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ABSTRACT

Building energy efficiency has been a cornerstone of greenhouse gas mitigation strategies for decades. However, impact evaluations have revealed that energy savings typically fall short of engineering model forecasts that currently guide funding decisions. This creates a resource allocation problem that impedes progress on climate change. Using data from the largest U.S. energy efficiency program, we demonstrate that a data-driven approach to predicting retrofit impacts based on previously realized outcomes is more accurate than the status quo engineering models. Targeting high-return interventions based on these predictions dramatically increases net social benefits, from $0.93 to $1.23 per dollar invested.

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Engineering models often project that residential energy efficiency is one of the most cost-effective strategies to reduce greenhouse gas emissions (IEA, 2019; McKinsey & Co, 2009). Consequently, it has become a key component of climate and energy policy worldwide, with billions of dollars invested each year to unlock its potential (European Parliament, 2012; EEA, 2018; ARB, 2017; Barbose et al., 2013). Energy efficiency projects are also often considered to be environmentally responsible stimulus for addressing an economy weakened by COVID-19.[1] However, savings have been found to typically fall short of projections.[2] As a result, some economists have begun to caution against prioritizing energy efficiency when applied to climate and economic stimulus policies (Fowlie, 2020; Auffhammer, 2021), as alternative approaches may be more cost-effective for these objectives (Gillingham and Stock, 2018).

The goal of this paper is to contribute to an ongoing debate on whether energy efficiency programs have a role for climate policy. In a recent study, Christensen et al. (2021) find significant heterogeneity in ex-post or realized benefits across retrofitted homes, demonstrating that many energy efficiency projects are cost-effective. The crucial policy question is whether it is possible for program implementers to better identify these projects ex-ante and thus substantially increase the cost-effectiveness of residential energy efficiency retrofit programs through improved allocation of funds. Currently, the vast majority of energy efficiency programs use engineering models to project savings and determine which retrofits should be done.[3] While economists and internal program evaluators have produced consistent evidence of upward bias in these projections (e.g., Fowlie, Greenstone, and Wolfram, 2018; Allcott and Greenstone, 2017; Berry and Gettings, 1998; Dalhoff, 1997; Sharp, 1994), researchers have not developed or tested the

[1]For example, President Biden's "American Jobs Plan" proposes to invest "$213 billion to produce, preserve, and retrofit more than two million affordable and sustainable places to live" (The White House, 2021). See also European Commission (2020) and Hepburn et al. (2020).

[2]This has been shown across a range of energy efficiency initiatives, including home retrofit programs (Fowlie, Greenstone, and Wolfram, 2018; Allcott and Greenstone, 2017; Zivin and Novan, 2016; Berry and Gettings, 1998; Dalhoff, 1997; Sharp, 1994), appliance rebate programs (Houde and Aldy, 2014; Davis, Fuchs, and Gertler, 2014), and in efficient new construction (Levinson, 2016; Bruegge, Deryugina, and Myers, 2019; Davis, Martinez, and Taboada, 2020).

[3]These models are based on equations describing the physical relationships between energy consumption, weather and home characteristics. They also incorporate demographic information, modelling effects of characteristics such as the number of occupants on energy consumption.

effects of more accurate prediction strategies.

The present study aims to fill this gap. Projecting the impacts of multiple retrofits in individual diverse buildings using engineering equations presents major modeling challenges, such as accounting for heat and air exchanges between a building and the surrounding environment, and interactions between different retrofits. To better capture unobserved and difficult to account for factors, we develop a data-driven approach that uses machine learning (ML) combined with demographics, weather, and housing structure variables to predict the impact of weatherization on home energy consumption. ML is well suited for this type of prediction exercise because energy consumption is a function of many complex, high-order interactions among the various observable aspects of a home and household. Our analysis uses data obtained for the Illinois Home Weatherization Assistance Program (IHWAP), which is the Illinois implementation of the U.S. Department of Energy's Weatherization Assistance Program (WAP). WAP's focus is on reducing energy costs for low-income households while also maintaining health and safety. It was started in the 1970's and carbon abatement is not one of the program's original mandates.[4] Given the potential to deliver low-cost reductions, however, residential energy efficiency has increasingly become a part of climate policy platforms. Because many retrofit initiatives (including IHWAP) rely on a common set of accepted structural engineering equations to make their predictions (Edwards et al., 2013; Sentech, 2010), our findings also have implications for determining the cost-effectiveness of these retrofits as a carbon abatement strategy. We focus on energy-related benefits, but the method we propose here could be extended to capture the benefits from effects on other measurable outcomes.

The first step of our analysis is to determine whether a data-driven approach based on previously realized outcomes can improve *ex-ante* prediction accuracy in energy efficiency programs. The ex-ante prediction framework is a form of out-of-sample prediction for which machine learning algorithms are optimized. It differs from the use of ML in ex-post program evaluations (e.g., Burlig et al., 2020) in that the researcher's goal is to mimic

[4]The program's enabling statute mentions energy security, health and safety, and a focus on low-income households, without any reference to carbon abatement or climate goals (US Code, 1964).

the role of a program implementer who is trying to predict the magnitude of treatment effects prior to an intervention. In an energy efficiency program, the implementer would build her model to predict monthly energy consumption using data on home characteristics, observed weather, and upgrades performed for homes that have previously been retrofitted. However, she needs to predict outcomes for new homes based on information available only prior to the retrofits. Along with household demographics and predicted weather, we consider two sets of house characteristics for the prediction exercise. For our primary model, we include the full suite of variables available from pre-weatherization energy audits. For a secondary model, we include only the home descriptors that are publicly available through a county assessor's office, (e.g., year built, square footage, number of bedrooms) and exclude data that can only be collected during the energy audit. This allows us to consider a targeting exercise that may occur even prior to recruitment.

With these data, we use a neural net algorithm with nested cross-validation to predict each home's energy consumption under three conditions: 1) pre-retrofit; 2) post-retrofit; 3) post-retrofit counterfactual, i.e., what consumption would have been in absence of the upgrades. Within this ex-ante framework and data-rich setting, we find that ML estimates of energy consumption based on similar homes, with similar upgrades performed, accurately predict household energy usage. On average, the predictions from both our primary model and the secondary restricted model are statistically indistinguishable from true energy consumption both pre- and post-retrofit.

We then turn to the primary goal of the paper, which is to test whether more accurate predictions of *net present benefits* (NPB) can be used to increase cost-effectiveness by targeting investments to the highest return projects. We begin by predicting the net present benefits for each home with its associated household by summing over the discounted predicted savings, which are determined by the difference between post-retrofit counterfactuals and post-retrofit predictions. We find that only about half of the homes in the IHWAP sample have positive *private* net present benefits, despite the fact that most retrofits (excluding health and safety) performed by the program should have a savings-to-investment ratio (SIR) greater or equal to one, according to the engineering

models. Ex-post analyses of IHWAP and other residential energy efficiency programs have also found low or negative net *social* benefits, at least on average (Christensen et al., 2021; Fowlie, Greenstone, and Wolfram, 2018; Allcott and Greenstone, 2017).

To maximize the total predicted NPB from the program, the implementer would choose to treat only those homes (or individual measures within homes) that have positive expected returns. We estimate predicted benefits at the home level and compare the ML-based targeting strategy to one that uses projections from the program's current engineering model. We evaluate the performance of both strategies against a set of ex-post NPB estimates from Christensen et al. (2021). The *ex-post* estimates are informed by both pre-treatment as well as post-treatment data, acting as a benchmark for assessing the accuracy of the two sets of *ex-ante* predictions. We find that the ML-based strategy significantly outperforms the engineering model and could have a drastic impact on program cost-effectiveness. With our primary model, targeting funds to the 43% of projects with positive predicted energy-related benefits dramatically increases social net benefits of a dollar spent from \$0.93 to \$1.23. Remarkably, 89% of this increase can be achieved from targeting funds to the same number of homes using the model restricted to publicly available data.

These findings are relevant to a broad literature on prediction policy problems (Mullainathan and Spiess, 2017), and more specifically on the development of ML-based approaches to identify heterogeneous treatment effects for optimal policy targeting (Athey and Wager, 2021; Wager and Athey, 2018). Similar methods have been applied to targeting studies that identify the most responsive subgroups across a range of public programs (Davis and Heller, 2020; Knittel and Stolper, 2019; Johnson, Levine, and Toffel, 2019; Erel et al., 2018). Our work belongs to a subset of the literature that quantifies the monetized benefits from targeting applications (Aiken et al., 2021; Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019; Lieber and Lockwood, 2019; Allcott and Kessler, 2019). We introduce a framework that is suited for targeting within programs that involve high fixed costs and generate benefits across long time horizons, which is an important feature of a wide range of infrastructure, energy/climate, and other public

programs. Our targeting function uses a net present value calculation that captures the costs from a wide range of project options and the collective stream of benefits associated with their heterogeneous lifespans.

We apply this framework to the context of greenhouse gas abatement technologies. Quantifying the cost-effectiveness of these technologies is important for policymakers, who often need to consider second- or third-best mechanisms to address climate change (Stiglitz, 2019; Gillingham and Stock, 2018). In considering various technologies, most previous work has focused exclusively on the average performance of GHG abatement investments. However, recent work estimating heterogeneous treatment effects has demonstrated that even interventions that are cost-effective on average, such as behavioral home energy report nudges, can achieve gains in net benefits by better targeting program participants (Allcott and Kessler, 2019; Knittel and Stolper, 2019; Gerarden and Yang, 2021). We find that improvements in predictive modeling could dramatically increase the returns from physical retrofits in energy efficiency programs: they can shift from net negative social benefits to one of the lowest cost vehicles for achieving greenhouse gas reductions. This is even true when we limit the model to publicly available housing characteristics, suggesting the potential to use data-driven predictions both to determine funding allocations among program participants and also to target recruitment efforts to high return homes even before energy audit data are available. These improvements could be realized in the near term and at low cost in government or utility-based programs such as IHWAP. A program's funding prioritization software could readily be modified to incorporate periodically updated estimates of realized savings, rather than relying solely on engineering modeling.

I Background

The WAP is the U.S.'s largest residential weatherization program. It aims to lower energy bills for low-income households while maintaining health and safety. Energy savings are achieved through a variety of measures including insulation, air sealing, heating/cooling system repair or replacement, and electric baseload measures such as lighting

and refrigerators. In order to qualify for WAP, applicants must demonstrate household income below 200% of the poverty guidelines established by the US Department of Health & Human Services (2020). After eligibility verification, energy audits are conducted for the homes of successful applicants. During those audits, detailed information on housing structure is collected (variables presented in Table 1). In IHWAP, data are entered into a program management software called WeatherWorks, which streamlines the steps required to complete a weatherization project, including: determining eligibility, assigning contractors, producing work orders, and determining retrofits to be implemented in each home.

The engineering model embedded in WeatherWorks projects the impacts of a given retrofit on energy savings using data collected during a pre-retrofit audit and a widely-used set of structural equations (Edwards et al., 2013; Sentech, 2010).[5] It estimates savings-to-investment ratios (SIR) for the full set of potential retrofits for each home by dividing the projected life cycle benefits for a candidate retrofit by its installation costs.[6] The WeatherWorks system then ranks all possible retrofits from highest to lowest SIR. Retrofits are performed in order of SIR until the per-home funding is exhausted or until there are no retrofits with SIR ≥ 1.0.[7] The WeatherWorks algorithm adjusts SIR depending on interactive effects between certain retrofits. For example, if attic insulation has the highest SIR, the algorithm accordingly recalculates the SIR for the subsequent measures.

II Data

We use comprehensive data on building structure characteristics, household demographics, the labor/materials costs of all retrofits considered and those completed, and monthly energy use from over 13,000 homes served by IHWAP between 2006-2016. The Illinois' Department of Commerce & Economic Opportunity provided the universe of mea-

[5]The Weatherworks model does not incorporate utility energy consumption data. See Appendix B.

[6]SIR estimates are based on private – not social – benefits. Private benefits are quantified using savings from retail electricity rates, whereas social benefits encompass the total benefits of avoided consumption, including avoided generation, transmission, and distribution costs, and pollution damages (Borenstein and Bushnell, 2018).

[7]The program occasionally must resolve serious health or safety issues even with low SIR.

surements collected during pre-treatment audits, including information on: family size, age, income and sex of householder; home's floor area, number of bedrooms, number of windows, presence of multiple stories, presence of attic, attic insulation, air sealing (blower door test); building vintage and shielding class; type, age, size and operation status of home's main heating equipment; operation status and setting of water heater; presence of air-conditioning; location (county) of home. Table 1 reports descriptive statistics for these measurements as well as information on audit and retrofit dates and retrofit-specific costs. The sample is comprised of low-income families (average income less than $16,800), with an average householder age of 53 years. We observe significant variation in housing structure. For example, air-tightness (as measured by blower door tests) varied from 980 CFM50 (cubic feet per minute, at 50 Pascals) to over 13,600 CFM50.[8] Similarly, we observe substantial variation in retrofit-specific expenditures across homes.

This study also incorporates monthly energy consumption from a major Illinois utility. We restrict the sample to homes that use either natural gas or electricity as their main heating fuel (representative of approximately 88% of homes in the state according to the US Census Bureau, 2013) and focus our analyses on the combined energy consumption from both fuels in MMBtu. Figure 1 plots the distribution of monthly energy use for non-winter (Panel a) and winter (Panel b) months, both before and after retrofits. In winter months, the median home consumes 15.1 MMBtu per month preceding retrofits and 12 MMBtu following retrofits – a 20% difference. During non-winter months, the median home consumes 5.1 MMBtu before retrofits and 4.6 MMBtu following retrofits – a 10% shift. IHWAP primarily targets home heating, but it can also improve the efficiency of cooling among homes that have air conditioning. Therefore, our analyses take into account efficiency improvements for heating and cooling, which are both important in Midwestern climates.

Finally, for each home and month, we collected data on minimum outdoor temperature, maximum outdoor temperature, and precipitation from the PRISM Climate

[8]The blower door tests output airflow measures in cubic feet per minute at 50 Pascals depressurization. Lower airflow values indicate tighter building envelopes.

Group (2018).[9] We use these measurements to calculate heating degree days (with bases $60F$ and $65F$), and cooling degree days (with base $75F$). Summary statistics of the weather variables are reported in Appendix Table A.1 Panel A. We project future weather realizations for use in predicting post-treatment energy usage, which retains the conceptual consistency of one of the main purposes of this study: to predict energy savings *ex-ante*, before weather can be observed. We first created daily "climate normals" for each home by calculating day-of-the-year average pre-treatment temperatures and precipitation. We then aggregated those measures up to the monthly (bill cycle) level for a given home by taking the average of the daily climate normals across the month.[10] We use these projections as the post-treatment weather data for use in our prediction model.[11]

III Empirical Strategy and Results

A Ex-Ante Estimates of Savings

The first step of our analysis evaluates the accuracy of ML-based predictions of the effects of energy efficiency programs in an *ex-ante* setting – before any retrofits have been installed. As it would be for planners making projections that guide funding decisions, our objective is to generate accurate estimates of expected savings for each home, conditional on building characteristics, household characteristics, predicted weather, and the expected costs of measures to be performed.

The ex-ante model of the effects of retrofits takes the form:

$$b_{it}^{EA} = \hat{Y}_{it}(1) - \hat{Y}_{it}(0) \ , \tag{1}$$

where b_{it}^{EA} is an ex-ante prediction of energy usage reductions resulting from retrofits for home i in month t, $\hat{Y}_{it}(1)$ is an ex-ante prediction of energy use in the presence of

[9] The PRISM Climate Group (2018) provides interpolated weather data for the US. We geocoded home addresses using an API from Google (2018) to match with weather data. Indoor temperature measures are not available for our study sample.

[10] For heating and cooling degree days we sum over all days in a given bill cycle, rather than taking averages.

[11] See Table A.1 Panel B for a summary of the projected weather variation, which closely approximates the observed variation in Panel A.

treatment, and $\hat{Y}_{it}(0)$ is an ex-ante counterfactual prediction of energy use in the absence of treatment. Negative values of b_{it}^{EA} represent energy savings.

We separately train two machine learning algorithms to obtain $\hat{Y}_{it}(1)$ and $\hat{Y}_{it}(0)$. We trained the model for $\hat{Y}_{it}(0)$ with untreated usage observations, and the model for $\hat{Y}_{it}(1)$ with treated usage observations. For our primary approach, the explanatory variables marked as "Full Model" in Table 1 were included: (1) the characteristics of homes and households collected during applications and pre-weatherization energy audits, and (2) the expenditures scheduled for each retrofit measure (used only for $\hat{Y}_{it}(1)$, not for $\hat{Y}_{it}(0)$).[12] Additionally, both models include monthly temperature and precipitation. In a secondary exercise, we train models for $\hat{Y}_{it}(0)$ and $\hat{Y}_{it}(1)$ with the subset of home characteristics marked as "Subset" in Table 1. For that, the rationale was to include only information that might be available prior to energy audits (i.e., at a recruitment phase).

We selected the best-performing prediction model from the following candidate algorithms: neural networks, gradient boosted trees, random forests and Lasso. To begin, we used standard five-fold cross-validation to evaluate the predictive performance of these algorithms. Our performance metric is the mean squared error for predicting the retrofits' treatment effects ($b_{it}^{EA} = \hat{Y}_{it}(1) - \hat{Y}_{it}(0)$), where the "ground truth" are the ex-post estimates of savings from Christensen et al. (2021). We chose to use neural networks, which exhibited the lowest mean squared errors (see Appendix Tables C.1 and C.2).[13] In addition, the consistency properties of neural networks are well-understood in the econometrics literature, including within two-step approaches (Farrell, Liang, and Misra, 2021a; Farrell, Liang, and Misra, 2021b).

We then turn to *nested cross-validation* (nested CV) to mimic the exercise of a program implementer needing to predict outcomes for future program participants, for which no outcome data are available. For our proposed procedure, energy consumption data is required only for training the ML algorithms. After those algorithms have been trained, an implementer would only need data on the explanatory variables for predicting

[12] Because the measures performed and their costs are determined as a function of the pre-retrofit audit, they are available ex-ante.

[13] See Appendix C.2.2 for performance metrics of the secondary "subset" model. The mean squared errors are approximately 50% higher than those obtained when the full set of controls.

savings for a set of "new homes." Nested CV guarantees that the subsample for which outcomes are being predicted is not only distinct from the subsample used to estimate model parameters, as is the case with standard cross-validation approaches, but also distinct from the subsample used for tuning the *hyperparameters*.[14]

Figure 2 illustrates our nested cross-validation design. We first split the full set of homes into four equally-sized random subsamples.[15] We then trained the neural net algorithm using three of the subsamples ('training set'), while holding a fourth out as the 'test set.' Within the training set, we performed an inner-layer of cross-validation where, in each iteration, we used two subsamples for training and a third for validation (i.e., to assess prediction accuracy). We selected the best hyperparameter configuration on the basis of lowest mean squared error in the validation set (see Appendix C.1). We repeated this process four times, such that each subsample serves once as the test set, for which entirely out-of-sample predictions are obtained for the full set of homes.[16]

Figure 3 plots the results of our predictions from the primary ML model with the full set of control variables.[17] The ML method is able to recover remarkably accurate household energy usage predictions both pre- and post-retrofit. The x-axis depicts months before and after weatherization. We normalized monthly consumption to make estimates comparable across homes treated at different points in the year such that the y-axis represents deviations from the mean pre-retrofit monthly usage.

The blue line and blue shaded area represent the normalized mean and 95% confidence interval corresponding to observed data. The orange line and orange vertical bars represent the normalized mean and 95% confidence interval for the out-of-sample ML predictions. The green line depicts counterfactual consumption, or predicted energy use

[14] Nested cross-validation, as opposed to standard cross-validation techniques, can significantly reduce bias of out-of-sample prediction errors (Varma and Simon, 2006). For neural networks hyperparameters, which are set by the researcher, include the number of layers, the number of neurons in each layer, and the specification of the activation function (see Appendix C.1). We consider different combinations of these hyperparameters and select those that exhibit lowest validation set mean squared errors.

[15] We use stratified sampling to assure that all monthly observations from a given home are in a single subsample.

[16] The ML models were trained with a sample of over 13,000 homes, while results were assessed for the subsample of 3,913 homes for which a complete year of post-retrofit data were available.

[17] An analogous plot for the subset model is presented in Appendix Figure C.3. It looks strikingly similar to the one produced with the primary model. See Appendix C.2.2.

in the absence of treatment. The red line depicts average energy savings according to the engineering projections. Those projections capture only annual rather than monthly savings, such that the red line is flat.[18]

In Figure 3, we note a slight drop in predicted counterfactual monthly energy use when compared to pre-treatment consumption. This can largely be attributed to discrepancies between observed and projected weather.[19] Estimates of the treatment effect for the average sample home are given by the difference between the green and blue lines illustrated by diagonal shading. Post-treatment predictions and realized energy usage fall substantially in the months following retrofit installation. The overlap between the orange bars and the blue shading in the months both preceding and following the installation of retrofits indicates that the ML predictions are statistically indistinguishable from the observed values. While the prediction errors are minimal on average, in Appendix C.3, we investigate differences in their distribution. Prediction errors in the pre-retrofit and post-retrofit periods are similar in magnitude and sign, reducing any bias in estimated effects of retrofits b_{it}^{EA}.

B Increased Cost-Effectiveness from Targeting

The ultimate goal of this study is to examine whether our data-driven approach to predicting net present benefits based on previously realized outcomes can be used to more effectively target investments to increase their cost-effectiveness. In the previous section, we describe how we predict savings for a project (defined as a home) with its suite of measures that were determined by the standard engineering model. We now examine whether program cost-effectiveness could be improved by choosing to treat (or not treat) homes based on ex-ante savings predictions. The results from this exercise provide a likely lower bound on the potential improvements in cost-effectiveness from improved predictive modeling. Better measure-specific ex-ante savings estimates could

[18] The engineering model predicts average savings of 29%, whereas realized savings are 15%, so that in percentage terms, the wedge is roughly 14 percentage points (Christensen et al., 2021). However, the engineering model predicts almost twice the observed energy consumption both pre- and post-weatherization, so that in units of energy the wedge is almost 3 MMBtu per home.

[19] In Appendix Figure A.1, panel b, we show that predictions using observed weather have closer alignment with pre-treatment consumption.

yield even larger improvements by reallocating funds not only among homes but across measures performed in each home.[20]

We convert predicted savings into monetary benefits by estimating the social benefits of avoided energy consumption, including avoided generation, transmission and distribution costs, as well as benefits from reduced GHG and local air pollution (Borenstein and Bushnell, 2018; Davis and Muehlegger, 2010).[21] The study focuses on energy-related benefits, although there may be other potential benefits such as improvements related to the health and safety (Tonn, Rose, and Hawkins, 2018; Pigg, Cautley, and Francisco, 2018).

We estimate the social net present benefit (NPB) of a project as follows:

$$\text{NPB}_i = \sum_{t=1}^{T_i} \left[\frac{\hat{\beta}_i^e \times \text{cost}_{\text{elec},t}}{(1+r)^t} + \frac{\hat{\beta}_i^g \times \text{cost}_{\text{gas},t}}{(1+r)^t} \right]_i - \text{TotalCost}_i \tag{2}$$

where $\hat{\beta}_i^e$ and $\hat{\beta}_i^g$ are ex-ante annual estimates of electricity and natural gas savings for home i;[22] $\text{cost}_{\text{elec},t}$ and $\text{cost}_{\text{gas},t}$ are the social costs of electricity and natural gas in year t; r is a discount rate; TotalCost_i represents the total costs of the retrofits for home i; and T_i denotes the expected lifespan of the retrofits installed in home i. Similarly, we can calculate benefit-cost ratios (BCR) by dividing the present value of benefits by total costs (details in Appendix E.2). The home-specific lifespans T_i are calculated based on expenditure-weighted averages across retrofits. Resulting average lifespans are close to 30 years. We assume a baseline a discount rate of 3%, which is recommended by the Department of Energy for evaluation of public programs. In Appendix E.3 we test the sensitivity of our estimates to lifetime and discount rate assumptions.

To assess the effect of prediction accuracy on cost-effectiveness, we compare a tar-

[20] This would require causal estimates of measure-specific effects. Given that there can be complex interactions among measures, which are not randomly assigned across homes in our setting, recovering causal effects of measure-specific savings would require strong assumptions about measure selection.

[21] State-level energy prices (reported in Appendix E) were obtained from the Energy Information Administration (EIA, 2017), and were adjusted based on Borenstein and Bushnell (2018); Davis and Muehlegger (2010). Appendix E.4 shows our results also hold when using retail energy prices to calculate benefits (i.e., private benefits).

[22] We estimated the average annual savings for each home in the sample by summing per-home month-of-year averages of b_{it}^{EA} (from equation 1) across twelve months. We assume that 17% of savings are attributable to electricity ($\hat{\beta}_i^e$) and 83% to natural gas ($\hat{\beta}_i^g$), as in (Christensen et al., 2021). More details in Appendix E.1.

geting exercise based on our ex-ante predictions of the effects of retrofits to two kinds of estimates: (1) ex-ante projections from the engineering model that currently guides decisions in the program and (2) from an ex-post evaluation. The first comparison estimates whether and how much the proposed method improves upon current estimates. The second comparison is akin to comparing the information available at the moment of decisions on retrofits to more complete information available years later. Since we cannot observe "true" savings, the ex-post estimates serve as a benchmark that is based on the more complete information set. State-of-the-art ex-post evaluation techniques are designed to account for unobserved factors (to the researcher) that may affect energy consumption patterns, such as changes in weather patterns, in consumer behavior, and in other economic factors that may occur simultaneously with treatment. We use the ex-post estimates from Christensen et al. (2021) as the benchmark (see Appendix D for details).[23]

In Figure 4, we report results from a simulation where we rank homes by net present benefits according to each of the models considered. The figure reports the cumulative social NPB from treating homes ranked highest to lowest.[24] The ex-post model, represented by the blue line, serves as a benchmark for the maximum possible NPB at every point along the x-axis. The first 42% of homes have positive social NPB, after which the cumulative NPB declines. This demonstrates the potential for accurate ex-ante predictions to improve program cost-effectiveness. Targeting investments to the top 42% of projects would maximize the program's energy-related returns with the fully informed ex-post model. Based on a comparison of cumulative benefit-cost ratios (Appendix Table E.1), we find that this corresponds to a possible increase in energy-related benefits from \$0.93 to \$1.36 for every dollar invested in efficiency retrofits.

[23] An implicit assumption is that the ex-post estimates from Christensen et al. (2021) are unbiased. One concern is that if ex-post treatment effect estimation errors are correlated with the errors from our ex-ante neural network approach, then we may obtain biased results on the benefits from targeting. We cannot test for this empirically because the "true" treatment effect errors are unobservable outside of simulated settings. Nevertheless, we argue that this type of bias is likely small in our setting because we use substantially distinct ex-ante and ex-post algorithms, and because our main results still hold when we use a limited set of variables for the ex-ante estimation (results below).

[24] Cumulative social NPB are calculated by summing over the home-specific average savings, where each home receives the same weight regardless of the variance of their expected savings. This implies that the program implementer is risk-neutral regarding the uncertainty of expected savings.

We assess the potential gains from ex-ante predictions by comparing the orange and green lines of Figure 4. To produce the orange lines, first we rank homes according to the ML ex-ante predicted savings from the primary model that includes all variables available at the time of treatment (post-recruitment) and secondary model that only contains the subset of publicly available variables that programs could access prior to recruitment. Then, we assign to those homes the "true" savings according to the ex-post model. Finally, we compute the cumulative "true" savings that would be achieved if homes were treated in the order of the ex-ante ML predicted rank. Similarly, for the green line we compute the cumulative "true" savings, but now following the order of the ex-ante engineering rank. The red line reflects a random ordering of homes treated by the program.

While both sets of ex-ante predictions exhibit better performance than ranking homes at random, the machine learning models yield predictions that more closely approximate the ranking from the ex-post evaluation. These simulations illustrate that targeting investments using predictions based on previously-realized outcomes can dramatically improve cost-effectiveness relative to models that currently guide funding allocations. In this sample, a ML-based targeting strategy using all information available prior to treatment would allocate funds to the top 43% of projects, increasing the social net benefits of a dollar invested from 0.93 to 1.23.[25] Remarkably, using only the information available prior to the energy audits (orange dashed line), the ML-based targeting strategy yields 89% of this increase. However, this does not imply that energy audits have little value for the WAP. While ex ante models can help identify homes with high potential returns, energy audits are still necessary for determining which retrofits (and at which levels) should be performed in the homes that are selected for treatment.[26] Additionally, on-site audits are critical for identifying health and safety issues that need to be addressed. Nevertheless, these findings indicate that the subset model can be used to target recruitment efforts to high return homes even prior to an energy audit.

[25] Based on a comparison of cumulative benefit-cost ratios – see Appendix Table E.1.

[26] Our project-level analysis takes the retrofits selected in the existing program as given. We do not construct or evaluate counterfactual returns based on ex ante predictions in the absence of an energy audit.

In Appendix E.3, we examine the sensitivity of our results to assumptions about the underlying lifespan and discount rate parameters and find that the gains from targeting according to the ML-based ranking are substantial across all scenarios considered.[27]

IV Conclusion

This study demonstrates that better ex-ante predictions could be important for optimizing investments in energy efficiency programs. Results indicate that: (1) predictions based on previously-realized outcomes can outperform status quo engineering models, (2) targeted investments based on this method could result in substantial increases in the cost-effectiveness of retrofit programs, and (3) most of these gains can be realized even with publicly available housing characteristics. While the sample analyzed in this study represents a single retrofit program with specific goals, our approach could provide value to a wide range of programs that rely on similar engineering models. The International Energy Agency has promulgated an increase in worldwide investments in energy efficiency from $140 Billion (currently expected) to $220 Billion per year by 2025 (IEA, 2018). Extrapolating the 21% increase in benefits from the Illinois sample to worldwide investments yields an order-of-magnitude estimate of $46 Billion in annual savings during the 5-year period. These savings would further increase as expenditures continue to ramp up on the basis of 2030 targets.

We identify several limitations in the present analysis to be addressed in future research. While the present study focuses on cost-effectiveness at the home level, the approach could be extended to applications that target measures within a given home. Second, the study makes predictions for homes with metered fuels (electricity and natural gas), while retrofits to a smaller fraction of properties using delivered fuels such as propane, fuel oil, and wood may have outsized effects on greenhouse gas emissions. Third, we are not able to quantify private costs of the applications and installations to households or any non-energy benefits such as improved health and safety. Future work

[27] We consider scenarios with lower and higher insulation lifespans, resulting in average home-specific lifespans of 20 and 40 years, respectively. We also consider alternative discount rates of 2% and 4%. In Appendix Table E.1, we show that the gains from targeting according to the ex-ante ML-based ranking range from $0.23 to $0.33 in net present benefits per dollar spent in the program.

could improve targeting by correlating predicted savings with a broader range of costs and benefits. For example, to the extent that reductions in the cost of home heating reduces the impact of temperature shocks on mortality in winter months (Chirakijja, Jayachandran, and Ong, 2019), then the overall benefits from targeting could be larger than the present estimates indicate.

We are not aware of any energy efficiency programs that use previously-realized outcomes to project savings to recruit households or to select among candidate retrofits. However, it would be straightforward to do so. Models as proposed in this paper need only be run periodically, perhaps by consulting or academic groups, and the resulting predictions could be fed into the back end of the engineering software for program management. Energy usage data would be needed on a subset of already treated homes to train the model, but it would not be necessary for predicting outcomes for new homes, for which home-level usage may not be as readily available.

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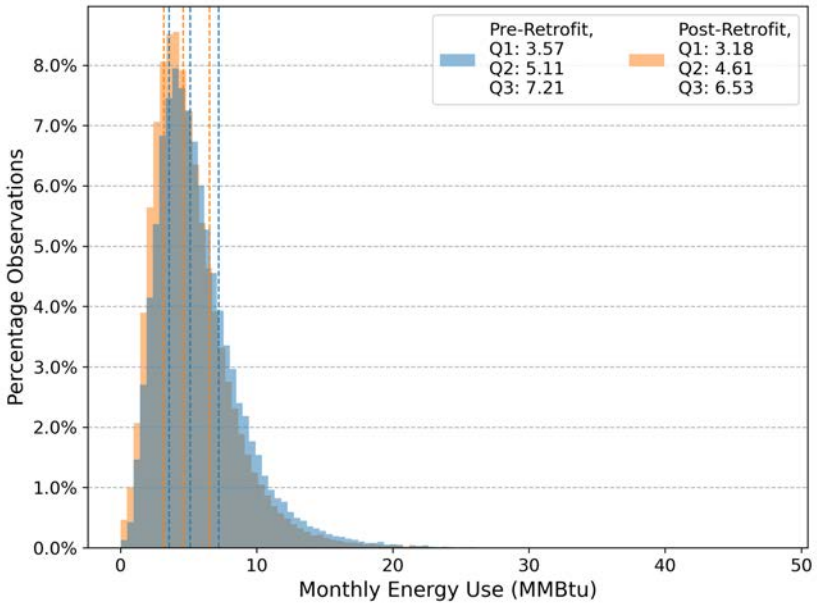
Table 1: Descriptive Statistics for Main Control Variables in the Study

	Average	Standard Deviation	Full Model	Subset
Demographics				
Family Income ($)	16,754.27	10,091.63	X	X
Family Size	2.68	1.65	X	X
Female Householder (%)	0.68	0.47	X	X
Householder Age	53.15	15.82	X	X
Renter (%)	0.06	0.24	X	X
County ID (Categorical)	43.95	26.04	X	X
Housing Structure				
Attic R-Value	11.43	10.96	X	
Floor Area (sqft)	1450.3	622.8	X	X
Pre-Retrofit Blower Door (CFM50)	3,648.79	1,786.18	X	
Main Heat Type (Categorical)	2.25	1.15	X	X
Main Heat Age	19.44	14.6	X	
Main Heat Size (BTU)	76,735.14	41,939.71	X	
Main Heat Operational (%)	0.83	0.38	X	
Building Vintage (Categorical)	6	2.44	X	X
Has Air-Conditioning (%)	0.01	0.11	X	
Has Attic (%)	0.7	0.46	X	X
Has Multiple Stories (%)	0.32	0.46	X	X
Num. Bedrooms	2.76	0.98	X	X
Num. Windows	15.12	5.4	X	
Shielding Class (Categorical)	1.85	0.87	X	
Operational Water Heater	0.99	0.12	X	
Water Heater Setting (Categorical)	2.02	0.4	X	
Administrative Variables				
Audit Month	6	3.4	X	
Audit Year	2010	2.29	X	
Retrofit Year	2011	2.21	X	X
Costs ($) per Retrofit Categories				
Air Conditioning	6.8	90.14	X	
Air Sealing	296.78	287.45	X	
Attic	930.71	714.49	X	
Baseload	175.65	232.23	X	
Door	341.58	360.11	X	
Foundation	300.73	500.35	X	
Furnace	1,352.84	1,179.08	X	
General	99.3	488.31	X	
Health and Safety	486.67	334.03	X	
Wall Insulation	274.75	622.03	X	
Window	668.82	890.98	X	
Water Heater	138.02	229.82	X	
Number of Homes in Sample	13,638	-	-	-

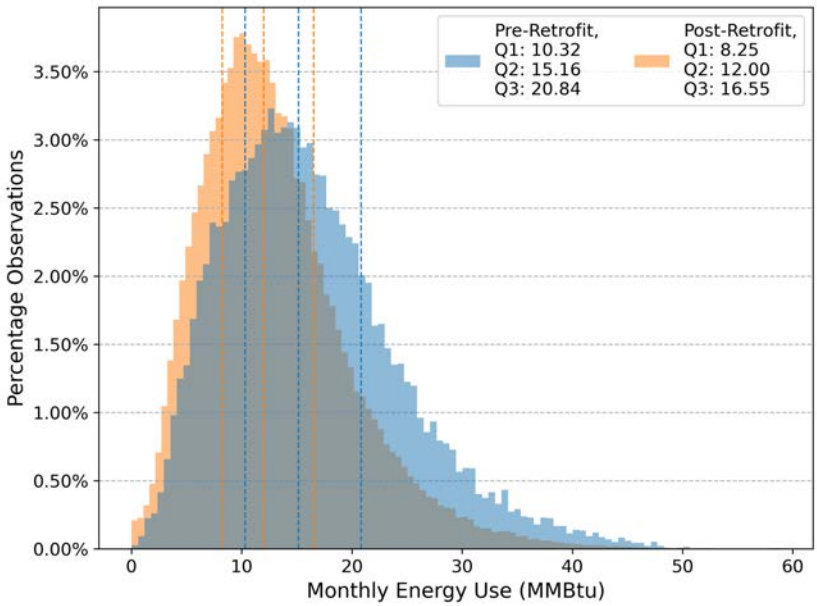
Notes: This table presents descriptive statistics for the main control variables used for training the machine learning algorithms. All monetary values have been inflation-adjusted, by converting to US dollars in 2017. We also consider transformations of floor area (squared and log), and winsorized Main Heat Size. The last two columns indicate, respectively, which variables were included in a model with full information (Full Model) versus in a model that assumes that the energy audit has not yet taken place (Subset).

Figures

Figure 1: Monthly Energy Use Before/After Energy Efficiency Retrofits



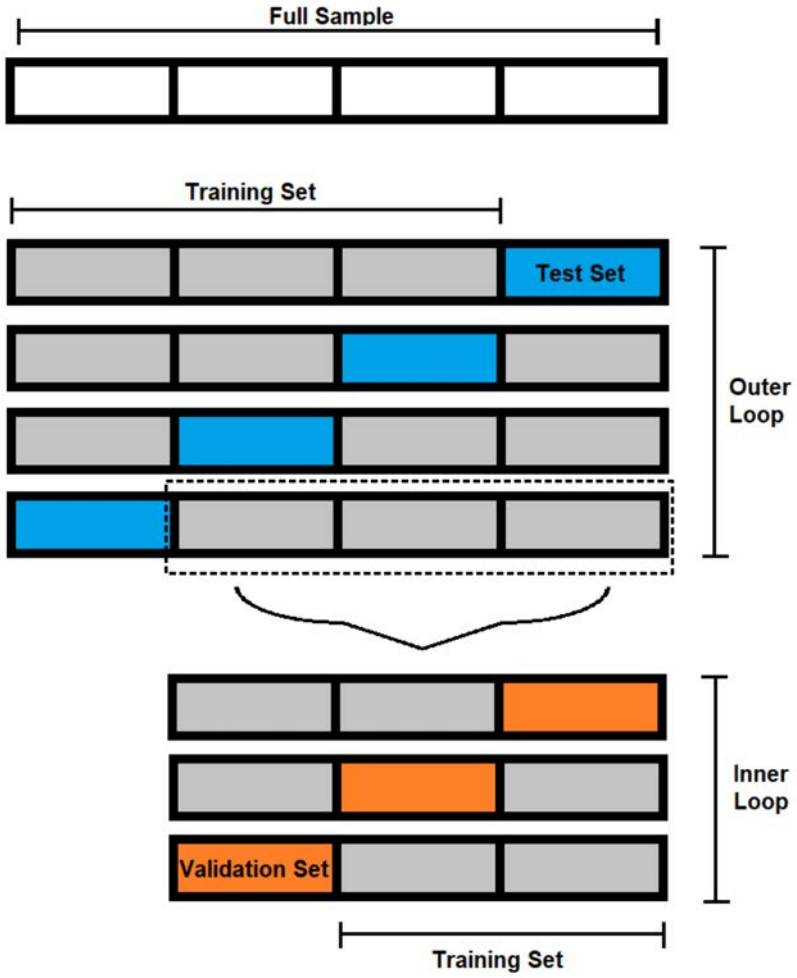
(a) Non-Winter Months



(b) Winter Months

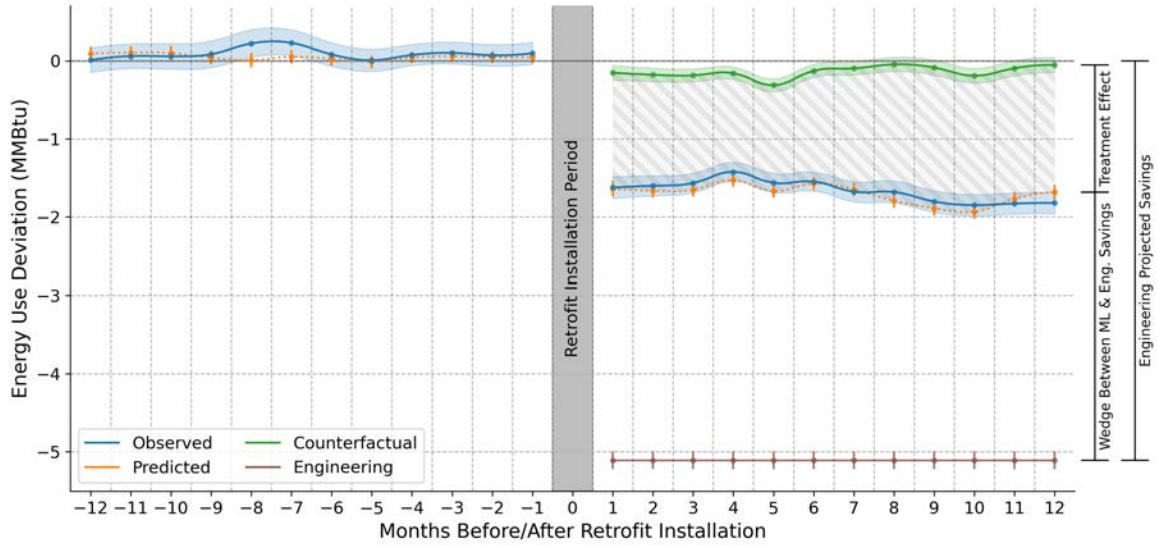
Notes: The figure compares pre-retrofit (blue) and post-retrofit (orange) monthly energy use for homes served by the energy efficiency program. Winter months are defined as November through March. The lower (Q1), middle (Q2), and upper (Q3) quartiles are represented by vertical dashed lines.

Figure 2: Nested Cross-Validation Design



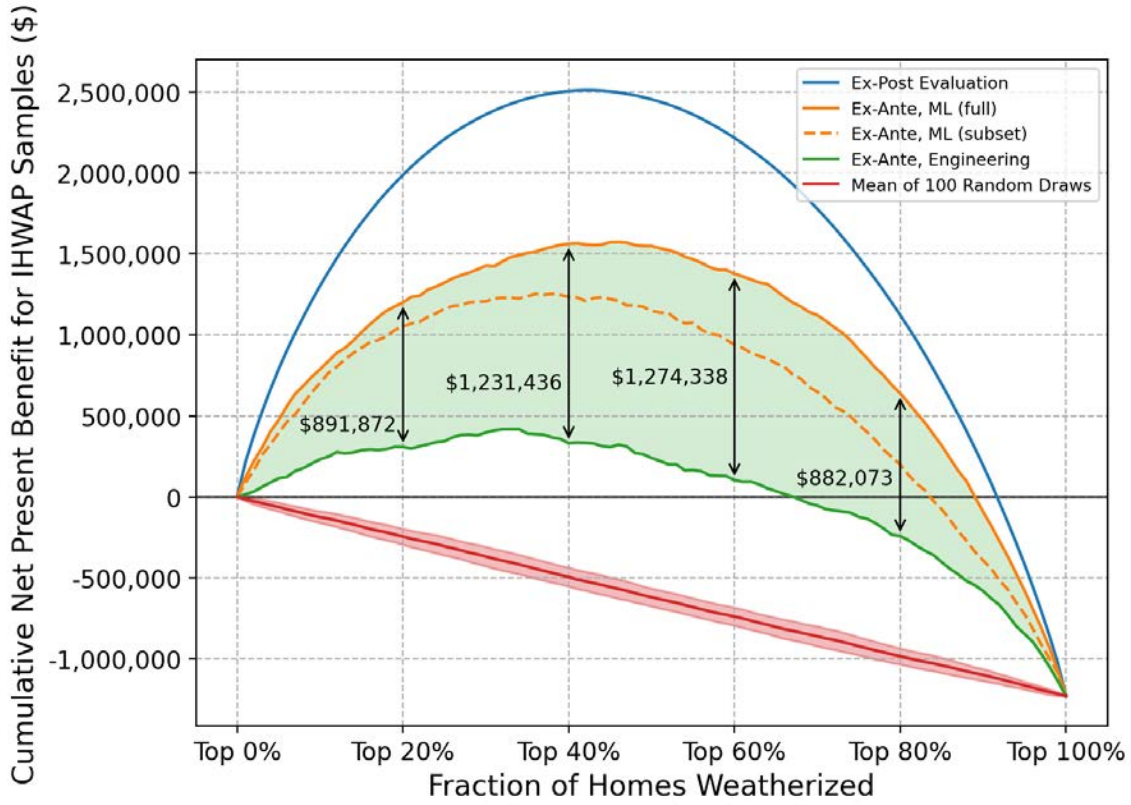
Notes: This figure illustrates our nested cross-validation (CV) design. We randomly split the full sample into four equally-sized subsamples. The top panel represents the outer CV loop. The subsamples illustrated in blue are the test set which, for each iteration, are unseen by the model and are used to generate out-of-sample predictions. Subsamples in gray are used for model training. The bottom panel of the figure represents the inner CV loops. For that case, subsamples in orange represent the validation set, which are used to obtain proxy out-of-sample errors, thus to guide hyperparameter tuning.

Figure 3: Predicted Effects of Energy Efficiency Retrofits



Notes: The figure reports averages and 95% confidence bands for observed (blue), ML predicted (orange), and ML counterfactual (green) energy use in retrofitted homes. The ML model from this figure uses the full set of variables from Tables 1 and A.1. The horizontal axis represents the number months relative to retrofit installation. Data were normalized to account for seasonality (Appendix A). Treatment effects are the difference between counterfactual and predicted use, $\hat{\beta}_{it}^{EA}$ from Eq. 1, illustrated by diagonal shading. The red line represents average energy savings according to the engineering projections. Those projections capture only annual rather than monthly savings, such that the red line is flat. The differences between engineering projected savings and our ex-ante ML savings are consistent with the ex-post realization rates reported in Christensen et al. (2021) Tables C.1 and C.2 (on average, 28% when comparing savings in levels, and 51% when comparing percentage point savings).

Figure 4: Net Present Benefits from ML-based Targeting



Notes: The figure reports estimates of cost-effectiveness when ranking homes based on the ex-ante predicted net present benefits generated by the full ML model including all variables (orange), the secondary ML model including only a subset of variables (dashed orange), the structural engineering model (green), and the mean of 100 iterations of random selections (red) with std. dev. as the red shaded region. The y-axis plots cumulative NPB according to ex-post estimates but following the ranking from each ex-ante approach. NPB calculations use home-specific retrofit lifespans (30 years on average), a 3% discount rate, and account for the social cost of carbon. ML models were trained using close to thirteen thousand homes. Results were assessed in a restricted sample of 3,913 homes for which a complete year of post-retrofit data was available. The total expenditures for this subset of homes was close to $18 million.

Appendix – For Online Publication

A Observed and Projected Weather

We use geocoded addresses to match all homes in the sample with daily minimum outdoor temperature, maximum outdoor temperature, and precipitation from the PRISM Climate Group (2018). PRISM compiles and validates observations from monitoring stations across the US, which are then interpolated based on climate models to produce fine resolution (4km grid cell) estimates of weather variation. We calculate the average daily maximum temperature, minimum temperature, heating degree days (with bases $60F$ and $65F$), cooling degree days (with base $75F$), and precipitation during all homes' (monthly) energy billing cycles using daily weather data from 2003 to 2017. Table A.1 Panel A presents descriptive statistics for the observed weather data, while Panel B presents descriptives for projected weather data.

Table A.1: Descriptive Statistics for Weather Variables

Panel A: Observed Variation				
	Average	Standard Deviation	Min	Max
Cooling Degree Days 75F	18.76	37.6	0	426.64
Heating Degree Days 60F	351.94	388.41	0	2577.13
Heating Degree Days 65F	443.15	442.4	0	2862.13
Precipitation (cm)	3.02	1.89	0	18.36
Max Temperature (C)	17.57	10.13	-7.05	37.1
Min Temperature (C)	6.73	9.44	-19.83	24.37
Number of Obs.	457,224	-	-	-
Panel B: Projected Variation				
	Average	Standard Deviation	Min	Max
Cooling Degree Days 75F	17.08	30.85	0	332.95
Heating Degree Days 60F	362.79	388.32	0	2403.6
Heating Degree Days 65F	455.14	442.28	0	2713.6
Precipitation (cm)	2.91	1.07	0	16.67
Max Temperature (C)	17.32	10.13	-5.84	36.65
Min Temperature (C)	6.31	9.24	-18.91	24.37
Number of Obs.	457,205	-	-	-

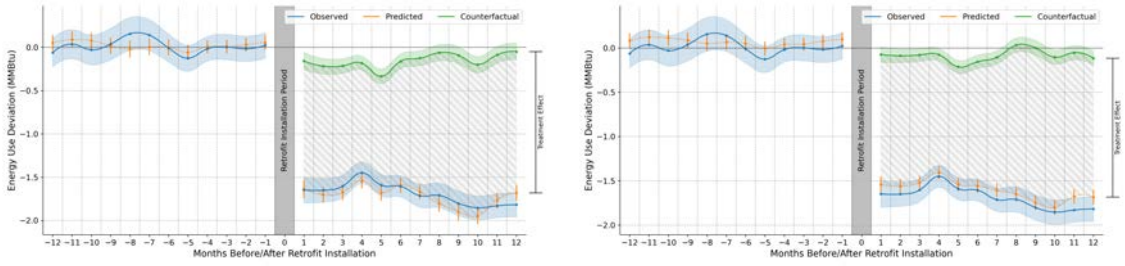
Notes: This table presents descriptive statistics for the observed and projected weather variables used in the analyses.

In Figure A.1, we provide evidence that the main results from this research are not highly sensitive to the use of projected instead of observed weather. The Figure plots energy predictions and treatment effects obtained with projected weather (panel a) and observed weather (panel b). We normalized energy use data to take into account seasonality, as follows: (i) we calculate the pre-retrofit mean energy usage for each month

in the sample; (ii) for the monthly energy usage of a given home, we subtracted by the mean pre-retrofit usage in each corresponding month. The y-axis thus represents deviations from the mean pre-retrofit monthly usage.

As expected, predictions are better aligned with actual energy consumption when the model uses observed weather. Nevertheless, the differences between predicted and real post-treatment usage are not economically or statistically significant when comparing a model with weather projections versus with realized weather observed ex-post. This suggests that projected weather yields savings predictions that are highly similar to those produced by a model with actual weather data. The shaded areas of the graphs reveal minimal differences in the estimated treatment effects from both approaches. Predictions from both approaches exhibit similar seasonal patterns. Finally, the home cost-effectiveness ranks produced with observed (not reported) or projected weather are also similar. Comparing the ranks with a Kendall rank correlation coefficient hypothesis test yields a p-value of 3.81×10^{-15}, thus rejecting the null hypothesis that the ranks produced by both approaches are independent from each other.

Figure A.1: Machine Learning Predictions; Projected Versus Observed Weather



(a) Projected Weather (b) Observed Weather

Notes: This figure presents energy usage prediction results from the machine learning approach, comparing a model that uses projected weather (a) versus one that uses observed weather (b).

B IHWAP's Model for Projecting Energy Savings

Program management for IHWAP is aided by a software called WeatherWorks. Within WeatherWorks, embedded engineering equations are used to project energy savings for an audited house, and to project savings-to-investment ratios (SIR). The current

formula for the whole-house SIR is defined as:

$$SIR_{ov} = (\$Heat_{sav} + \$AC_{sav} + \$Base_{sav} + \$WH_{sav})/(TotalCost) \tag{B.1}$$

where SIR_{ov} represents the overall SIR for a given home; $\$Heat_{sav}$ are heating savings; $\$AC_{sav}$ are air-conditioning savings; $\$Base_{sav}$ are baseload savings (i.e., from refrigerators, lightbulbs, and other electric appliances); $\$WH_{sav}$ are water heater savings; and $TotalCost$ are the total costs of the retrofits.

Each element from the numerator of SIR_{ov} is estimated with complex formulas based on assumed relationships between heat exchange and energy consumption within homes. Once energy savings are obtained, they are transformed into monetary terms by multiplying by fuel costs, discounted with a 3% annual rate, and assuming different types of retrofits have different expected lifespans. For example, the assumed lifespans for a few of the major retrofits are: 25 years for insulation; 20 for air sealing; 20 for furnace replacement; 15 for central ACs; 10 for window ACs; 15 for water heater replacements; 15 for refrigerators; and 5 for fluorescent light bulbs. Further details on each element from equation B.1 are presented in the "WeatherWorks General Design" document, which is available upon request.

For the purpose of this research, SIR_{ov}, $TotalCost$, and the combined whole-house WeatherWorks projected savings have been provided directly to the authors. Section E presents comparisons between SIR_{ov} from WeatherWorks and benefit-cost ratios estimated according to alternative models. Further, with whole-house projected savings it is possible to obtain monetized WeatherWorks projected benefits for each home, which can then be subtracted by $TotalCost$ to obtain net present benefits. Comparisons of NPB across models are also presented in Appendix E.

C Machine Learning Algorithms

C.1 Neural Networks

We use feedforward neural networks for predictive tasks as an intermediate step for ex-ante estimation of program savings. Feedforward neural networks take features (or covariates) $\mathbf{X}$ as inputs, and map them onto functions to generate predictions of a given outcome y (energy consumption). Importantly, these functions are connected in a chain. Following Goodfellow, Bengio, and Courville (2016), let f^1, f^2, ..., f^5 denote the functions of a neural network with 5 layers. A complete neural network can then be expressed as: $f(\mathbf{X}) = f^5(f^4(f^3(f^2(f^1(\mathbf{X})))))$. Often, the outputs of some of the layers are not know to the researcher, making them "hidden layers."

Further, each layer is itself a combination of many neurons (or sub-functions), where the output of all neurons will be stacked to generate the output of each layer. Figure C.1 illustrates the neural networks used in this study. The first layer is the feature layer, for which each numeric feature is normalized and each categorical feature is one-hot encoded (separate binary features for each category). Temperature variables were split into 5 bins to allow for non-linear effects. We also added an indicator for winter months, defined as November through March. The feature layer is followed by three hidden layers, constituted of leaky-ReLU activation functions (described below). The first leaky-ReLU layer contains 64 neurons, the second contains 32 neurons, and the last one contains 16 neurons. The final (5th) layer uses a simple linear activation function to generate the model predictions.

Each neuron in a layer is a (linear or non-linear) function that takes a vector of inputs, multiplies it by a weight vector and outputs a transformed outcome. Each neuron can therefore be defined as:

$$y = f(\boldsymbol{\beta}\boldsymbol{X}),$$

where $\boldsymbol{X}$ is the input vector, $\boldsymbol{\beta}$ is the learnable weight vector and y is the output of the

neuron. For the linear layer, the $f(\cdot)$ function is simply a linear function: $y = \boldsymbol{\beta X}$.

For the leaky-ReLU layers, the $f(\cdot)$ function is non-linear. Specifically, the the output of each neuron in the leaky-ReLU layer is:

$$y = f(\boldsymbol{\beta X}) = \begin{cases} \boldsymbol{\beta X} & \text{if } \boldsymbol{\beta} \cdot \boldsymbol{X} \geq 0 \\ \alpha * \boldsymbol{\beta X} & \text{otherwise.} \end{cases}$$

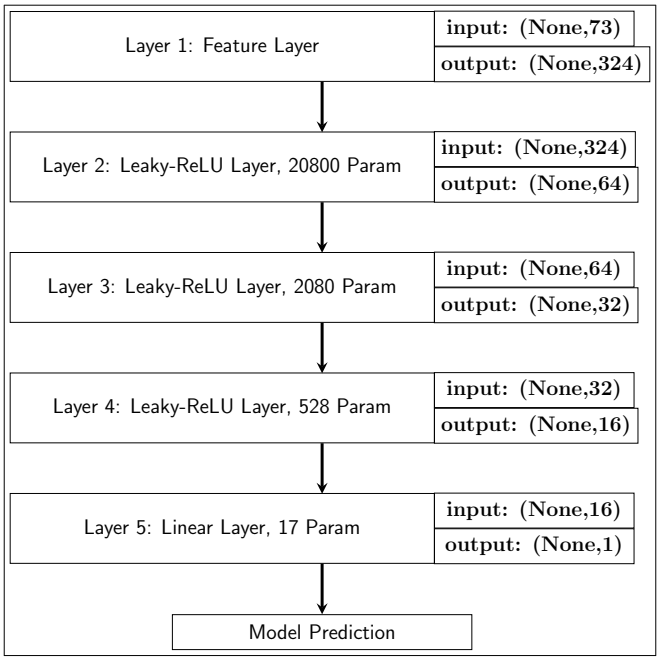
where α is a hyperparamter defined by the researcher. The algorithm described above was trained using the TensorFlow library (Martín Abadi et al., 2015). For this study, a default value of $\alpha = 0.3$ was used. Also, an L1 regularization penalty is applied to each neuron, with varying regularizers depending on the model being considered (Table C.1). An RMSprop optimizer with learning rate equal to 0.00009 is used to find the optimal parameters of the neural network (Hinton, Srivastava, and Swersky, 2013), using mean squared error as the loss function.

We train two separate models: one with the objective of predicting pre-retrofit and counterfactual consumption; and the other for predicting post-retrofit consumption. Both models are first trained on the complete sample for 10 epochs, to learn general patterns. One of the models is then further trained for 30 epochs on pre-retrofit data, while the other is separately trained for 30 epochs on post-retrofit data, to learn specific patterns under each counterfactual scenario. Observed weather data was used for pre-retrofit predictions, while projected weather was used for post-retrofit and counterfactual predictions. Finally, ex-ante predicted treatment effects were obtained by computing the difference between the post-retrofit predictions and the predicted counterfactuals.

C.2 Algorithm Selection and Hyperparameter Tuning

Model selection and hyperparameter tuning were implemented via nested cross-validation (CV). While other cross-validation approaches, such as k-fold cross-validation, may be biased for out-of-sample errors, nested CV has been shown to significantly reduce such bias (Varma and Simon, 2006). Also, nested CV is more desirable in the context of this paper because it is better aligned with a social planner's problem: that is, the

Figure C.1: Neural Network Layers



Notes: This figure illustrates the configuration of the preferred neural network used in this study, selected based on validation-set predictive performance.

social planner must make decisions ex-ante, based on models trained without information about the homes that are candidates for targeting. Our nested CV design is as follows. Prior to training the candidate algorithms, the full sample of observations from this study was randomly split into four equally-sized subsamples, stratifying by home such that all monthly observations of a given home were allocated to only one of the subsamples. Our nested CV design, illustrated by Figure 2 from the main text, thus has an outer loop with four iterations, and inner loops with three iterations each. As shown in Figure 2, for each iteration of the outer loop, the subsamples colored in blue represent the test set which are used to obtain out-of-sample estimates reported in the main text. Subsamples in gray are used to train the models. For the inner loops, subsamples in orange are the validation set, used to assess prediction errors and for hyperparameter tuning. Specifically, the best models were selected based on the Mean Squared Error (MSE) for predicting annual home-specific energy reductions (i.e., the program's Treatment Effect).

C.2.1 Tuning the model with full controls

Here we present hyperparameter tuning results for the full model that includes all the control variables from Tables 1 and A.1. The configurations and prediction accuracy metrics for neural networks are in Table C.1, while accuracy metrics for other algorithms are in Table C.2. These other algorithms were considered at an earlier stage of the project where we found, via standard 5-fold cross-validation, that neural networks resulted in substantially lower MSE (as noted in a comparison of Tables C.1 and C.2). We thus chose to focus on neural networks, further implementing *nested* cross-validation for those.

All neural networks considered have three hidden layers with 64, 32, and 16 neurons, respectively (as illustrated in Figure C.1), with varying regularizers. Table C.1 presents treatment effect MSE for all outer CV subsamples separately, both for when they served as the validation set and when they served as the test set. The first three columns, for example, present results for the iteration with Fold 1 as the test set. The first column presents the regularizers considered, the second column presents the validation set MSE, and the third column presents the test set MSE. The rows in gray highlight the best-performing models, selected based on validation set MSE.

Comparing columns two and three from Table C.1, for example, it can be noted that validation and test set MSE are similar throughout, suggesting that our nested CV design is unlikely to produce biased out-of-sample errors. For some folds, the test set MSE are even slightly smaller than validation set MSE. Overall, the MSE range from 37 to 45, resulting in Root Mean Squared Errors (RMSE) ranging from 6 to 6.7. These represent approximately 34% to 38% of the average per-home annual savings from the program (around 17.7 MMBtu according to the ex-post ML method). These errors are not negligible. Nevertheless, the ex-ante model still results in substantially more accurate estimates than the status quo model currently used by the retrofit program, as discussed in the main text.

Table C.1: Nested CV Results and Hyperparameter Tuning For Neural Networks – Full Model

Fold 1 Test Set			Fold 2 Test Set			Fold 3 Test Set			Fold 4 Test Set		
Regularizer	Validation Set MSE	Test Set MSE	Regularizer	Validation Set MSE	Test Set MSE	Regularizer	Validation Set MSE	Test Set MSE	Regularizer	Validation Set MSE	Test Set MSE
1, 0.6, 0.8	41.0267	38.4655	1, 0.9, 0.8	41.2119	38.9581	1, 0.9, 0.8	40.2521	38.2661	1, 0.9, 0.8	41.2605	41.9979
1.2, 0.6, 0.8	41.4340	39.1346	0.9, 0.9, 0.8	40.7673	39.6166	1.1, 0.9, 0.8	40.8743	38.5912	1.1, 0.9, 0.8	41.6940	42.0887
0.9, 0.6, 0.8	40.7797	38.1490	0.8, 0.9, 0.8	40.4860	37.0120	0.9, 0.9, 0.8	39.8543	38.0942	0.9, 0.9, 0.8	40.9128	42.9775
0.8, 0.6, 0.8	41.1950	37.4924	0.7, 0.9, 0.8	40.3389	37.0238	0.8, 0.9, 0.8	39.5619	37.7234	0.8, 0.9, 0.8	40.8355	44.0094
0.9, 0.5, 0.8	40.9162	38.2768	0.6, 0.9, 0.8	40.8131	39.0279	0.7, 0.9, 0.8	39.3125	37.6872	0.7, 0.9, 0.8	40.7608	43.9808
0.9, 0.7, 0.8	40.6887	37.9356	0.7, 0.8, 0.8	40.3027	37.2739	0.6, 0.9, 0.8	39.1242	38.0720	0.6, 0.9, 0.8	40.8901	44.9226
0.9, 0.8, 0.8	40.5172	37.7860	0.7, 0.7, 0.8	40.5172	37.7411	0.5, 0.9, 0.8	39.7495	38.8418	0.7, 1.0, 0.8	41.4424	43.7979
0.9, 0.9, 0.8	40.3097	37.6383	0.7, 0.9, 0.8	40.3389	37.0238	0.6, 0.8, 0.8	39.4183	37.9601	0.7, 0.8, 0.8	40.8598	44.3152
0.9, 1.0, 0.8	40.3184	37.6173	0.7, 0.8, 0.9	40.7823	38.4516	0.6, 1.0, 0.8	39.1401	38.1964	0.7, 0.7, 0.8	40.9488	44.7300
0.9, 0.9, 0.7	40.5537	37.5104	0.7, 0.8, 0.7	40.1696	36.4351	0.6, 0.9, 0.9	40.1263	38.6208	0.7, 0.9, 0.9	41.4700	43.7533
0.9, 0.9, 0.9	40.7879	37.6167	0.7, 0.8, 0.6	40.2189	36.7940	0.6, 0.9, 0.7	38.6978	37.7130	0.7, 0.9, 0.7	40.2058	44.5816
0.7, 0.9, 0.7	41.4070	37.0017				0.6, 0.9, 0.6	38.7996	37.7797	0.7, 0.9, 0.6	40.3276	45.5583

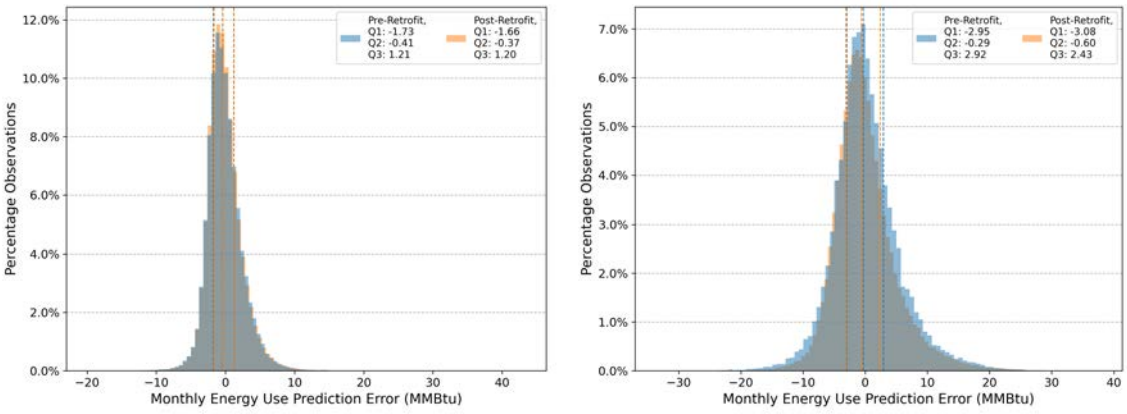
Notes: This table presents results from the nested cross-validation procedure for neural network models. These are results for the model using the full set of control variables. The first three columns present results for the iteration with Fold 1 as the test set (i.e., for that iteration, no data from Fold 1 was used for training the models). Columns 4 through 6 present results for when Fold 2 is the test set, and so on. We present both Validation Set Mean Squared Error (MSE) and Test Set MSE for estimating the treatment effect (i.e., comparing the benchmark treatment effect from the ex-post model with treatment effects according to the ex-ante models). All models have three hidden layers with 64, 32, and 16 neurons, respectively (as illustrated in Figure C.1). The first column from each corresponding fold shows the regularizer that was used in each layer. The rows in gray highlight the model that was selected for each iteration of the nested cross-validation procedure, based on the validation set MSE.

Table C.2: Cross-Validation Results for Candidate Algorithms – Full Model

Model ID	Model Type	Model Parameter	MSE (Treatment Effect)	MSE (MMBtu)	MSE (Pre, MMBtu)	MSE (Post, MMBtu)
1	GradientBoosting	boosting stages = 100, subsample = 0.8	47.308	12.652	13.804	12.383
2	GradientBoosting	boosting stages = 120, subsample = 0.8	44.685	12.526	13.639	12.266
3	RandomForest	number of trees = 20	72.722	13.323	14.336	13.086
4	RandomForest	number of trees = 30, max_depth = 4	279.469	16.171	19.468	15.400
5	RandomForest	number of trees = 30	67.992	13.122	14.078	12.898
6	Lasso	alpha = 1	365.241	19.466	25.483	18.059
7	Lasso	alpha = 0.1	109.867	15.717	18.252	15.124
8	Lasso	alpha = 0.01	58.700	14.610	16.949	14.063
9	Lasso	alpha = 0.005	59.786	14.508	16.838	13.963

Notes: This table presents results from 5-fold cross-validation for candidate machine learning algorithms considered in this study. Full performance metrics for neural networks and nested cross-validation are presented in Table C.1.

Figure C.2: Distribution of Pre- and Post-Retrofit Prediction Errors – Full Model



(a) Non-Winter Months (b) Winter Months

Notes: This figure presents validation set prediction errors based on household by month observations. Winter months are defined as November through March.

C.2.2 Tuning the subset model

Table C.3 below presents performance metrics for neural networks trained only with the subset of control variables available prior to energy audits. The top panel reports results from an initial exploration of the configuration of regularizers, using outer CV fold 4 as the test set. Note that Model ID 7, highlighted in gray, was the best-performing: its validation set MSE was 60.6 (about 50% higher than the MSE for models trained with all controls). The bottom panel of Table C.3 shows that the MSE with this configuration remains stable across outer CV folds. In comparing Tables C.3 and C.1, we find that the optimal regularizers differ substantially depending on the controls that are included, which attests the importance of the tuning procedure.

In Figure C.3, we further inspect the accuracy of the subset model. This is analogous to the event study Figure 3 from the main text. Visually, these two figures are

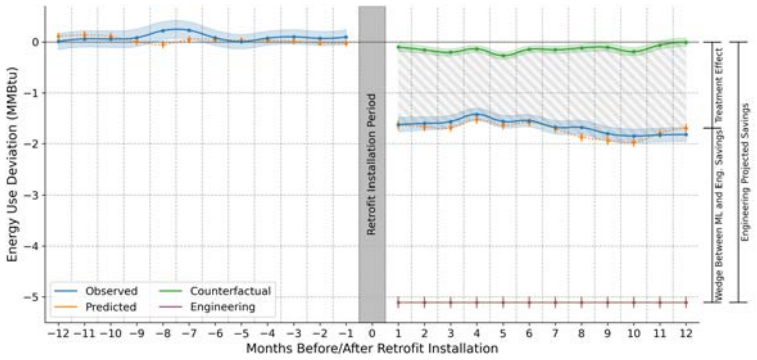
strikingly similar, despite the substantial underlying differences in mean squared errors. This provides supporting evidence that the full and the subset model differ mostly in terms of variance, rather than bias.

Table C.3: Nested CV Results and Hyperparameter Tuning For Neural Networks – Subset Model

	Performance with CV Fold 4 as Test Set		
Model ID	Regularizer	Validation Set MSE	Test Set MSE
1	3.0, 2.0, 2.0	63.404	55.408
2	4.0, 2.0, 2.0	63.866	55.234
3	2.0, 2.0, 2.0	61.033	54.495
4	1.0, 2.0, 2.0	61.094	54.745
5	2.0, 1.0, 2.0	62.445	55.634
6	2.0, 3.0, 2.0	61.611	54.459
7	2.0, 2.0, 1.0	60.600	53.986
8	2.0, 1.0, 1.0	61.636	53.819
9	2.0, 3.0, 1.0	60.778	53.805
10	3.0, 2.0, 1.0	61.504	54.725
	Performance in each outer CV fold, using Model ID 7		
	Regularizer	Validation Set MSE	Test Set MSE
Fold 1 Test Set	2.0, 2.0, 1.0	59.489	61.290
Fold 2 Test Set	2.0, 2.0, 1.0	57.763	57.383
Fold 3 Test Set	2.0, 2.0, 1.0	58.887	60.525
Fold 4 Test Set	2.0, 2.0, 1.0	60.600	53.986

Notes: This table presents results from the nested cross-validation procedure for neural network models. These are results for the model using only a subset of control variables collected before the energy audits. All models have three hidden layers with 64, 32, and 16 neurons, respectively (as illustrated in Figure C.1). The top panel shows results with different configurations of the regularizers. The row highlighted in gray (Model ID 7) was selected as best-performing, based on the validation set MSE. The bottom panel presents details on validation versus test set MSE for each outer CV fold of the best-performing configuration.

Figure C.3: Predicted Effects of Energy Efficiency Retrofits – Subset Model



Notes: The figure reports averages and 95% confidence bands for observed (blue), ML predicted (orange), and ML counterfactual (green) energy use in retrofitted homes. The ML model from this figure uses the only a subset of variables available prior to energy audits. The horizontal axis represents the number months relative to retrofit installation. Data were normalized to account for seasonality (Appendix A). Treatment effects are the difference between counterfactual and predicted use, $\hat{\beta}_{it}^{EA}$ from Eq. 1, illustrated by diagonal shading. The red line represents average energy savings according to the engineering projections. Those projections capture only annual rather than monthly savings, such that the red line is flat.

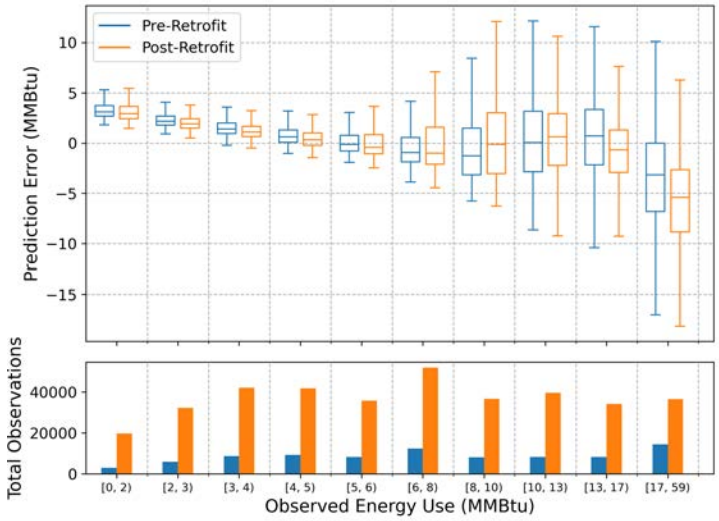
C.3 Decomposing Out-of-Sample Prediction Errors

Returning to the full model with all controls, Figure C.2 presents the distributions of validation set errors for predicting energy usage both before and after the retrofits. It is clear that the errors are centered around zero, both for winter and non-winter months, such that biases along that dimension are unlikely. Absolute errors are less than 2 MMBtu for more than 75% of non-winter months, and less than 3 MMBtu for more than 75% of winter months.

Figure C.4 plots prediction errors by bins of observed usage. This allows for a more precise identification of regions of the sample that may have biased predictions. The top panel presents the errors for each bin, while the bottom panel presents the number of observations in each corresponding bin. The selected algorithm overestimates energy usage for months at the low end, and possibly underestimates usage for months at the high end. That is expected, as those could constitute outlier months when, for example, households were not occupying their residences, or when there was a gas leak. The selected algorithm should not be accurate for predicting outlier observations, otherwise there is a risk of overfitting. Also, bias operates in the same directions for both pre- and post-retrofit observations, such that they cancel and reduce bias in the residuals of estimated treatment effects.

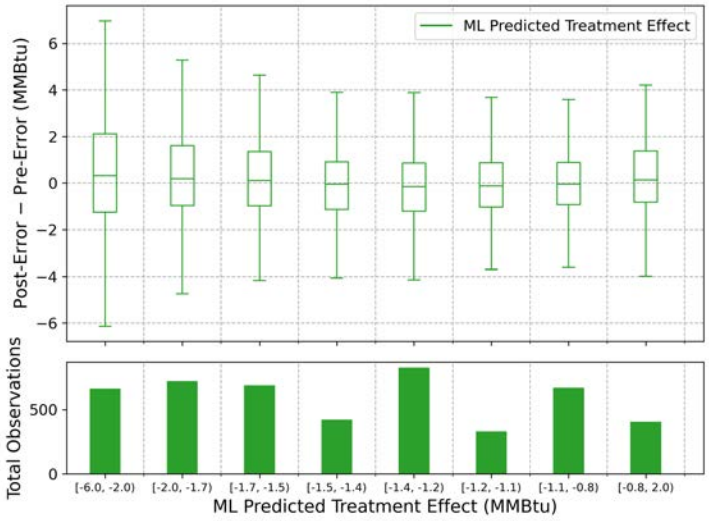
To further assess potential bias, Figure C.5 plots the per-home differences between pre- and post-retrofit prediction errors. Those are plotted across several bins of estimated treatment effects. The figure reveals that the pre- and post-retrofit predictions errors are highly correlated, such that their difference is close to zero, on average. That result holds across all bins of estimated treatment effects.

Figure C.4: Usage Prediction Errors (MMBtu) by Bins of Observed Usage



Notes: The top panel presents validation-set prediction errors, based on household by month observations. The x-axis represents bins of observed energy use. The bottom panel presents the number of observations each corresponding bin.

Figure C.5: Treatment Effect Prediction Errors (MMBtu) by Bins



Notes: The top panel presents the difference between pre- and post-retrofit prediction errors in the validation folds, based on household level observations. The x-axis represents bins of predicted treatment effect. The bottom panel presents the number of households each corresponding bin.

D Ex-Post Evaluation Method

For estimation of ex-post program savings, this paper implements a machine learning-based event study approach. That is a frontier method which has been used for recent impact evaluations, especially of energy efficiency programs (Burlig et al., 2020; Christensen et al., 2021). The advantage of that method, compared to traditional regressions, is that it allows more precise estimation of the program effects for each treated home in the sample. Traditional approaches, such as fixed effects regressions, were designed to estimate average effects, thus fail to capture heterogeneity. It has also been shown that while fixed effects regressions can result in short-term biased estimates in the presence of heterogeneity (Chaisemartin and D'Haultfoeuille, 2020; Goodman-Bacon, 2021), the machine learning-based approach does not (Souza, 2019).

The first step of the approach is to predict counterfactual energy consumption in absence of the retrofits. Then, similar to equation (1) from the main text, energy savings are estimated as:

$$b_{it}^{EP} = Y_{it}(1) - \hat{Y}_{it}(0) \ , \tag{D.1}$$

where b_{it}^{EP} is an *ex-post* estimation of the reduction in energy use resulting from energy efficiency retrofits for home i in month t, $Y_{it}(1)$ is *observed* energy use in the presence of treatment, and $\hat{Y}_{it}(0)$ is a *counterfactual* prediction of energy use in the absence of treatment. Note that since post-treatment data are available, in this case it is only necessary to predict counterfactual energy consumption $\hat{Y}_{it}(0)$ in absence of treatment.

The ex-post savings used in this paper are taken directly from Christensen et al. (2021), who employ Gradient Boosted Trees for counterfactual predictions. Once initial estimates of b_{it}^{EP} are obtained, it is then possible to add structure based on knowledge on how the program operates and on which type of retrofits were implemented in each home. For that, a second-step regression is implemented as follows:

$$b_{it}^{EP} = \boldsymbol{\gamma}\mathbf{X}_{it} + \varepsilon_{it} \ , \tag{D.2}$$

where $\mathbf{X}_{it}$ is a vector including information about demographics, housing structure, program costs, a constant, and an idiosyncratic error term ε_{it}. Simulations demonstrate the improved performance of implementing that two-step approach (Souza, 2019). Finally, predictions obtained from the model described in equation (D.2) are aggregated in order to represent a home's annual energy savings attributable to the retrofits:

$$\hat{b}_i^{EP} = \sum_{t=jan}^{dec} \hat{b}_{it}^{EP} \ , \tag{D.3}$$

where $\hat{b}_{it}^{EP}$ represents the average predicted savings for home i in a given month of the year (January through December); and $\hat{b}_i^{EP}$ is the ex-post estimate of annual energy savings for home i.

Note that ex-post savings obtained in this way are robust to potential confounders, such as changes in weather patterns or the macroeconomic context before and after the retrofits. Other ex-post methods that rely on simple comparisons between pre- and post-retrofit usage and that do not incorporate a causal framework are likely to produce biased estimates of savings for several homes, thus producing an inaccurate ranking of cost-effectiveness. This paper therefore focuses on the frontier ex-post model described above as the most accurate benchmark for ex-ante models.

E Details on Net Present Benefits

E.1 Assumptions

The ML approach described in the main text provides estimates of annual combined energy savings $\hat{\beta}_i$, rather than gas and electricity savings separately. We disaggregated savings by assuming that 17% of those are attributable to electricity consumption and 83% to natural gas, based on prior literature (Christensen et al., 2021). An annual discount rate of $r = 3\%$ is assumed throughout, as recommended by Department of Energy (DOE) for evaluation of governmental programs (Rushing, Kneifel, and Lippiatt, 2012).

Results from the main text incorporate energy costs that account for the social costs of carbon emissions in the energy sector (Borenstein and Bushnell, 2018; Davis

and Muehlegger, 2010), although the program that we used for this analysis uses private benefits due to the nature of program goals. Following prior literature, citygate natural gas prices were used for the marginal private costs of gas (to which social costs of carbon were added) based on emissions factors from the US Environmental Protection Agency (EPA, 1998). Estimates assume a price of \$40 per ton for CO_2 emissions. Based on a similar approach, prior literature provides estimates of the social marginal costs of electricity for the state of Illinois (Borenstein and Bushnell, 2018). The resulting energy prices that incorporate costs of carbon were \$6.74 and \$33.95 per MMBtu for natural gas and electricity, respectively.

Appendix E.4 evaluates results using an alternative approach that calculated energy costs using the average residential energy prices for Illinois over 2009-2016. Those were obtained from the US Energy Information Administration (EIA, 2017), resulting in \$8.32 and \$34.26 per MMBtu for natural gas and electricity, respectively. Price escalation was applied to project future energy prices, also based on recommendations from the DOE (Rushing, Kneifel, and Lippiatt, 2012). Results from this approach reflect the private benefits to consumers that face reduced energy bills thanks to the retrofits. Note that those prices are slightly higher than the ones that incorporate social costs of carbon as a result of energy taxes in Illinois. Figures from Appendix E.4 show that results from this study are robust to assumptions regarding energy prices.

Different types of retrofits installed by the program might have different expected lifespans. To account for these differences, the per-home expected lifespan T_i is calculated as a weighted average based on expenditures across retrofits. For example, a home with expenditures predominantly on wall insulation will have a relatively higher expected lifespan (closer to 25 years) than a home with expenditures predominantly on the water heater (closer to 15 years). Retrofit-specific lifespan recommendations from WeatherWorks documentation suggest home-specific lifespans are around 20 years on average. However, updated estimates from recent engineering literature suggest that some insulation measures may have up to 50-year lifespans (Kono et al., 2016). Retrofit lifespans used in preferred estimates account for longer longevity of insulation measures, resulting

in home-specific lifespans of approximately 30 years. Figures from Appendix E.3 show that results from this study are robust to assumptions regarding retrofit lifespans and discount rates.

E.2 Calculation of Benefit-Cost Ratios

As an alternative to net present benefits, for each model we also calculate benefit-cost ratios (BCR), as follows:

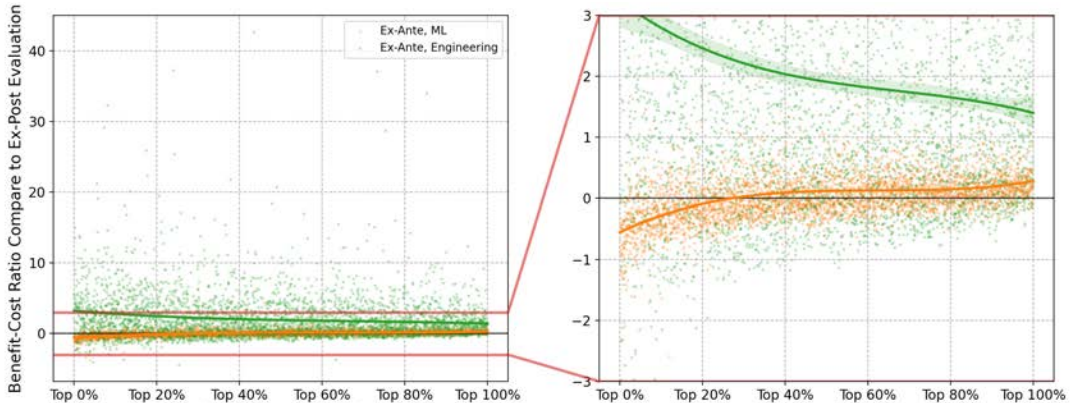
$$\text{BCR}_i = \sum_{t=1}^{T_i} \left[\frac{\hat{\beta}_i^e \times \text{cost}_{\text{elec},t}}{(1+r)^t} + \frac{\hat{\beta}_i^g \times \text{cost}_{\text{gas},t}}{(1+r)^t} \right]_i \Big/ \text{TotalCost}_i$$

We compare ex-ante estimated benefit-cost ratios with those obtained from the ex-post approach. Figure E.1 plots benefit-cost ratio prediction errors for the ex-ante ML method with full controls (orange) and for the ex-ante engineering approach (green). Each point represents the error for a given home, while the lines represent cubic fits. Errors are sorted based on the cost-effectiveness ranking from the ex-post model. The panel on the right zooms in to illustrate the most relevant regions for the sample. The errors from the ML approach are substantially lower than those from the engineering model. The majority of ML absolute errors are lower than 1 and the cubic fit curve ranges from -0.5 to 0.2. Errors from the engineering approach are several times larger, and could be over 30 for some homes. Errors from the engineering model systematically *overestimate* savings. This stark discrepancy may partially explain the poor performance of traditional engineering approaches for targeting funding (Figure 4 from the main text). The mean squared relative error of the benefit-cost ratios is 272.1 for the ML approach, and 686.6 (more than 2 times larger) for the engineering approach.

E.3 Sensitivity to Lifespan and Discount Rate Assumptions

This section presents results for cumulative net present benefits and benefit-cost ratios, with varying assumptions regarding retrofit lifespans and discount rates. The objective is to analyze the sensitivity of the main findings reported in the study to these parameter assumptions. In the main text, the assumed lifespan is close to 30 years and the discount rate is 3%. Figure E.2 presents results with varying retrofit lifespans, hold-

Figure E.1: Household Benefit-Cost Ratio Prediction Errors Ranked by Ex-Post Evaluation



Notes: This figure compares errors in benefit-cost ratios (BCR) generated by the ex-ante ML and engineering approaches. The errors are sorted by the ex-post evaluation rank. BCR are calculated using 30-year retrofit lifespans, a 3% discount rate, and incorporating the social cost of carbon. The dots represent errors for a given home, while the lines represent cubic fits.

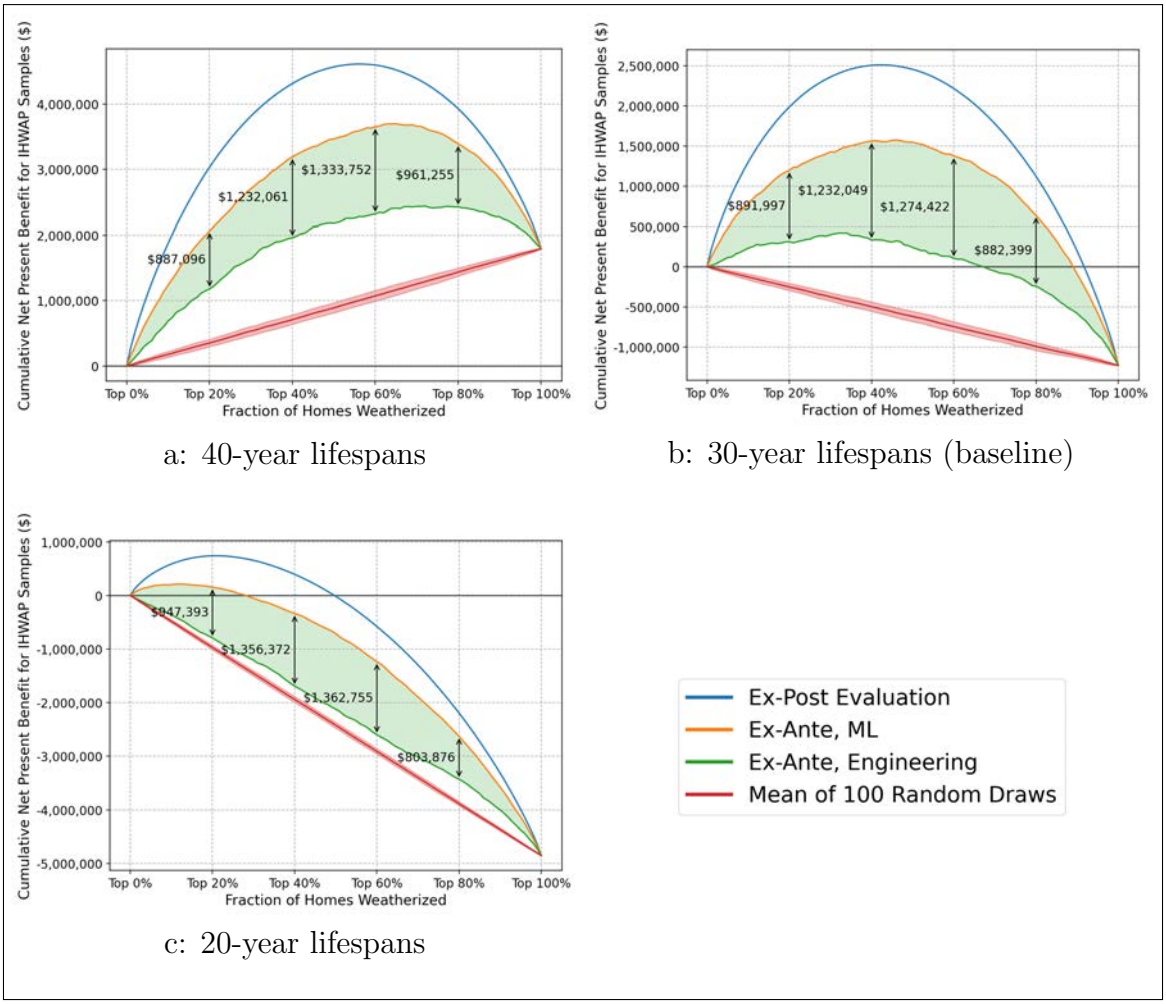
ing the discount rate at 3%. Panel (a) suggests that the program results in almost $2 million in net benefits if the retrofits are assumed to have 40-year lifespans. However, with 20-year lifespans (Panel c) the program is associated with almost $5 million in losses. Nevertheless, the ranking of homes remains stable across lifespan assumptions. Importantly, note that the gains from the ex-ante ML ranking (compared to the engineering approach) are substantial in all three panels, ranging from $1.23 to $1.36 million for the top 40% homes. The implication is that targeting with ML methods will have similarly beneficial impacts even if overall program cost-effectiveness is low.

Similarly, Figure E.3 presents results with varying discounts rates, but holding lifespans at 30 years. Again, the program's overall cost-effectiveness varies substantially, depending on assumed discount rates. Cumulative net benefits are reduced by almost $4.5 million when moving from a 2% to a 4% discount rate. Nevertheless, the conclusions from the main text still hold: rank-distributions produced by the ex-ante ML approach lead to substantial gains. The gains from ML modeling are strikingly similar regardless of discount rate assumptions.

Finally, Table E.1 presents cumulative benefit-cost ratios according to each approach, and with varying assumptions. Monetary "gains" from targeting are calculated by comparing the full sample BCR (first line of Table E.1), with the cumulative BCR that

would be obtained according to each of approaches considered. Conclusions are consistent with those obtained from analyses of net present benefits. Gains from the ex-ante ML approach range from 0.225 to 0.332 for each dollar invested in the program. With baseline assumptions (3% discounts and 30-year lifespan), the subset model achieves about 89% ($\frac{0.264}{0.297}$) of the gains from the full model.

Figure E.2: Cumulative Net Present Benefits, Varying Retrofit Lifespans



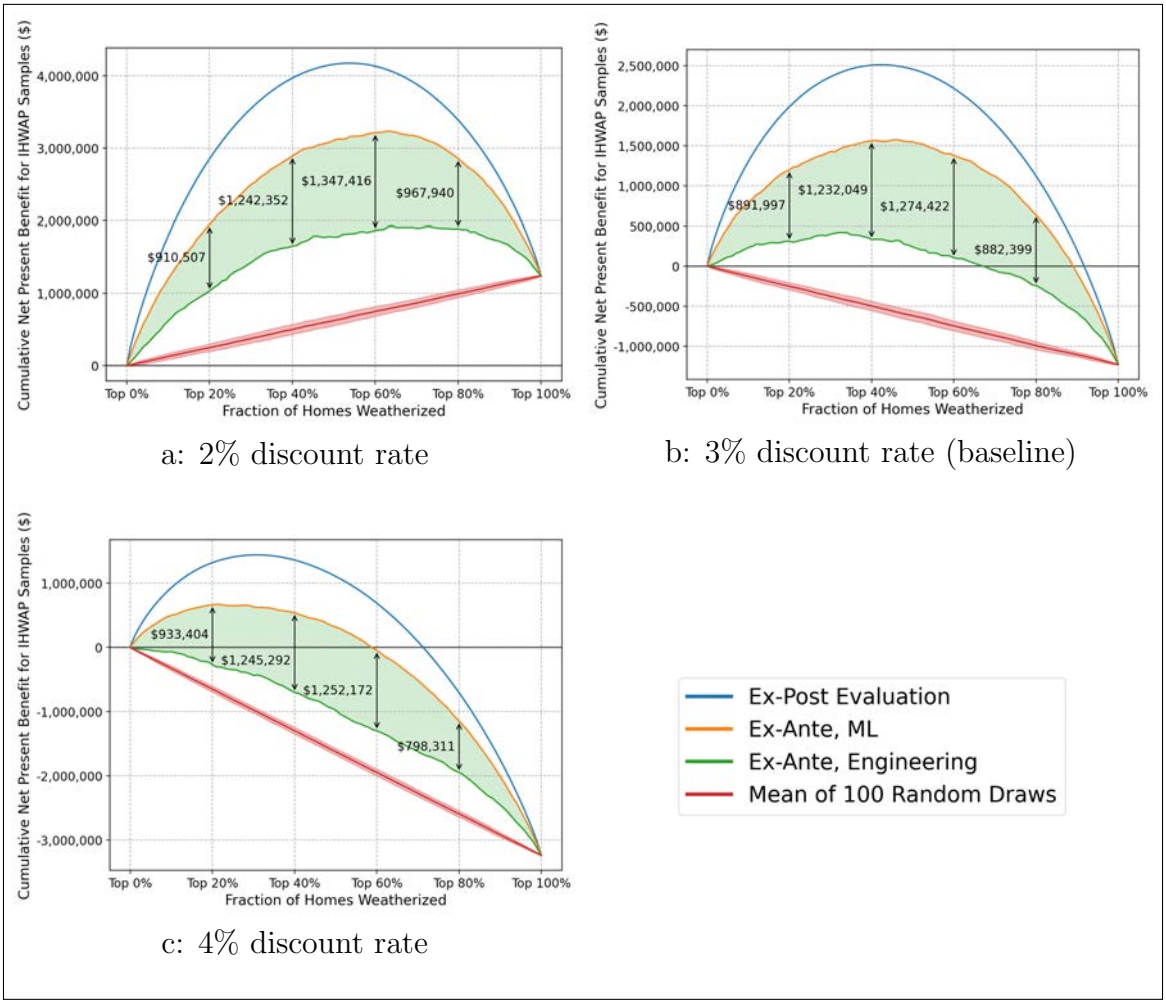
a: 40-year lifespans

b: 30-year lifespans (baseline)

c: 20-year lifespans

Notes: This figure compares presents cumulative net present benefits according to the different models, and with varying retrofit lifespan assumptions. Panel (b) are the results with baseline assumptions (30-year lifespans, and 3% discount rate). Panel (a) presents results with lifespans increased to 40 years, while Panel (c) is for reduced lifespans of 20 years.

Figure E.3: Cumulative Net Present Benefits, Varying Discount Rates



a: 2% discount rate

b: 3% discount rate (baseline)

c: 4% discount rate

Notes: This figure compares presents cumulative net present benefits according to the different models, and with varying discount rates. Panel (b) are the results with baseline assumptions (30-year lifespan, and 3% discount rate). Panel (a) presents results with the discount rate reduced to 2%, while Panel (c) is for an increased discount rate of 4%.

Table E.1: Max Benefit-Cost Ratios, Varying Lifespan and Discount Rate Assumptions

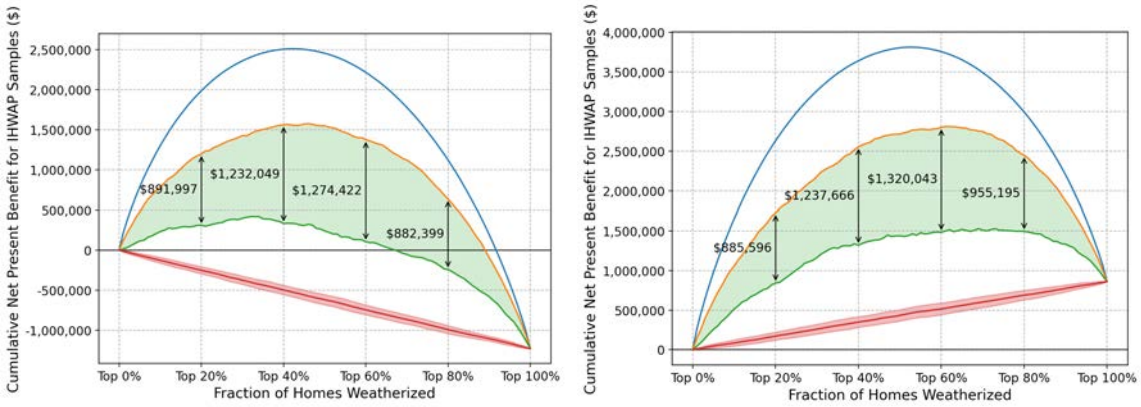
	30-year lifespan, varying discount rates			3% discount rate, varying lifespans		
	2%	3%	4%	40 years	30 years	20 years
Full sample BCR (3,913 homes)	1.069	0.932	0.820	1.100	0.932	0.731
Max BCR, ex-post approach	1.457	1.362	1.306	1.477	1.362	1.252
Gains from ex-post targeting	0.388	0.430	0.486	0.378	0.430	0.522
Max BCR, ex-ante ML approach (full)	1.344	1.229	1.145	1.367	1.229	1.063
Gains from ex-ante targeting (full)	0.275	0.297	0.325	0.268	0.297	0.332
Max BCR, ex-ante ML approach (subset)	1.294	1.196	1.125	1.311	1.196	1.024
Gains from ex-ante targeting (subset)	0.225	0.264	0.305	0.211	0.264	0.293
N homes selected, ex-ante ML approach	2,175	1,685	1,189	2,303	1,685	779

Notes: This table presents the sensitivity of estimates of benefit-cost ratios (BCR) to varying assumptions of retrofit lifespans and discount rates. We present BCR for treating homes in order of net benefits, up to the maximum points (i.e., when marginal benefits equal marginal costs) according to each approach and across scenarios. Each approach serves to produce different rankings of homes, while "true" net benefits from those rankings are always assessed based on the ex-post estimates.

E.4 Private versus Social Benefits

Results from the main text incorporate the social cost of carbon to the net present benefit calculations, as described in detail above. An alternative approach is to consider only the private benefits to the households served by the program, in which case retail energy prices should be used. Results with retail energy prices are presented in Figure E.4, panel (b). Results with baseline assumptions (panel a) are presented for ease of comparison. Note that the overall program cost-effectiveness increases when considering only the program's private benefits to consumers. That is because retail energy prices in the state of Illinois are higher than prices from adding marginal production costs plus the social costs of carbon (Borenstein and Bushnell, 2018; Davis and Muehlegger, 2010). That is most likely due to the energy taxation policies in the state. Nevertheless, the gains from using the ML approach remain similar comparing social versus private benefits: for the top 40% homes, the gains are $1.232 versus $1.237 million in net present benefits.

Figure E.4: Social Costs of Carbon and Retail Energy Prices



(a) Cumulative NPB, social costs of carbon (b) Cumulative NPB, retail energy prices

Notes: This figure compares cumulative cost-effectiveness according to the different models, and with varying assumptions regarding energy prices. Panel (a) presents the same results as in Figure 4 from the main text, which incorporates the social cost of carbon. Panel (b) presents cumulative net present benefits using retail energy prices, thus representing private benefits to the consumers. Note that retail energy prices in Illinois are higher than prices constituted of marginal production costs plus the social costs of carbon (Borenstein and Bushnell, 2018; Davis and Muehlegger, 2010).