-124.2	-87.7	-149.3	-59.4*	-3.8*	20.4	107.7
	(77.7)	(110.9)	(143.9)	(102.6)	(35.0)	(2.3)	(93.3)	(92.6)
Technology change $_{t-3}$	-326.8***	-112.3	-118.2	-159.3	-60.2	-4.0	-0.8	107.3
	(94.2)	(124.3)	(174.2)	(118.8)	(41.8)	(2.6)	(124.2)	(103.3)
Retrofit installation $_{t-4\ forward}$	-354.9***	-5.8	-114.1	-162.3	-90.2	-3.6	-26.8	58.8
	(120.7)	(150.5)	(231.9)	(143.1)	(56.6)	(3.1)	(177.9)	(106.5)
H_0: designation$_{(t0-t4)}$ = 0	0.002	0.015	0.293	0.512	0.307	0.112	0.875	0.389
R^2	0.72	0.71	0.58	0.71	0.67	0.76	0.68	0.67
Observations	106,440	50,394	38,645	65,126	194,888	59,600	62,280	201,670

Dependent variable(s): total combined energy consumption (models 1-3 and 7-8), or electricity consumption only (models 4 and 5), or natural gas consumption only (model 6). Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. All models include indicator variables for years 1, 2, and 3 before designation, years 0-3 after designation, and year 4 forward. Of these eight indicator variables, the first seven are equal to one only for 12-months, while the final variable is equal to one in each month starting with the fourth year after retrofit installation. Standard errors in parentheses are clustered by house to allow for arbitrary correlation of residuals within each house. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include individual house-by-month fixed effects and billing period fixed effects. See appendicies for additional models using alternate dependent variables.

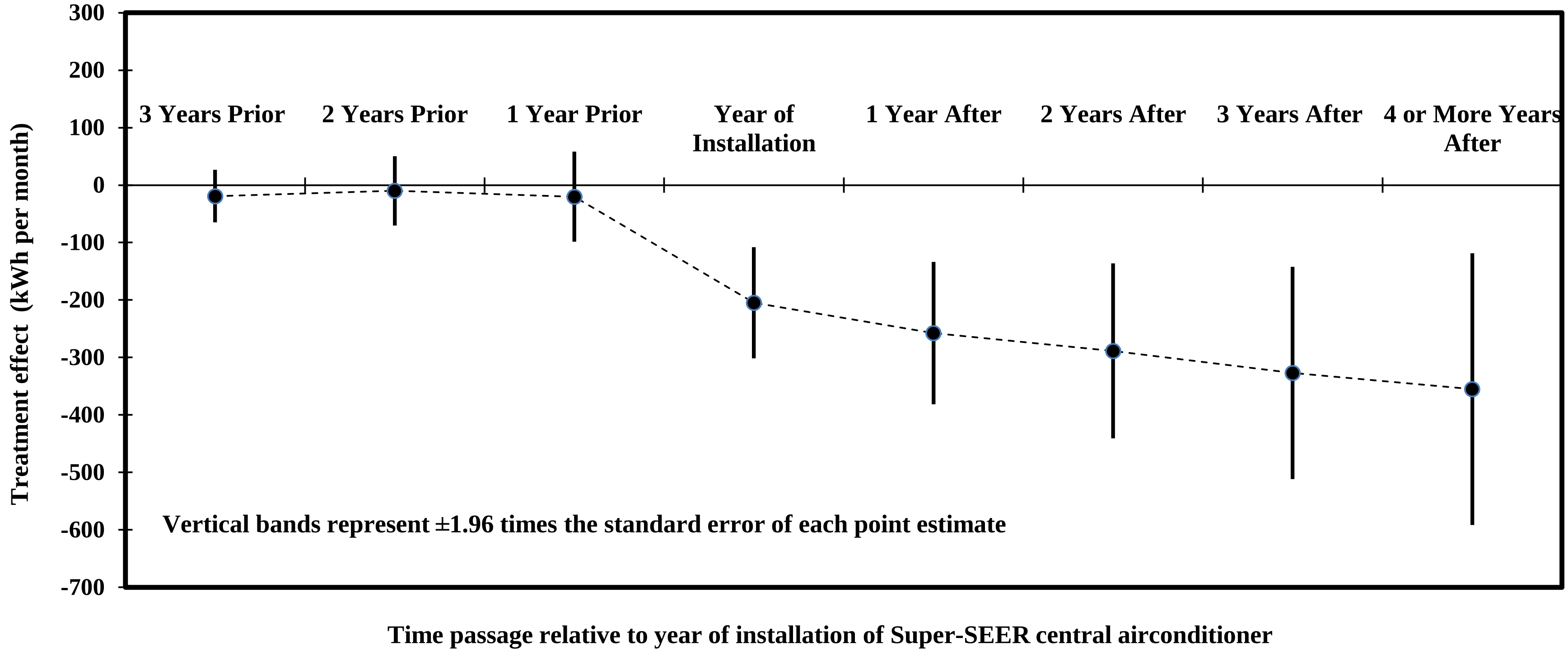

Figure 3 Estimated effects of Super-SEER central air conditioner installation for years before, during, and after retrofit installation. (See table 4, model 1). Dependent variable is total energy consumption (electricity and natural gas combined).

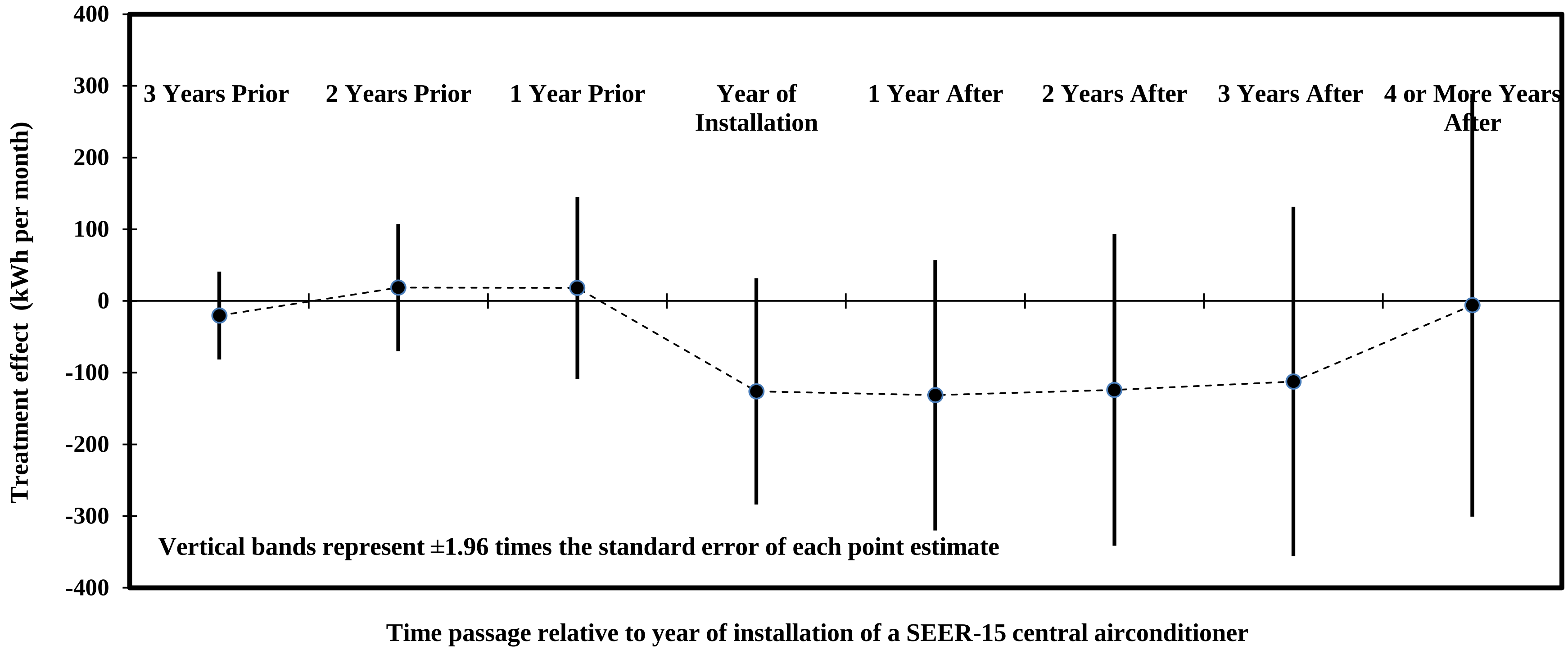

Figure 4 Estimated effects of SEER-15 central air conditioner installation for years before, during, and after retrofit installation. (See table 4, model 2). Dependent variable is total energy consumption (electricity and natural gas combined).

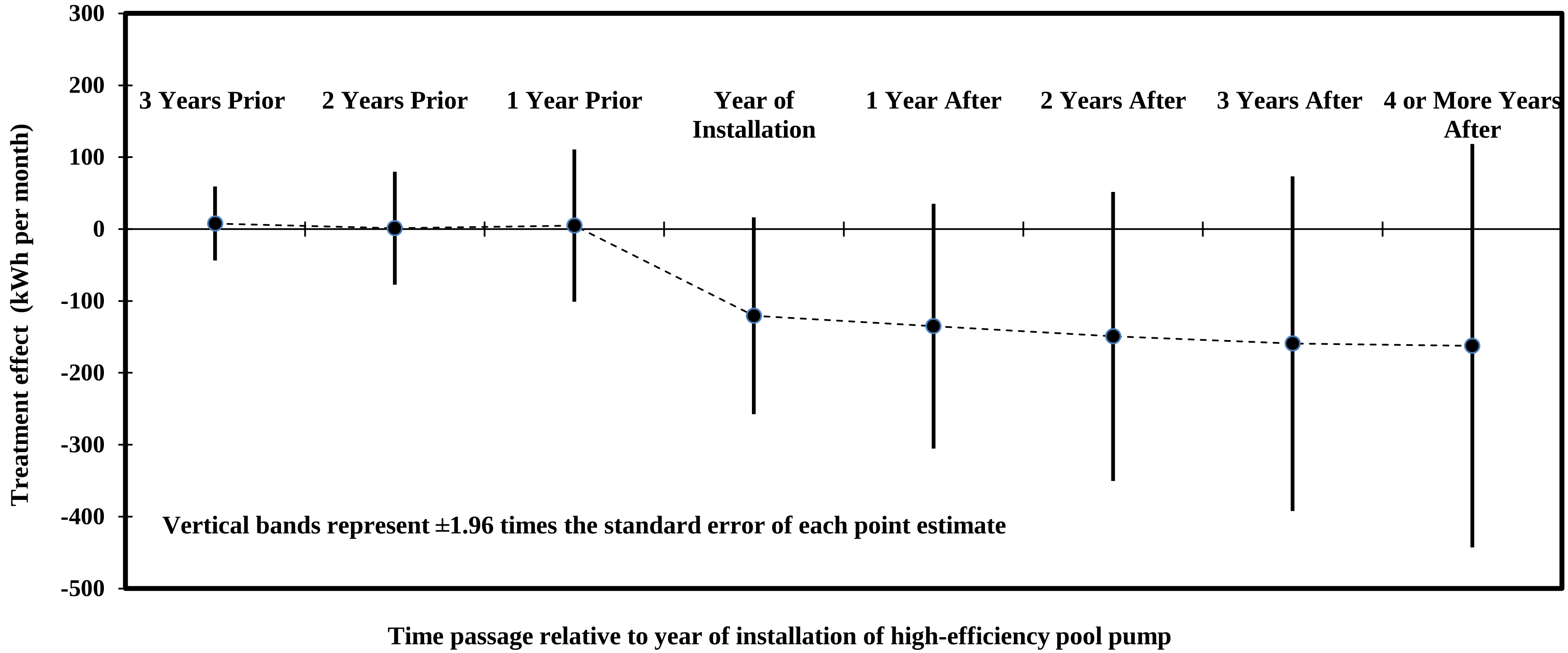

Figure 5 Estimated effects of high-efficiency pool pump installation for years before, during, and after retrofit installation. (See table 4, model 4). Dependent variable is electricity consumption (kWh per month).

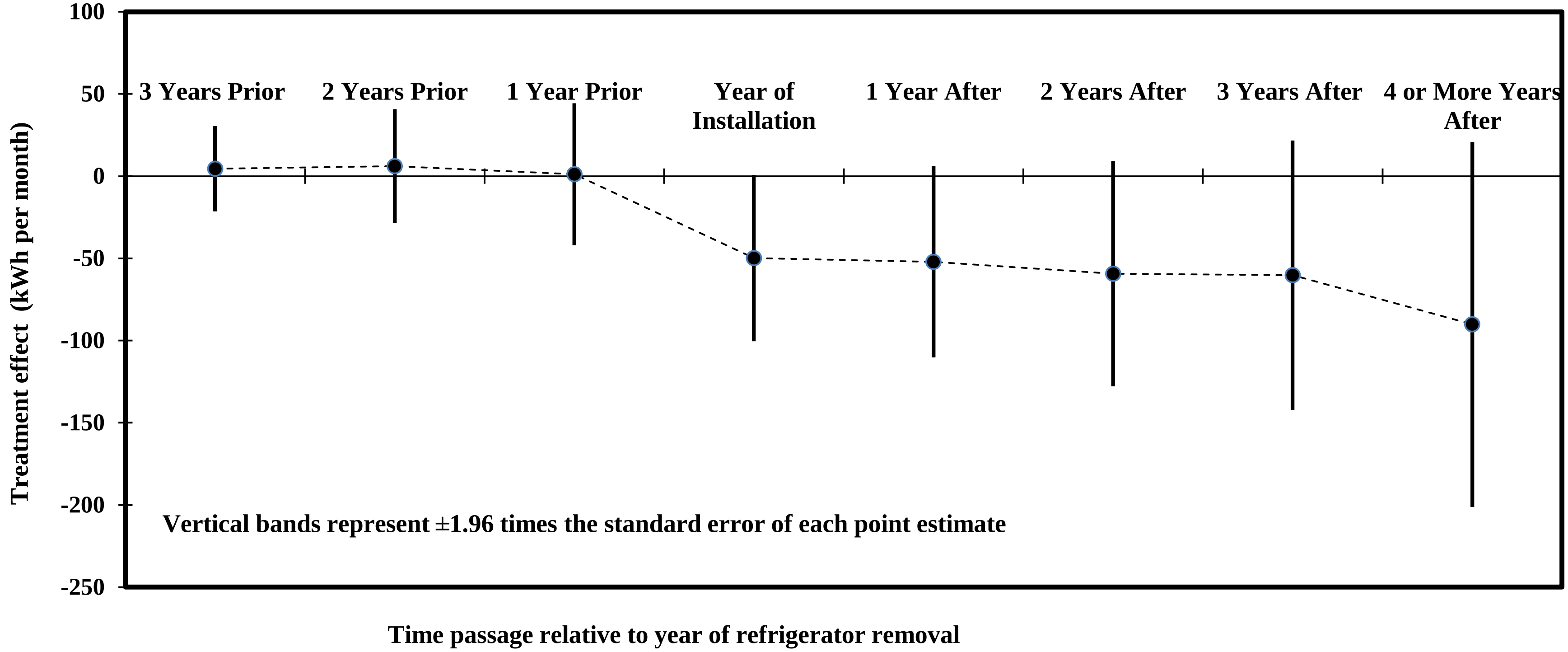

Figure 6 Estimated effects of refrigerator removal for years before, during, and after removal event. (See table 4, model 5). Dependent variable is electricity consumption (kWh per month).

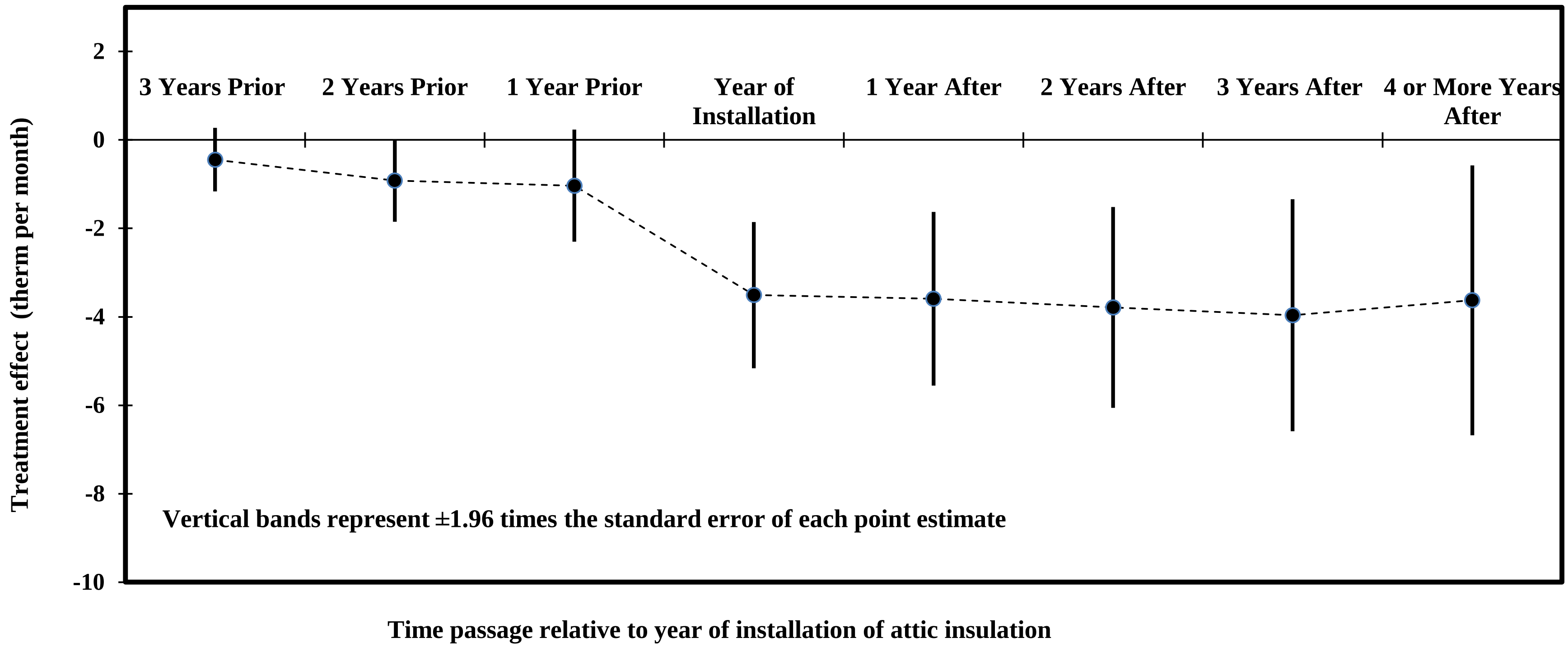

Figure 7 Estimated effects of attic insulation for years before, during, and after retrofit installation. (See table 4, model 6). Dependent variable is natural gas consumption (therms per month).

Appendix 1.1 Estimated Effects of Retrofit Installation on Total Combined Energy Consumption: Temporal Dynamics Using Leads and Lags

	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioner Maintenance
Retrofit installation leads and lags:								
Technology change $_{t+3}$	-19.3	-20.4	19.2	-8.0	9.9	-16.0	27.6	54.0*
	(23.3)	(31.4)	(40.2)	(41.2)	(18.7)	(27.0)	(28.6)	(28.8)
Technology change $_{t+2}$	-9.8	18.7	50.4	-43.1	-0.4	-37.2	49.1	61.1
	(30.8)	(45.3)	(59.6)	(59.9)	(25.5)	(35.7)	(41.4)	(46.0)
Technology change $_{t+1}$	-20.1	18.3	28.6	-7.8	-17.6	-6.7	49.4	106.0
	(39.9)	(64.7)	(72.7)	(79.3)	(31.1)	(47.5)	(54.2)	(65.5)
Technology change $_{t0}$	-204.7***	-126.0	29.8	-122.9	-62.1*	-83.5	-1.6	100.9
	(49.4)	(80.5)	(90.1)	(104.0)	(36.8)	(57.9)	(61.4)	(75.7)
Technology change $_{t-1}$	-257.5***	-131.4	-37.1	-143.2	-59.8	-93.8	12.3	100.4
	(63.2)	(96.2)	(115.1)	(128.1)	(42.8)	(67.9)	(74.8)	(83.0)
Technology change $_{t-2}$	-288.5***	-124.2	-87.7	-214.3	-69.0	-97.5	20.4	107.7
	(77.7)	(110.9)	(143.9)	(153.1)	(51.1)	(77.8)	(93.3)	(92.6)
Technology change $_{t-3}$	-326.8***	-112.3	-118.2	-235.9	-48.5	-50.5	-0.8	107.3
	(94.2)	(124.3)	(174.2)	(175.1)	(62.1)	(90.0)	(124.2)	(103.3)
Retrofit installation $_{t\text{-}4\text{ forward}}$	-354.9***	-5.8	-114.1	-273.1	-105.2	-23.6	-26.8	58.8
	(120.7)	(150.5)	(231.9)	(212.3)	(84.8)	(115.5)	(177.9)	(106.5)
H_0: designation$_{(t0\text{-}t4)} = 0$	0.002	0.015	0.293	0.581	0.033	0.026	0.875	0.389
R^2	0.72	0.71	0.58	0.65	0.66	0.64	0.68	0.67
Observations	106,440	50,394	38,645	65,249	195,681	98,043	62,280	201,670

Dependent variable is total combined electricity and natural gas consumption (kwh per month). Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. All models include indicator variables for years 1, 2, and 3 before designation, years 0-3 after designation, and year 4 forward. Of these eight indicator variables, the first seven are equal to one only for 12-months, while the final variable is equal to one in each month starting with the fourth year after retrofit installation. Standard errors in parentheses are clustered by house to allow for arbitrary correlation of residuals within each house. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include individual house-by-month fixed effects and billing period fixed effects. See appendix for additional models using alternate dependent variables.

Appendix 1.2 Estimated Effects of Retrofit Installation on Electricity Consumption: Temporal Dynamics Using Leads and Lags

	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioner Maintenance
Retrofit installation leads and lags:								
Technology change $_{t+3}$	-21.7	-32.9	36.4	7.8	4.5	-10.2	20.4	29.9
	(16.4)	(24.9)	(32.3)	(26.3)	(13.2)	(19.0)	(19.8)	(20.2)
Technology change $_{t+2}$	-14.0	0.8	81.7*	1.1	6.1	-23.4	44.8	25.7
	(22.2)	(35.4)	(44.6)	(40.2)	(17.7)	(24.5)	(27.8)	(31.2)
Technology change $_{t+1}$	-1.0	-5.6	86.8	4.8	1.1	9.7	55.8	58.6
	(28.7)	(49.6)	(54.6)	(54.0)	(22.0)	(32.7)	(37.4)	(46.0)
Technology change $_{t0}$	-141.2***	-88.5	76.4	-120.4*	-49.8*	-15.3	30.6	58.2
	(36.2)	(61.6)	(66.9)	(69.9)	(25.8)	(38.8)	(42.8)	(53.3)
Technology change $_{t-1}$	-153.1***	-88.2	33.0	-135.2	-52.1*	-28.9	38.8	58.1
	(44.3)	(71.5)	(82.4)	(86.8)	(29.7)	(45.4)	(52.0)	(58.0)
Technology change $_{t-2}$	-163.6***	-79.3	6.3	-149.3	-59.4*	-35.6	44.4	61.1
	(54.1)	(80.0)	(99.8)	(102.6)	(35.0)	(52.9)	(63.3)	(64.1)
Technology change $_{t-3}$	-178.6***	-64.7	-25.2	-159.3	-60.2	-6.9	46.9	62.6
	(64.8)	(90.1)	(118.1)	(118.8)	(41.8)	(61.2)	(82.7)	(71.3)
Retrofit installation $_{t\text{-4 forward}}$	-196.1**	-1.3	-0.1	-162.3	-90.2	25.3	59.7	35.3
	(82.7)	(110.2)	(156.5)	(143.1)	(56.6)	(77.9)	(119.5)	(73.6)
H_0: designation$_{(t0\text{-}t4)} = 0$	0.003	0.012	0.034	0.512	0.307	0.061	0.980	0.495
R^2	0.77	0.73	0.59	0.71	0.67	0.67	0.69	0.68
Observations	106,191	50,267	38,332	65,126	194,888	97,310	62,087	201,004

Dependent variable is electricity consumption (kWh per month). Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. All models include indicator variables for years 1, 2, and 3 before designation, years 0-3 after designation, and year 4 forward. Of these eight indicator variables, the first seven are equal to one only for 12-months, while the final variable is equal to one in each month starting with the fourth year after retrofit installation. Standard errors in parentheses are clustered by house to allow for arbitrary correlation of residuals within each house. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include individual house-by-month fixed effects and billing period fixed effects. See appendix for additional models using alternate dependent variables.

Appendix 1.3 Estimated Effects of Retrofit Installation on Natural Gas Consumption: Temporal Dynamics Using Leads and Lags

	Super-SEER Central Air Conditioner	SEER-15 Central Air Conditioner	Room Air Conditioner	Pool Pump	Refrigerator Removal	Attic Insulation	Duct Leakage Repair	Air Conditioner Maintenance
Retrofit installation leads and lags:								
Technology change $_{t+3}$	0.3	0.5	-1.1	-0.1	-0.1	-0.4	0.2	0.7*
	(0.6)	(0.9)	(0.9)	(0.9)	(0.4)	(0.7)	(0.7)	(0.4)
Technology change $_{t+2}$	0.3	1.1	-2.6	-1.0	-0.8	-0.9	0.5	1.0
	(0.8)	(1.2)	(1.6)	(1.4)	(0.6)	(0.9)	(1.0)	(0.8)
Technology change $_{t+1}$	-0.4	1.9	-4.8**	0.0	-1.2	-1.0	0.5	1.5
	(1.1)	(1.7)	(2.4)	(1.9)	(0.7)	(1.3)	(1.2)	(1.1)
Technology change $_{t0}$	-2.5*	-1.2	-5.1	0.6	-1.0	-3.5**	-0.8	1.4
	(1.4)	(2.1)	(3.1)	(2.5)	(0.9)	(1.7)	(1.5)	(1.5)
Technology change $_{t-1}$	-4.3***	-1.6	-7.2*	-0.1	-1.2	-3.6*	-0.6	1.5
	(1.7)	(2.6)	(3.9)	(3.1)	(1.1)	(2.0)	(1.7)	(1.8)
Technology change $_{t-2}$	-5.0**	-0.9	-9.0*	-2.1	-1.1	-3.8*	-0.5	1.6
	(1.9)	(3.1)	(4.7)	(3.6)	(1.3)	(2.3)	(2.1)	(2.1)
Technology change $_{t-3}$	-5.3**	-1.0	-10.7*	-2.1	-0.9	-4.0	-1.0	1.8
	(2.2)	(3.6)	(5.6)	(4.2)	(1.5)	(2.6)	(2.4)	(2.4)
Retrofit installation $_{t-4\ forward}$	-5.7**	0.6	-11.4*	-1.3	-1.8	-3.6	-2.0	1.7
	(2.6)	(4.1)	(6.4)	(5.0)	(1.7)	(3.1)	(2.8)	(2.9)
H_0: designation$_{(t0-t4)}$ = 0	0.024	0.222	0.524	0.141	0.412	0.112	0.725	0.910
R^2	0.80	0.80	0.68	0.75	0.77	0.76	0.80	0.80
Observations	70,822	26,252	19,583	44,522	126,233	59,600	39,195	128,741

Dependent variable is natural gas consumption (therms per month). Each column is a separate model. All models include individual house-by-month fixed effects and billing period fixed effects. All models include indicator variables for years 1, 2, and 3 before designation, years 0-3 after designation, and year 4 forward. Of these eight indicator variables, the first seven are equal to one only for 12-months, while the final variable is equal to one in each month starting with the fourth year after retrofit installation. Standard errors in parentheses are clustered by house to allow for arbitrary correlation of residuals within each house. Asterisks denote significance at levels of 1, 5, and 10 percent (***, **, *). All models include individual house-by-month fixed effects and billing period fixed effects. See appendix for additional models using alternate dependent variables.