Authors uncorrected proof.
For the published version at Nature Sustainability journal:
https://www.nature.com/articles/s41893-024-01314-w

Housing policies and energy efficiency spillovers in low and moderate income communities

Omar Isaac Asensio[1,2*], Olga Churkina[1,3], Becky D. Rafter[1] and Kira E. O'Hare[4]

[1*]School of Public Policy, Georgia Institute of Technology, Atlanta, GA, USA.
[2*]Harvard Business School, Boston, MA, USA.
[3]Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA, USA.
[4]H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA, USA.

*Corresponding author(s). E-mail(s): asensio@gatech.edu;

Abstract

Housing policies address the human dimensions of increasing urban density, but their energy and sustainability implications are hard to measure due to challenges with siloed civic data. This is especially critical when evaluating policies targeting low- and moderate-income (LMI) households. For example, a major challenge to achieving national energy efficiency goals has been participation by LMI households. Standalone energy efficiency policies, like information-based programs and weatherisation assistance, tend to attract affluent, informed households or suffer from low participation rates. In this article, we provide evidence that federal housing policies, specifically community development block grants, accelerate energy efficiency participation from LMI households, including renters and multifamily residents. We conduct record linkage on 5.9M observations of housing program participation and utility consumption to quantify the hidden benefits of locally administered housing block grants in a typical entitlement community in the U.S. Southeast. We provide long-run evidence across 16,680 properties that housing policies generate 5-11%

energy savings as spillover benefits to economically burdened households not conventionally targeted for energy efficiency participation.

Keywords: housing, energy efficiency, civic data science, sustainability, equity

For several decades, U.S. housing investment policies, such as community development block grants, have distributed more than $5.8B per year in public assistance to distressed communities. [1]. Block grants offer flexible mechanisms that preserve local control over and prioritisation of administered public funds. However, evidence that these policies effectively serve low-and-moderate income (LMI) households has been unclear. A fundamental challenge in quantifying these program's benefits is that the civic data needed for impact evaluation is often siloed across city information systems.

Block grants administered by the U.S. Department of Housing and Urban Development (HUD) address the human dimensions of increasing urban density and land use. More generally, these housing policies can be important mediating strategies in scenarios of human affluence and environmental impact [2], including estimates of building energy use or resource consumption at various geographic scales [3, 4]. This notion of housing as a driver of resource consumption is important as renewed federalism debates over public funds for housing assistance also affect modelling assumptions about sustainable urban growth, social equity, and climate resilience. Yet, despite over three decades of programmatic evidence and evaluation, the energy and sustainability outcomes of HUD-funded programs have been largely missing from public decision-making (Supplementary Note 1). Consequently, the analysis of sustainability trade-offs or sustainability co-benefits from housing investment has been invisible to the policy process.

A hurdle for policymakers is that the community benefits of these programs are often hard to measure. Scholars have suggested dedicated funds be set aside to develop more sophisticated, holistic approaches for impact evaluation [5]. A principal limitation for evaluators is usually structural. For example, the disaggregated data required to rigorously evaluate the benefits of these programs, such as energy, water, or resource use, are often inaccessible across information systems or city bureaucracies. Other performance data reported to HUD are commonly in the form of community surveys or self-reported information from program participants. However, due to the limited availability of contemporaneous data from non-participants, which are necessary to construct credible reference groups for evaluation, obtaining consistent, reliable estimates of program impacts for block grants is rare.

In this article, we describe a multi-year effort on the use of open data in the public sector. We linked siloed data on energy consumption and housing program participation. Using an open data hub, we created an automated housing registry to process large datasets from over a dozen independently administered databases and multiple city departments (Supplementary Note 2). This process of combining and standardising records from relational databases is referred to in the data science community as data fusion [6]. The housing registry's capabilities include access to open data with geographic information systems (GIS) mapping, and a community engagement analytics platform. Importantly, the registry links housing and utility consumption records at the property-address level. These records are more granular than common evaluation studies at the parcel- or county-scale, which typically do not permit analyses of individual household behaviour.

We investigated long-term sustainability outcomes for two of the largest HUD-administered block grants, the Community Development Block Grant (CDBG) entitlement program and the HOME Investment Partnerships (HOME) program (Supplementary Note 3). We analysed 16 years of evidence (2004-2019) from the City of Albany, GA, a typical, small-to-mid-sized entitlement community in the U.S. Southeast. The data include 5.9 million monthly observations of participating and non-participating households. We asked whether HUD-administered block grants, which fund housing capital improvements, could generate hidden spillover benefits to private citizens through energy savings. In quantifying possible spillover benefits of housing assistance, we investigated potential policy innovation to use housing program targeting as an entry strategy to include LMI communities often left out of energy conservation upgrades. Although the connection between block grant programs and energy efficiency might not be immediately obvious, we found that home upgrades and rehabilitation greatly affect household resource consumption. We document that housing programs can increase energy efficiency in LMI communities, including households with a lower awareness of or interest in energy efficiency.

Block grants for LMI households

Program "targeting" is a central tenet of U.S. federal housing policies but creates fundamental challenges for research and evaluation. HUD-administrated block grants are mean-tested policies that distribute targeted federal resources to state and local officials to build more resilient communities [1]. A key feature of the block grant funding mechanism is that cities have decentralised authority over these funds.

Advocates for block grants praise the program's flexibility. They suggest that local public administrators will seek the most efficient and cost-effective means to deliver program services as those officials have better information about community needs. Local administrators are also presumed to be more "visible" and, thus, can be held more accountable by citizens versus federal administrators [1, 7]. However, critics argue that block grants have too much flexibility. For example, grantees can redirect program targeting away from individuals with the greatest need or shift program services with long-term payoffs in favour of short-term initiatives with less impact.

When local governments receive federal grants, it often stimulates higher levels of spending than theory would predict from local revenues, a phenomenon known as the "flypaper effect" [8, 9]. Nevertheless, debates persist about whether increased expenditures lead to higher levels of public service provision, especially within LMI communities [10, 11]. In the context of block grants and housing, scholars have argued that the actual value of block grant funding tends to diminish over time [12]. As a result, block grant programs have been criticised for gradually decreasing services to the neediest or most vulnerable populations [5, 13, 14]. CDBG and HOME programs reduce capital and information barriers for entitlement communities to be able to access and receive governmental assistance. However, it remains an open question whether income-qualified households meaningfully participate in and benefit from these federal funds. We, therefore, investigated whether a broader range of co-benefits from housing assistance, such as energy savings and other unmeasured sustainability benefits, might be generated by housing block grants.

The energy-relevant program activities under CDBG include energy efficiency projects, rental rehabilitation, and emergency repairs, i.e., roof replacements, heating, ventilation, and air conditioning (HVAC), electrical, plumbing, and other repairs that bring structures up to current building codes. Under HOME grants, the relevant program activities include the rehabilitation of owner-occupied housing units, acquisition, rehabilitation, or construction of rental units as affordable housing for low-income individuals, and tenant-based rental assistance. For a more detailed list of CDBG and HOME activities and program rules, see refs. [1, 15].

Our field site, Albany, GA, is 74% Black or African American, and its poverty rate is 30.8%—nearly triple the U.S. national average (Supplementary Discussion). Albany is ideally suited for formula targeting under block grant eligibility rules due to its population size, ageing housing stock, and high poverty rate. Based on the city's data, we calculated the average household energy consumption in Albany as 13,255 kilowatt-hours (kWh) p.a., making it an important population of interest. This is nearly 25% higher than the U.S. national average (10,649 kWh) [16]. For a review of causes and correlates of household energy burden in low-income communities, see ref. [17]. Given the high energy and cost burdens, we could expect to observe substantial improvements from policy intervention.

Results and discussion

Program targeting

We evaluated the household characteristics of program participants in Albany to assess evidence of program targeting. The most common housing problems include cost-burdening, crowding, and substandard housing (e.g. lacking complete plumbing, kitchen facilities, or weatherisation) [18]. The city has 7,985 LMI renter households and 2,232 LMI owner households that spend more than 30% of their monthly income on housing costs, including utilities (Supplementary Note 4). Given this high share of cost-burdened households, it is understandable that the demand for housing assistance far exceeds the available funds with long waiting lists of income-qualified applicants. In Fig. 1, we show the spatial distribution of 549 HUD-funded housing projects across 16,680 properties participating in either CDBG or HOME by census tract. While there are funded activities across all six city wards, a high proportion of participating properties are also located within Federal Opportunity Zones (Fig. 1).

Although energy intensity is not a consideration in targeting or eligibility criteria, we found that participating households who received HOME or CDBG funds are heavily concentrated in areas with high poverty rates and where energy burdens are prevalent (Fig. 1). Out of 10,127 households at 80% AMI or below, 5,714 have a severe cost burden (4,440 renters and 1,274 owners); these households comprise a significant share, 38% of LMI households [18]. In these tracts, the ratio of median electricity bill charges to median income is 8-12%—higher than the national threshold (Fig. 1). This type of evidence has previously been hard to discover given the persistent data silos and lack of researcher access to integrated utility data for evaluation. Next, we compared program targeting under federal housing rules to more conventional policies targeting energy efficiency.

Prior work has shown that self-selection into energy efficiency programs generally has low take-up rates among LMI households, even when energy efficiency services are subsidised or free [19, 20]. Given the upfront investment, administrative, or coordination costs necessary to achieve large-scale savings, dedicated energy efficiency programs can actually have negative rates of return [20]. Further, when standalone energy efficiency policies are not means-tested, they also tend to attract participation in higher-income areas [21]. This situation raises questions about inframarginal participation—whether participants would have invested in energy efficiency without public subsidies or benefits [22]. Yet, although not all activities covered under HOME and CDBG may be relevant for energy conservation, we argue that program targeting under housing block grant rules could be a favourable alternative to standalone energy efficiency policies that are not necessarily means-tested or have a low service take-up. This is because the housing program selection process simultaneously attracts the most energy-intensive and energy-burdened households in situations where the demand for services is also strong.

Surprisingly, we found that housing policies can accelerate participation in energy efficiency among capital-constrained homeowners or renters, even in cases where participants were not initially motivated by energy conversation measures. For example, one resident said, “When they put the roof on it was like night and day. I could feel the warmth of the house.” In the next section, we quantify the realised energy savings within targeted LMI communities.

Energy savings from housing programs

We estimated the long-run energy savings in kWh per sq.ft. for participating properties in CDBG and HOME programs. These spillover energy savings can be conceptualised as a bonus in program performance beyond core housing program objectives. To calculate energy savings, we implemented several matching models with regression adjustment to construct suitable statistical reference groups pre- and post- program participation. To mitigate observational bias, we used algorithmic matching procedures with a genetic search algorithm [23] to achieve covariate balance between treated and counterfactual observations. We also implemented staggered difference-in-differences (DID) estimators that mitigate potential biases of two-way fixed effects with heterogeneous effects (Materials and Methods). For transparency in protocols, we report the bias reduction in Fig. 2 and note that in staggered DID models without matching, the energy savings can be understated (Supplementary Table 1). We report the most conservative estimates, robust to various matching procedures and estimators (for more, see Materials and Methods).

HUD-funded housing projects in Albany, GA, generated statistically significant monthly average energy savings of 5-11% for participating households as compared to multivariate matched properties with similar characteristics (Table 1). For the subset of energy-relevant projects estimated by staggered difference-in-differences estimators (i.e., Energy Efficiency, Emergency Repairs, and Homeowner Rehabilitation), we report energy savings of 11-14% after correcting for potential estimation biases due to treatment effect heterogeneity under staggered participation (Table 1 and Supplementary Table 2). We note that point estimates can be higher when considering staggered designs. While there is year-to-year variability in performance depending on the mix of implemented projects, the energy savings for housing participants are relatively stable across years, with increasing performance in the last 2 years of the study period (Supplementary Fig. 1).

Overall, HUD-funded block grants in Albany, GA reduced electricity use by 4.72 million kWh over the study period. The reduction in non-baseload emissions is equivalent to 3.70 million pounds of coal not being burned or the carbon sequestered by 3,695 acres of forest (Supplementary Note 5). These long-term savings are remarkable, given that energy efficiency is not an explicit criterion for these policies.

Participating properties in the CDBG program achieved monthly savings of 6-14% (Supplementary Table 1, 95% CI). Emergency repairs, where households could elect for one critical repair (e.g., HVAC), comprised of 248 projects, generated 6% energy savings. Albany's CDBG-funded Energy Efficiency program, offering new insulation and windows, comprised of 62 projects, generated about 13% energy savings. The largest savings came from the CDBG-funded Rental Rehabilitation program, which focuses on structural upgrades (e.g., roof) to city-owned rental properties, comprised of 22 projects, generated 32% energy savings. This performance is consistent with the high savings associated with major building upgrades reported in voluntary and information-based programs [21, 24, 25].

The HOME portfolio had more mixed results. On the one hand, Homeowner Rehabilitation, which provided households with a full range of repairs, comprising of 29 projects, generated around 11% energy savings. HOME had a larger share of projects not relevant to energy savings (e.g., Tenant Based Rental Assistance). Unsurprisingly, these 160 unrelated HOME projects were associated with a 15% increase in energy consumption. Therefore, we found evidence of energy savings across a broad portfolio of CDBG projects and, to a more limited extent, HOME projects.

To further contextualise savings from the HUD-funded CDBG programs, we translated the lower and upper range of estimated energy savings (e.g., 6% for Emergency Repairs and 32% for Rental Rehabilitation) to dollar amounts using an average monthly electricity bill in Albany, GA ($125). When annualised, housing participants saved anywhere from $75 to $482 in direct kWh charges. According to the Bureau of Labor Statistics consumer price index (CPI) [26], these savings are equivalent to nearly two months of groceries for households in the region (Supplementary Table 3).

Housing spillovers versus energy conservation programs

We evaluated how meaningful these savings are in comparison with dedicated energy efficiency programs reported in the literature. First, we compared the magnitude of energy savings for both non-LMI- and LMI-targeted programs and found that housing spillovers meet or exceed the reported energy savings from standalone programs. For example, Gillingham et al. (2018) reported savings from 0% to 25% for a broad range of interventions involving capital upgrades [24]. Savings from behavioural and information-based interventions also range from 0% to 20%, depending on the intervention type and methodology [27–30].

We found that energy savings from housing program spillovers (which range from 6% to 32%, Supplementary Table 1) are generally consistent with and sometimes exceed previous reports for non-LMI targeted interventions. In another review, Benartzi et al. (2017) reported energy savings of 0.9% to 8.2% for non-LMI targeted informational nudges for energy conservation [31]. Although energy savings from capital improvements often generate substantially larger savings, we acknowledge that information and behavioural nudges can also offer other benefits. For example, treatment effects from information-based interventions can persist for years after the treatments are discontinued [32, 33]; or they can generate conservation spillovers from one form of resource consumption to another. Reported cases include water to energy savings [34]; waste sorting to waste reduction [35]; or hot water savings to space heating conservation [36]. We acknowledge that energy savings may not be the only important outcome measure for program evaluation.

Additionally, we benchmarked the energy savings from housing spillovers to standalone energy efficiency programs where LMI households were the principal recipients of the energy savings. Studies of standalone energy efficiency programs geared toward LMI households, like the Weatherization Assistance Program (WAP), Low-Energy Efficiency Plus (LEEP-Plus), and Energy Savings Assistance Program (ESAP), have reported energy savings in the range of 2% to 7%, albeit with challenges in program uptake [20, 37, 38]. Therefore, given the range of treatment effects in this study, we found that housing spillovers are competitive with and occasionally exceed the energy savings from standalone energy efficiency programs targeting LMI communities.

Comparatively, housing spillovers are also meaningful in effectively reaching a broader range of LMI households versus standalone programs. This is because LMI households in need of home repairs are generally a larger subset of the population than those actively seeking specialized energy efficiency support. Notably, the majority of grantees are simultaneously concentrated in areas with high poverty rates and, surprisingly, high energy consumption which has been previously unknown (Fig. 1). We believe this profile is notable as it differs from descriptions of low LMI participation in dedicated energy efficiency programs [20, 37].

Cost-effective comparisons

Although energy savings is not the intended aim of CDBG and HOME block grants, we calculated cost-effectiveness ratios in kWh saved per dollar spent for four energy-relevant housing programs: Emergency Repairs, Energy Efficiency, and Rental Rehabilitation (under CDBG) and Homeowner Rehabilitation (under HOME). Because of our unique partnership with City of Albany public administrators, we were able to access program and administrative costs at the project level. The fiscal period for which we had access to the costs is October 2007 to May 2018, spanning 11 years. We noted that such long-term evaluations of block grant outcomes have been uncommon [5]. For details on cost-effectiveness calculations, see Materials and Methods. Within CDBG, we report cost-effectiveness ratios of 83.5 kWh/$ for Rental Rehabilitation, 10.8 kWh/$ for Energy Efficiency, and 3.7 kWh/$ for Emergency Repairs. Within the HOME program, we report the cost-effectiveness ratio of 0.8 kWh/$ for Homeowner Rehabilitation.

Further, we benchmarked the cost-effectiveness ratios (in $2021) of housing spillovers against reported estimates from dedicated energy efficiency programs. We considered recent meta-reviews [24, 31] and other highly cited studies published in the last 20 years. In Fig. 3, we provide a comparison, beginning with standalone Capital Upgrades programs, which include both LMI- and non-LMI-targeted programs. We also compared housing spillovers to non-LMI targeted programs including Information & Behavioral Programs and Rebates & Financial Incentives. We found that housing spillovers from Rental Rehabilitation in the CDBG program are nearly 2.9 times more cost-effective than common Capital Upgrades programs, such as utility-based retrofitting (i.e., 29.0 kWh/$) [17]. As the Rental Rehabilitation funds upgrades in city-owned properties, we learned that Rental Rehabilitation is revenue generating (unlike non-city owned properties in homeowner rehabilitation). Therefore, the cost-effectiveness ratio is substantially higher because administrators can also leverage program income to re-invest in additional upgrades. We consider split incentives issues within rental rehabilitation in the Supplementary Discussion. Spillovers from Emergency Repairs and other block grant programs are also within the reported cost-effectiveness ratios from dedicated programs that target LMI communities, including WAP, LEEP-Plus, and ESAP [17, 20, 38]. Similarly, we find that cost-effectiveness ratios from housing spillovers are also competitive with non-LMI-targeted Capital Upgrades programs, such as building labels and building codes (i.e., ranging from 21.3 to 4.7 kWh/$) [21, 39, 40] (Fig. 3).

As expected, the cost-effectiveness ratios of housing spillovers are less favourable than those estimated for Information & Behavioural programs [27, 28, 32, 33, 41, 42] (i.e., ranging from 64.3 to 0.1 kWh/$ (Fig. 3), which do not typically involve capital upgrades. We also compared cost-effectiveness ratios in this study to Rebates & Financial Incentives, such as appliance replacement (refrigerator, heat pump), electricity bill credits, other rebates (i.e., ranging from 29.3 to 0.4 kWh/$) [43–48]. In contrast to nudge interventions, we find that the cost-effectiveness ratios in this study are generally competitive with Rebates & Financial incentives (Fig. 3). This is intriguing since direct monetary incentives for energy efficiency, unless restricted by program rules, do not generally target LMI communities. Although outside the scope of this paper, we did back-of-the-envelope calculations of the implied internal rates of return for housing program spillovers for interested readers (Supplementary Note 8) [49]. Over the study period, the implied internal rates of return are about 40% and higher. Many dedicated energy efficiency programs, like weatherisation, have reported variable rates of return as low as 3% to over 100% [20, 30]. For further discussion of rates of return in energy efficiency program evaluation, see refs. [50–58].

In summary, whether a comparable program is LMI-targeted or not, we found that the cost-effectiveness ratios from housing spillovers are generally competitive with dedicated energy efficiency programs across a broad range of intervention types.

Evidence of program uptake

To further understand the drivers of performance in CDBG and HOME program administration, we conducted semi-structured interviews with public administrators and residents (see Supplementary Discussion). Engaging with public administrators and residents allowed us to compare program uptake for dedicated energy efficiency programs with the uptake for housing programs. This is important because program uptake has been a critical barrier to accelerating energy efficiency participation in LMI communities. Through our interviews, we found evidence of persistent barriers contributing to low program uptake in dedicated energy efficiency programs and strong drivers of program uptake within housing.

We know from the literature that barriers to uptake of residential energy efficiency programs can typically include: 1) capital, resource, and liquidity constraints; 2) information barriers and behavioural or cognitive biases; and 3) transaction and process costs [24]. We found evidence for many of these same barriers in Albany, GA, including a less-documented barrier: 4) local mistrust of government. First, evidence of low take-up of energy efficiency programs is commonly due to a lack of capital and other resources. According to the housing program director, most applicants in Albany, GA, are "elderly and on fixed incomes." A resident shared, "The [financial] barrier is having those resources to conserve." Another resident stated, "... a lot of my fellow homeowners cannot afford homeowners insurance, without which you cannot get weatherization and stuff." Second, when asked why more residents were not participating in the programs, a resident proffered that they "don't understand and don't get the information right." Another said, "I don't know what type of appliance would be available to say, this will help you decrease your electricity." Third, evidence of process and transaction costs came up in several interviews. For program participation to occur, public administrators for the City of Albany must "see a lot of customers"; work "24/7"; always be "on call"; and put in "110 or more percent." One resident shared, "[The administrators] have funds available for Energy Assistance, but they take you through so much to get whatever they're going to give you. If they're going to help you, you'll be so burned out because it takes so much." While we confirmed that high-involvement processes might be necessary on the local level, additional transaction costs limit the scalability of and so increase the uptake of dedicated energy efficiency programs.

A fourth barrier, local mistrust of government, has been discussed in the public management literature for a broad range of services, but less so for energy efficiency [59–61]. Public administrators in Albany are aware of this issue. For example, one official shared, "It's hard to convince people to do energy efficiency and let folks into their homes." According to some public administrators, certain residents have "... perceptions that [the city government is] going to put a lien on [their property]." They say, "The mistrust is enormous" and that residents "don't believe [city administrators are] doing what it is they say they're doing." Evidence from our interviews demonstrates that mistrust of local government service delivery, in addition to capital constraints, cognitive biases, and transaction costs (among others), may also limit energy efficiency program uptake in LMI communities.

In contrast, housing programs have high demand and participation. These programs attract a broad range of eligible participants from LMI households. According to the City of Albany's 5-Year Consolidated Plan, "Over 2,000 families are on waiting lists for a total of just 1,117 public housing units, and the occupancy rate for existing units is virtually 100%" [18]. This evidence of high take-up of public housing assistance — nearly twice the availability

— reveals the broad reach of the city's housing programs' HUD block grants in our study. Stakeholder meetings conducted by the city revealed that 'high utility costs may be a common issue for low income, disabled, senior, and minority households living in older and less energy efficient homes'. These households comprise the vast majority of entitlement grantees in Albany, GA. Other stakeholders testified that "while households may be able to afford their homes, units may lack appliances or are in need of significant repairs" [18]. Reports of high utility costs and the need for housing repairs confirm the high complementarity between energy efficiency and housing program uptake. Residents' interviews further illustrate the potential impacts. "You're talking about [sic] putting... money toward buying food and groceries versus paying utility bills; so [the housing policies] can have a big impact," said one resident. Another stated, "I only get $1,200 a month, and my utilities is $4 almost $5 [hundred], and my mortgage is $765." Such resident feedback confirms that the policies can have an impact in financially struggling households regardless of awareness of or interest in energy efficiency measures. Considering that housing policies have strong demand, we conclude that expansions in housing program participation can lead to strong energy and sustainability co-benefits for a broader range of LMI households.

Dedicated energy efficiency policies tend to attract affluent and informed households, but suffer from low participation rates among LMI households [37]. We found substantial energy savings from housing program spillovers in situations where demand for services is also strong. These sustainability co-benefits have remained largely hidden from program evaluation and policy decision-making due to widespread data silos at the city scale. Through data innovation in record-linkage procedures, we have been able to uncover previously unmeasured energy savings impacting low-and-moderate income communities. For a family facing trade-offs between essential household needs, the quantified energy savings can make a dramatic difference: nearly two months of groceries. For the community writ large, the energy co-benefits accelerate long-term participation from households facing structural and persistent barriers to energy efficiency. We argue that energy and sustainability-oriented outcomes should be further integrated into federal housing program evaluation criteria, and we expect that doing so will uncover a multitude of other hard-to-measure social benefits.

Materials and methods

Data and program details

Administrators in the City of Albany, GA have used open data tools to respond to local demands for greater transparency and accountability in the delivery of public services. These open data initiatives are becoming increasingly common among similar sized cities across the U.S. For the current study, the city provided data access to 5.9M housing-related open data records from more than 12 city departments. The dataset included monthly electricity consumption for all residential properties in Albany, GA, from 2004 to 2019. After we linked housing and energy consumption data by property identifiers, we obtained a proper subset of 2,931,406 panel observations covering 16,680 residential properties.

Out of nearly 20 programs funded under HOME and CDBG, we focused the analysis on programs directly related to household energy use. These are Energy Efficiency, Emergency Repairs, Homeowner Rehabilitation, and Rental Rehabilitation. These energy-relevant projects comprise 65% of the whole project portfolio during the analysis period from 2004-2019. Emergency Repairs for example constituted a significant share of the total housing portfolio, and it represented more than 30% of all treated properties in our analysis. Programs unrelated to energy use, such as Tenant Based Rental Assistance or New Construction, in which rental support can travel with the individual and not necessarily the housing unit, were used for falsification (placebo) testing.

The unit of analysis is the property address (we use property address and household interchangeably). The dependent variable used for analysis is the monthly electricity consumption in kWh per square foot. We log-transformed the dependent variable and multiplied by 100 for ease of interpreting the estimated coefficients directly as a percentage change. The policy indicator variable was coded as 1 for months in which CDBG or HOME projects started and continued to be active and 0 otherwise before a project's implementation. The policy indicator variable for properties that never received treatment and were thus available for counterfactual analysis was coded as 0 for all the periods. Given the large dataset of counterfactual, non-treated observations, we mitigated selection bias by matching households based on similar baseline electricity usage and household characteristics within the same city [21, 42]. We combined matching models for bias reduction and covariate balance with staggered difference-in-differences or two-way fixed effects estimators for estimation efficiency. For more details, see Supplementary Note 10.

To evaluate the characteristics of treated and control units, we compiled data from the 2019 5-year American Community Survey [62] and the Dougherty County Tax Assessor's database of property records. This dataset included important property, demographic, and neighborhood characteristics known to affect household energy consumption. The most important pre-treatment property-level characteristics include the average monthly baseline energy consumption (in kWh per month per household), property size (in square feet), property age (in years), number of bedrooms, number of bathrooms. Demographic and neighborhood characteristics include the household median income (in dollars), share of female head of household (in percentage), the share of Black or African American population (in percentage), and alternative economic measures at the tract level such as the share of the population below poverty level (in percentage), share of the households with gross rent more than 35% of household income (in percentage), and the population on SNAP (in percentage). These physical and demographic characteristics are widely used in the building energy efficiency literature as matching or conditioning variables to reduce imbalance between treated and control properties [21, 63].

To mitigate the effect of possible unobservables on energy use, we included the fair market property value as a proxy for other potentially unobserved quality attributes [64]. Because property values could be influenced by housing program criteria with the explanatory variable, we conducted additional analyses to show the main results with and without the property value as a conditioning variable to check for any potential biasing effect. Excluding property value in the conditioning variables generated somewhat higher treatment effects by 10% to 19% (Supplementary Table 4). However, given possible unobserved factors related to housing stock quality, we included the property value in our models and reported the more conservative estimates. We also conducted additional robustness checks with an expanded set of testing variables related to age, homeownership, and disability status to confirm bias reduction across further occupant characteristics. To mitigate other time-varying factors related to outdoor ambient temperatures on energy demand, we also included archival weather station data from the National Oceanic and Atmospheric Administration (NOAA) to adjust for seasonal heating and cooling degree-days [65]. We used data for the nearest weather station in Albany, which is located 4 miles from downtown Albany at the Southwest Georgia regional airport.

Selection bias and protocols for bias reduction

As expected in impact evaluation studies with voluntary programs, we found evidence of strong self-selection bias. Prior to implementing the matching models, the treated and non-treated properties had large differences in observable property characteristics. Descriptive statistics revealed statistically significant differences across key testing variables (Supplementary Table 5). For example, participating properties receiving HUD funding are about 30% smaller in square footage and have almost two times lower property values (Supplementary Table 5), which characterises the profile of units that typically receive federal housing assistance. For further pre-treatment comparisons across other conditioning variables, including demographic and neighborhood features, see Supplementary Table 5. Fig. 2 shows a summary of the pre- and post-matching differences and covariate balance between treated and non-treated properties expressed as standardised percent bias (Supplementary Note 9).

Matching algorithms

Prior to analysis by difference-in-differences, we implemented multivariate matching procedures as a pre-processing step to construct statistical reference groups for analysis and to mitigate observational bias. Prior research in building energy efficiency has demonstrated significant performance gains in large datasets, particularly with the availability of high-performance computing resources [21]. We implemented algorithmic matching procedures with genetic matching, which automatically finds the optimal solution and fitness parameters that achieve maximum covariate balance [23, 66]. Genetic matching automates the process of covariate-balancing under various objective functions such as maximizing p-values or minimizing standardised mean differences in empirical quantile-quantile (EQQ) distances across all matching variables.

We used matching protocols "with replacement" that allowed us to preserve a larger sample size while not exceeding the ratio of controls over treated units that degrade performance. We ran the Genmatch script with all possible ratios of treated to control observations in the range from up 1 to 100. This grid search resulted in a local optimum at a ratio of 19:1, meaning that up to 19 untreated properties weighted on their characteristics were available to each of the treated units for comparison. To fine-tune the ratio parameter, we implemented a rule-based optimisation procedure that (i) maximized the average reduction in standardised mean differences, and (ii) minimized the number of pruned observations in the counterfactual [66]. Supplementary Fig. 2 shows the sensitivity of the standardised mean differences to changes in the ratio parameter for genetic matching, while Supplementary Fig. 3 shows the sensitivity of standardised mean differences to changes in observations pruned for the same values of the ratio parameter. Given the extended run times for genetic matching, we used multiple cores on a high performance computing cluster to reduce computation time.

To benchmark our matching results, we conducted propensity score matching (PSM). We found a local optimum for bias reduction at a ratio of 21:1 of non-treated to treated units. In Supplementary Fig. 4, we show the sensitivity of standardised mean differences to changes in the ratio parameter, while Supplementary Fig. 5 shows shows the sensitivity of standardised mean differences to changes in observations pruned for the same values of the treated to untreated ratio.

Our best-performing model was genetic matching, which achieved an average and median bias reduction of 91% and 93%, respectively. This is significantly better than the 78% average and 84% median bias reduction achieved with propensity score matching across our conditioning and testing variables in Fig. 2. One limitation of propensity score models is that they might require a researcher's discretion in the selection of parameters of interest [67]. For this reason, we favored use of the automated methods with genetic matching, which also achieves better bias reduction in this application.

Balance-Size Matching Frontier

To provide additional evidence on the comparative performance of the matching models, we implemented the Matching Frontier technique by King, Lucas, and Nielsen [68], which allows us to estimate the theoretical limit to jointly maximise covariate balance and sample size. We used a specialised R package that allows for synchronous optimisation of covariate balance and sample size (for details, see the Code Availability Statement). These results are presented in Supplementary Fig. 6. Genetic matching achieves a larger bias reduction, but it also produces a lower absolute loss imbalance (L1) compared to the PSM approach. These findings confirm that genetic matching is more efficient and gets closer to the balance/sample size frontier. The genetic matching procedures weakly dominate PSM matching across the key conditioning and testing variables. Therefore, given the richness of the current dataset, we were able to confirm that genetic matching is the preferred matching algorithm for this domain of building energy efficiency, as introduced in ref. [21].

Sensitivity of matching procedures to unobservables

We conducted Rosenbaum's sensitivity analysis using protocols described in refs. [69, 70]. We calculated the critical value of the sensitivity parameter Γ, which captures the level of influence an unobserved confounder should need to affect the monthly kWh/sqft outcome in order to change our inference. We estimated the changes in p-values or significance levels based on different values of Γ from 1 to 3 with a step size of 0.05. The critical gamma value is 1.45, where the confidence interval includes zero (Supplementary Table 6). This means that an unobserved covariate would have to change the energy intensity (in kWh/sqft) of participating households by approximately 45% before changing our inference at the 90% confidence level.

Although there could be other selection processes or time-varying unobservables not captured in our conditioning and testing variables, we believe it is unlikely because an unobserved confounder would have to exceed our threshold of 45% on the impact on the outcome variable in kWh/sqft.

Estimating treatment effects

To estimate causal program impacts, we analysed the panel data using 16 years of monthly energy consumption records (in kWh/sqft) with and without matching. We used a two-way fixed effects estimator (TWFE) with standard errors clustered at the property address level, as reported in Table 1, as well as staggered difference-in-differences estimators. We provide additional details on the policy indicator in Supplementary Note 10. The reported treatment effects are robust to various levels of one-way and two-way clustering options (Supplementary Table 7).

To address potential estimation biases due to treatment effect heterogeneity in the presence of staggered program adoption [71], we implemented staggered DiD estimators [72, 73]. We implemented two alternative protocols. The first approach in Callaway & Sant'Anna (2021) [72] uses not-yet-treated observations in a given period as counterfactual, while the second approach in Chaisemartin & D'Haultfoeuille (2020) [73] calculates the average treatment effect among switchers. We note that not every HUD-funded project in our study is subject to staggered adoption, which means that concerns about potential estimation biases with fixed effects estimators apply only to a subset of the studied projects. In Table 1, we report the results for three out of four energy-related projects that had staggered participation based on the project start date (e.g., Energy Efficiency, Emergency Repairs, and Homeowner Rehabilitation).

Supplementary Fig. 1 compares the dynamic DiD treatment effects with TWFE estimators after matching. Although, there is some divergence in the dynamic treatment effect estimates in the later periods after more than 10 years or 40 quarters of performance data, we found that the staggered DiD treatment effect estimates were broadly consistent and within the 95% confidence intervals of each other for nearly all years in the study period (Supplementary Table 2). For interested readers, in Supplementary Fig. 7, we also provide evidence of parallel trends for years prior to the start of housing projects and program data collection. Importantly, given the quality of the data, we note that we do not rely on cross-sectional results for statistical significance, and we are able to measure year-to-year impacts using multiple approaches with matching prior to estimation of the event study (Supplementary Fig. 1). Due to covariate imbalances, the coupling of matching with DiD estimators was preferred such that covariates of never-treated units match treated units. Recent econometric literature also points to the merits of matching prior to DID analysis [74, 75]. For a more general discussion of design issues to staggered DiD approaches, see refs. [71, 76–78].

Placebo tests and other robustness checks

We implemented placebo tests in multiple ways to confirm the validity of our technical approach. First, we implemented a placebo test by analyzing treated properties prior to any HUD investment from 2004 to 2007, where no effects are logically possible. We found treatment effects not statistically different from zero with two-way fixed effects and in models with and without matching as shown in our main results in Table 1. As an additional falsification test, we considered funded CDBG and HOME projects not directly related to energy consumption, such as Tenant Based Rental Assistance or New Construction, to test for the direction of treatment effects. As shown in Supplementary Table 1, we found positive treatment effects up to 15% for non-energy projects with and without matching as expected.

Another potential concern in treatment effect estimation is the uncertainty of the exact date ranges of project completion. This could introduce a source of measurement error, even as the benefits of capital improvements (HVAC unit, window sealing, roof repairs, etc.) persist. Following ref. [30], we tested additional specifications by dropping observations where the treatment status is uncertain. Of 549 treated projects, we excluded 43 projects tagged as "incomplete" (7.8% of treated projects). We confirmed that results with and without incomplete projects are all within the reported 95% confidence intervals under our three main specifications (Supplementary Table 8). This is expected given that the share of "incomplete projects" in the sample is relatively small compared to the overall number of the studied projects. Access to project status, tracked by the program administrators and subsequently shared with the researchers, indicates minimal uncertainty in the date-range as a possible source of evaluation error.

Cost-effectiveness

To calculate the cost-effectiveness ratios, we considered the total kWh saved across all program years divided by the total cost, which includes program plus administrative costs. We used the most conservative treatment effect estimates (i.e., genetic matching with two-way fixed effects), which provide a lower bound on the cost-effectiveness ratios. The program costs are the direct entitlement (EN) funds, and administrative (AD) costs are the share of indirect costs as reported to HUD, excluding program income (Supplementary Note 7). For this analysis, we did not consider other indirect costs, such as the social cost of carbon.

Administrator interviews and community engagement

To understand the localised administrative drivers of the CDBG and HOME programs, we conducted 10 semi-structured interviews with public administrators, including the City of Albany's Manager's Office, DCED — which manages the HUD projects and funding, Technology and Communications, and Utility Operations departments. We also conducted 40 semi-structured interviews with Albany residents to assess the program effectiveness in the field. Of the 40 interviewees, 24 received a CDBG or HOME treatment at some point during the project period, and 16 did not receive the treatment. Participants in the Emergency Repairs program made up 55% of all interviewees and 92% of all treated households. All interviews were conducted via phone from May 2020 — August 2020. We recruited resident interviewees in several ways: cold called DCED lists of past participants; mailed 927 postcards to past participants, which included contact information and a link to an online form to sign up for the interviews; circulated a press release and social media posts via the city's communications office (from which we received two press articles); and sent personalised hand-addressed letters to 15 past HOME participants. All interviewees gave their informed consent for research purposes; personal data was anonymised and saved separately from interview recordings and transcripts.

Data availability

The anonymized data have been deposited in human and machine-readable format to Dataverse: https://doi.org/10.7910/DVN/SF1DRW [79]. Additional data related to CDBG and HOME funded projects is available at the Albany Open Data GeoHub: https://geohub.albanyga.gov [80].

Code availability

All computer code needed to replicate the findings in this study have been deposited to Zenodo: https://doi.org/10.5281/zenodo.5684354 [81].

Acknowledgments

This work was partially supported by awards from the National Science Foundation (NSF) Award No. 1945332 (OIA); ESRI, Inc. (OIA); the Georgia Smart Communities Challenge (OIA); and the Institute for the Study of Business in Global Society (OIA). We thank collaborators at the Albany Department of Community and Economic Development, Dougherty County, the Georgia Initiative for Community Housing, and Fight Albany Blight for supporting this study. For invaluable feedback and engagement, we thank public administrators in Albany, GA, including Steven Carter, Shelena Hawkins, Shuronda Hawkins, Sharon Subadan, Dianne Cooper, Monique Broughton, Phyllis Brown, Phyllis Whitley-Banks, Darrius Hughley, Mary Petty, Carolyn Mathis, Charliesa Fisher, John Dawson, Rodrick Smith, Javaugn Zackery, Shaw'Q Beale, Ciceli Brown, Stephen Collier, and the Emerging Technologies Team. For valuable discussions and collaboration, we thank Andrew Turner, Debra Lam, Chris Le Dantec, Amanda Meng, Craig Mesimer, Manushi Majumdar, Jay Dev, Jenn Mendez, Greg McCormick, Steven Hodges, and Ximin Mi. This study would not have been possible without the research assistance of Olivia Fiol, William Jang, Daniel Marchetto, Mirabel Reid, and David Reynolds, who conducted pre-analysis of data. We also thank 40 anonymous community residents for their participation. For valuable discussant feedback, we thank Larry Goulder and conference participants at the Stanford Organizations and Environmental Sustainability conference, and the Alliance for Research on Corporate Sustainability (ARCS) conference. This research was supported in part through research cyberinfrastructure resources and services provided by the Partnership for an Advanced Computing Environment (PACE) at the Georgia Institute of Technology, Atlanta, Georgia, USA.

Author contributions

Conceptualisation: O.I.A.; Methodology: O.I.A., O.C., B.R., K.E.O.; Software: O.C., K.E.O.; Validation: O.C., B.R.; Investigation: O.I.A., O.C., B.R., K.E.O.; Resources: O.I.A.; Data Curation: O.C., B.R., K.E.O.; Visualisation: O.C., B.R., K.E.O.; Writing – Original Draft: O.I.A., O.C., B.R.; Writing – Review and Editing: O.I.A., O.C., B.R.; Project Administration: O.I.A.; Funding Acquisition: O.I.A.

Ethics declarations

Competing interests

The authors declare no competing interests.

Human subjects protection

Human subjects protocols were conducted under Georgia Tech Institutional Review Board (IRB) protocol number H20089.

Table 1 Long-run energy savings from housing programs, 2004-2019.

		Genetic Matching			
	No. of Projects	TWFE Estimate (S.E.)	Staggered DiD Estimate (S.E.)	Ratio: Controls/ Treated	No. of Observations
All HUD-funded Projects	549	-5.03^{**} (1.90)	—	9.30	986,450
HUD-funded Projects with Staggered Adoption	359	-8.32^{***} (1.88)	-10.99^{***} (3.20)	15.05	952,149
Placebo Test Pre-Treatment	359	-0.89 (2.07)	0.26 (5.66)	15.05	952,149

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. *Standard errors are clustered at the household level by property ID. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as a percentage change. In this table, project savings are calculated by two-way fixed effects and staggered difference-in-differences using Callaway & Sant'Anna [72]. The estimates incorporate a genetic algorithm for bias reduction across a range of property, demographics, and neighbourhood characteristics. The projects with staggered adoption include Energy Efficiency, Emergency Repairs, Homeowner Rehabilitation. Additional program estimates are provided in Supplementary Tables 1 and 2.*

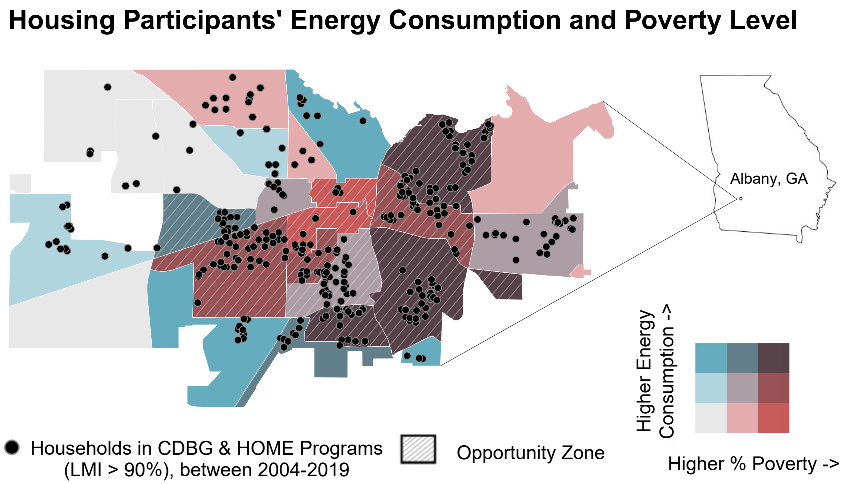


Fig. 1 Housing policies target households with higher energy burdens.

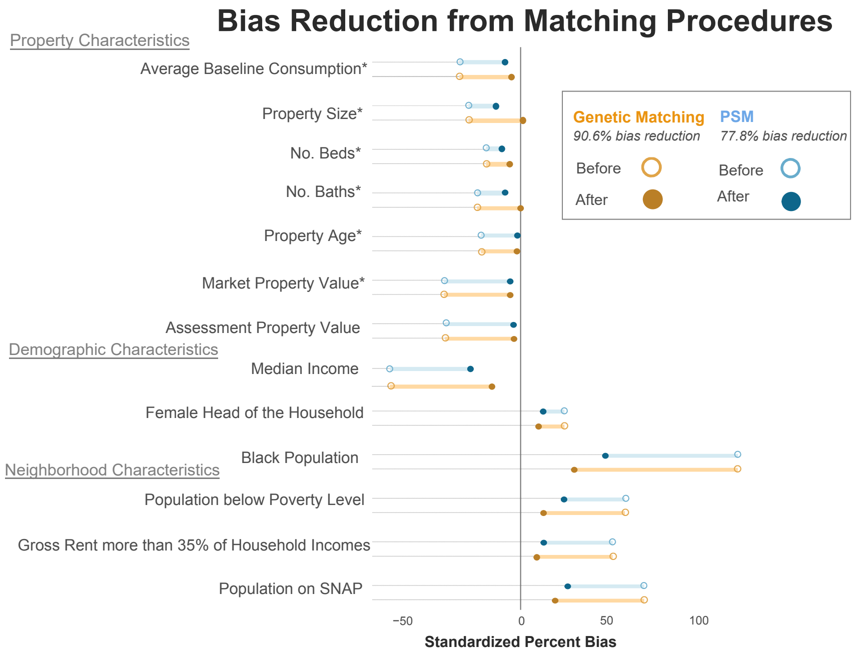


Fig. 2 **Matching algorithms reduce observational bias.**

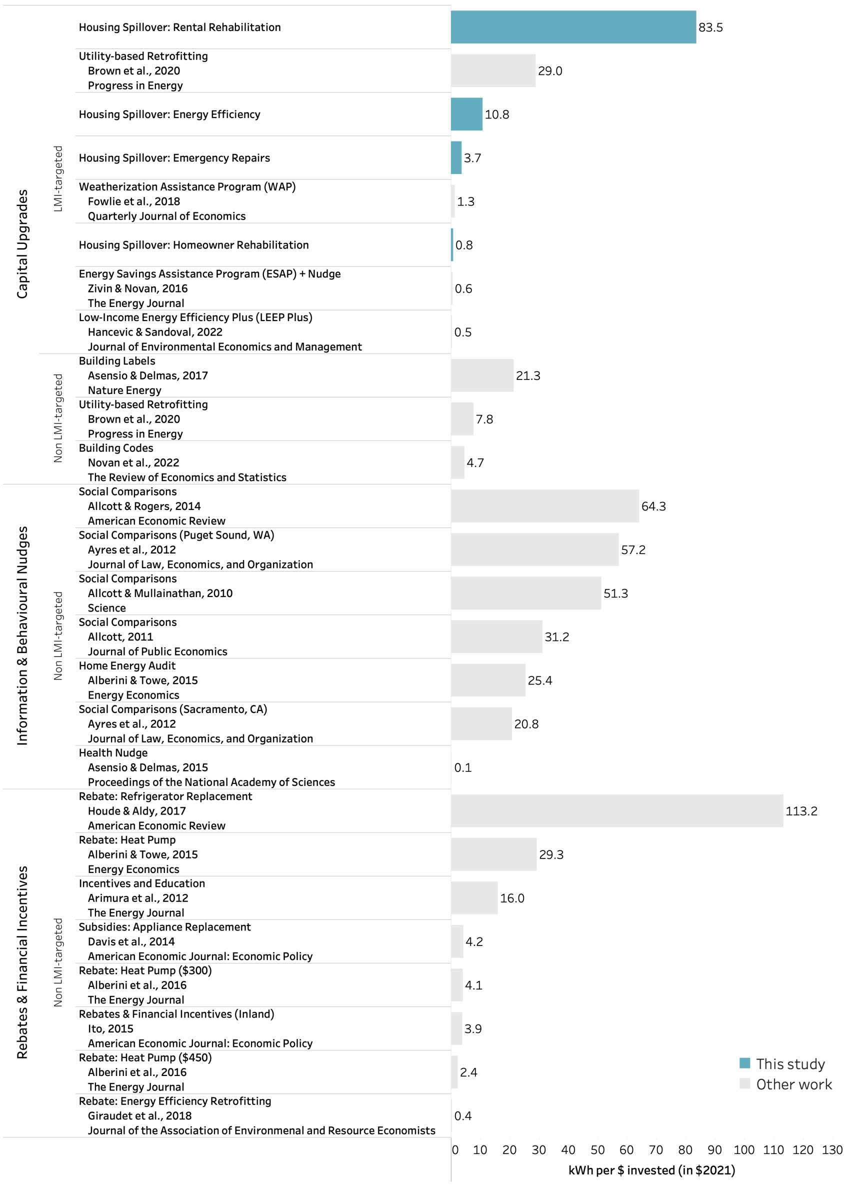


Fig. 3 **Cost-effectiveness of housing spillovers versus standalone energy efficiency programs.**

Fig.1 Housing policies target households with higher energy burdens.
This figure shows the locations of 549 CDBG and HOME participating households in U.S. Census tracts within the City of Albany, GA. The households receiving federal assistance are generally concentrated in areas with relatively higher electricity consumption per square foot and/or higher poverty rate, including many in Albany's federally designated Opportunity Zones. Over 90% of participating households are at or below 80% of the Area Median Income, which provides evidence of the effective program targeting for energy efficiency.

Fig.2 Matching algorithms reduce observational bias.
This figure shows the relative performance of genetic matching and propensity score matching (PSM) in standardised percent bias. The key conditioning and testing variables shown include property, demographic, and neighborhood characteristics. The conditioning variables are identified with asterisks and include observable property characteristics (average baseline consumption, property size and age, number of beds and baths). To mitigate the effect of possible unobservables on energy use, the market value of the property was added to the set of matching variables as a proxy for unobserved quality attributes. Genetic matching achieved 90.6% bias reduction while propensity score matching achieved 77.8% bias reduction; therefore, the remaining bias in standardised percent bias is -9.6% and -22.2%, respectively. Although both methods substantially reduce median bias and offer a high degree of covariate balance, the genetic matching algorithm is preferred over PSM.

Fig.3 Cost-effectiveness of housing spillovers versus standalone energy efficiency programs.
This figure provides a comparison of cost effectiveness ratios in kWh saved per dollar for housing spillovers in this study with other dedicated energy efficiency programs. This includes peer-reviewed point estimates for the most common interventions including Capital Upgrades; Information & Behavioral Nudges; and Rebates & Financial Incentives. Values for Allcott, 2011 [32]; Arimura et al., 2012 [44]; Asensio & Delmas, 2015 [28]; and Ito, 2015 [47], were derived from Benartzi et al., 2017 [31]. Values for Alberini & Towe, 2015 [42]; Alberini et al., 2016 [46]; Ayres et al., 2012 [41]; Davis et al., 2014 [45]; and Novan et al., 2022 [39], were derived from Gillingham et al., 2018 [24]. Values for Allcott & Mullainathan, [27]; Brown et al., 2020 (Residential with participant costs) [17]; Fowlie et al., 2018 [20]; Giraudet et al., 2018 [48]; Hancevic & Sandoval, 2022 [37]; and Zivin & Novan, 2016 [38], were derived from information reported in those studies. Values are exact and have been scaled to $2021 U.S.

References

[1] Jaroscak, J. V., Lawhorn, J. M. & Dilger, R. J. Block grants: Perspectives and controversies. *Congressional Research Service* **R40486**, 1–25 (2020). URL https://crsreports.congress.gov/product/pdf .

[2] Wiedmann, T., Lenzen, M., Keyser, L. & Steinberger, J. K. Scientists' warning on affluence. *Nature Communications* **11** (3107) (2020). https://doi.org/10.1038/s41467-020-16941-y .

[3] Guneralp, B. *et al.* Global scenarios of urban density and its impacts on building energy use through 2050. *Proceedings of the National Academy of Sciences* **114**, 8945–8950 (2017). https://doi.org/10.1073/pnas.1606035114 .

[4] Dietz, T. & Rosa, E. A. Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences* **94**, 175–179 (1997). https://doi.org/10.1073/pnas.94.1.175 .

[5] Bostic, R. W. CDBG at 40: Opportunities and obstacles. *Housing Policy Debate* **24**, 297–302 (2014). https://doi.org/10.1080/10511482.2013.866973 .

[6] Bleiholder, J. & Naumann, F. Data fusion. *ACM Comput. Surv.* **41** (1) (2009). https://doi.org/10.1145/1456650.1456651 .

[7] Handley, D. M. & Howell-Moroney, M. Ordering stakeholder relationships and citizen participation: Evidence from the community development block grant program. *Public Administration Review* **70**, 601–609 (2010). https://doi.org/10.1111/j.1540-6210.2010.02181.x .

[8] Hines, J. & Thaler, R. The flypaper effect. *Journal of Economic Perspectives* **9**, 217–226 (1995). https://doi.org/10.1257/jep.9.4.217 .

[9] Inman, R. P. *Flypaper Effect in The New Palgrave Dictionary of Economics*, 1–6 (Palgrave Macmillan UK, London, 2009).

[10] Wong, K. K. & Peterson, P. E. Urban response to federal program flexibility: Politics of Community Development Block Grant. *Urban Affairs Quarterly* **21** (3), 293–309 (1986). https://doi.org/10.1177/004208168602100302 .

[11] Finegold, K. *et al.* *Block grants: Historical overview and lessons learned New Federalism Issues and Options for States, Series A, No.A-63, The Urban Institute* (2004).

[12] Reich, D., Shapiro, I., Cho, C. & Kogan, R. Block-granting low-income programs leads to funding declines over time, history shows (2017). URL https://www.cbpp.org/sites/default/files/atoms/files/2-22-17bud.pdf.

[13] Collinson, R. A. Assessing the allocation of CDBG to community development need. *Housing Policy Debate* **24**, 91–118 (2014). https://doi.org/10.1080/10511482.2013.854945 .

[14] Dilger, R. J. & Boyd, E. *Block grants: Perspectives and controversies* (Congressional Research Service Washington, DC, 2014).

[15] Jones, K. *An Overview of the HOME Investment Partnerships Program* (Congressional Research Service Washington, DC, 2014).

[16] U.S. Energy Information Administration (2021). URL https://www.eia.gov/. Accessed: 2021-08-09.

[17] Brown, M. A., Soni, A., Lapsa, M. V., Southworth, K. & Cox, M. High energy burden and low-income energy affordability: conclusions from a literature review. *Progress in Energy* **2** (042003) (2020). https://doi.org/10.1088/2516-1083/abb954 .

[18] City of Albany Department of Community & Economic Development, M. 2016-2021 Consolidated Plan and 2016-2017 Annual Action Plan, City of Albany, Georgia, OMB Control No: 2506-0117 (2016).

[19] Reames, T. G. A community-based approach to low-income residential energy efficiency participation barriers. *Local Environment* **21** (12), 1449–1466 (2016). https://doi.org/10.1080/13549839.2015.1136995 .

[20] Fowlie, M., Greenstone, M. & Wolfram, C. Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *Quarterly Journal of Economics* **133**, 1597–1644 (2018). https://doi.org/10.1093/qje/qjy005 .

[21] Asensio, O. I. & Delmas, M. A. The effectiveness of US energy efficiency building labels. *Nature Energy* **2** (17033) (2017). https://doi.org/10.1038/nenergy.2017.33 .

[22] Boomhower, J. & Davis, L. W. A credible approach for measuring inframarginal participation in energy efficiency programs. *Journal of Public Economics* **113**, 67–79 (2014). https://doi.org/10.1016/j.jpubeco.2014.03.009 .

[23] Diamond, A. & Sekhon, J. S. Genetic matching for estimating causal Effects: A general multivariate matching method for achieving balance in observational studies. *The Review of Economics and Statistics* **95** (3),

932–945 (2013). https://doi.org/10.1162/REST_a_00318 .

[24] Gillingham, K., Keyes, A. & Palmer, K. Advances in evaluating energy efficiency policies and programs. *Annual Review of Resource Economics* **10**, 511–532 (2018). https://doi.org/10.1146/annurev-resource-100517-023028 .

[25] Gillingham, K. & Palmer, K. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy* (2020). https://doi.org/10.1093/reep/ret021 .

[26] Consumer-Price-Index (2019). URL https://www.bls.gov/regions/southeast/news-release/consumerpriceindex_south.htm. Accessed: 2021-08-09.

[27] Allcott, H. & Mullainathan, S. Behavior and energy policy. *Science* **327** (5970), 1204–1205 (2010). https://doi.org/10.1126/science.1180775 .

[28] Asensio, O. I. & Delmas, M. A. Nonprice incentives and energy conservation. *Proceedings of the National Academy of Sciences* **112** (6), 510–515 (2015). https://doi.org/10.1073/pnas.1401880112 .

[29] Delmas, M. A., Fischlein, M. & Asensio, O. I. Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy* **61**, 729–739 (2013). https://doi.org/10.1016/j.enpol.2013.05.109 .

[30] Christensen, P., Francisco, P., Myers, E. & Souza, M. Decomposing the Wedge between Projected and Realized Returns in Energy Efficiency Programs. *The Review of Economics and Statistics* 1–46 (2021). https://doi.org/10.1162/rest_a_01087 .

[31] Benartzi, S. *et al.* Should governments invest more in nudging? *Psychological science* **28** (8), 1041–1055 (2017). https://doi.org/10.1177/0956797617702501 .

[32] Allcott, H. Social norms and energy conservation. *Journal of Public Economics* **95** (9-10), 1082–1095 (2011). https://doi.org/10.1016/j.jpubeco.2011.03.003 .

[33] Allcott, H. & Rogers, T. The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review* **104** (10), 3003–37 (2014). https://doi.org/10.1257/aer.104.10.3003 .

[34] Jessoe, K., Lade, G. E., Loge, F. & Spang, E. Spillovers from behavioral interventions: Experimental evidence from water and energy use. *Journal of the Association of Environmental and Resource Economists* **8** (2), 315–346 (2021). https://doi.org/10.1086/711025 .

[35] Alacevich, C., Bonev, P. & Söderberg, M. Pro-environmental interventions and behavioral spillovers: Evidence from organic waste sorting in Sweden. *Journal of Environmental Economics and Management* **108**, 102470 (2021). https://doi.org/10.1016/j.jeem.2021.102470 .

[36] Kumar, C. H. C. C. F. F. . S. R., P. Analyzing spillovers from food, energy and water conservation behaviors using insights from systems perspective. *Behavioural Public Policy* **7** (3), 773–807 (2023). https://doi.org/10.2139/ssrn.3919454 .

[37] Hancevic, P. I. & Sandoval, H. H. Low-income energy efficiency programs and energy consumption. *Journal of Environmental Economics and Management* **113**, 102656 (2022). https://doi.org/10.1016/j.jeem.2022.102656 .

[38] Zivin, J. G. & Novan, K. Upgrading efficiency and behavior: electricity savings from residential weatherization programs. *The Energy Journal* **37** (4) (2016). https://doi.org/10.5547/01956574.37.4.jziv .

[39] Novan, K., Smith, A. & Zhou, T. Residential building codes do save energy: Evidence from hourly smart-meter data. *Review of Economics and Statistics* **104** (3), 483–500 (2022). https://doi.org/10.1162/rest_a_00967 .

[40] Levinson, A. How much energy do building energy codes save? evidence from california houses. *American Economic Review* **106** (10), 2867–94 (2016) .

[41] Ayres, I., Raseman, S. & Shih, A. Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. *The Journal of Law, Economics, and Organization* **29** (5), 992–1022 (2013). https://doi.org/10.1093/jleo/ews020 .

[42] Alberini, A. & Towe, C. Information v. energy efficiency incentives: Evidence from residential electricity consumption in Maryland. *Energy Economics* **52**, S30–S40 (2015). https://doi.org/10.1016/j.eneco.2015.08.013 .

[43] Houde, S. & Aldy, J. E. Consumers' response to state energy efficient appliance rebate programs. *American Economic Journal: Economic Policy* **9** (4), 227–55 (2017). https://doi.org/10.1257/pol.20140383 .

[44] Arimura, T. H., Li, S., Newell, R. G. & Palmer, K. Cost-effectiveness of electricity energy efficiency programs. *The Energy Journal* **33** (2) (2012). https://doi.org/10.5547/01956574.33.2.4 .

[45] Davis, L. W., Fuchs, A. & Gertler, P. Cash for coolers: evaluating a large-scale appliance replacement program in Mexico. *American Economic Journal: Economic Policy* **6** (4), 207–38 (2014). https://doi.org/10.1257/pol.6.4.207 .

[46] Alberini, A., Gans, W. & Towe, C. Free riding, upsizing, and energy efficiency incentives in Maryland homes. *The Energy Journal* **37** (1) (2016). https://doi.org/10.5547/01956574.37.1.aalb .

[47] Ito, K. Asymmetric incentives in subsidies: Evidence from a large-scale electricity rebate program. *American Economic Journal: Economic Policy* **7** (3), 209–37 (2015). https://doi.org/10.1257/pol.20130397 .

[48] Giraudet, L.-G., Houde, S. & Maher, J. Moral hazard and the energy efficiency gap: Theory and evidence. *Journal of the Association of Environmental and Resource Economists* **5** (4), 755–790 (2018). https://doi.org/10.1086/698446 .

[49] Remer, D. S. & Nieto, A. P. A compendium and comparison of 25 project evaluation techniques. Part 1: Net present value and rate of return methods. *International Journal of Production Economics* **42** (1), 79–96 (1995). https://doi.org/10.1016/0925-5273(95)00104-2 .

[50] Metcalf, G. E. & Hassett, K. A. Measuring the energy savings from home improvement investments: evidence from monthly billing data. *Review of Economics and Statistics* **81** (3), 516–528 (1999). https://doi.org/10.1162/003465399558274 .

[51] Giandomenico, L., Papineau, M. & Rivers, N. A systematic review of energy efficiency home retrofit evaluation studies. *Annual Review of Resource Economics* **14**, 689–708 (2022). https://doi.org/10.1146/annurev-resource-111920-124353 .

[52] Allcott, H. & Greenstone, M. Is there an energy efficiency gap? *Journal of Economic Perspectives* **26** (1), 3–28 (2012). https://doi.org/10.1257/jep.26.1.3 .

[53] Tuominen, P. *et al.* Economic appraisal of energy efficiency in buildings using cost-effectiveness assessment. *Procedia Economics and Finance* **21**, 422–430 (2015). https://doi.org/10.1016/S2212-5671(15)00195-1 .

[54] Nikolaidis, Y., Pilavachi, P. A. & Chletsis, A. Economic evaluation of energy saving measures in a common type of Greek building. *Applied*

Energy **86** (12), 2550–2559 (2009). https://doi.org/10.1016/j.apenergy.2009.04.029 .

[55] Kim, J. J. Economic analysis on energy saving technologies for complex manufacturing building. *Resources, Conservation and Recycling* **123**, 249–254 (2017). https://doi.org/10.1016/j.resconrec.2016.03.018 .

[56] DOE. Benefit-Cost Evaluation of U.S. Department of Energy Investment in HVAC, Water Heating, and Appliance Technologies. RTI Project Number 0214666 (2017). URL https://www.energy.gov/sites/default/files/2017/09/f36/DOE-EERE-BTO-HVAC_Water%20Heating_Appliances%202017%20Impact%20Evaluation%20Final.pdf. Accessed: 2022-10-10.

[57] Sutherland, R. J. Market barriers to energy-efficiency investments. *The Energy Journal* **12** (3) (1991). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol12-No3-3 .

[58] Lai, Y. *et al.* Building retrofit hurdle rates and risk aversion in energy efficiency investments. *Applied Energy* **306**, 118048 (2022). https://doi.org/10.1016/j.apenergy.2021.118048 .

[59] Lee, Y. & Schachter, H. L. Exploring the relationship between trust in government and citizen participation. *International Journal of Public Administration* **42** (5), 405–416 (2019). https://doi.org/10.1080/01900692.2018.1465956 .

[60] Miller, D. & Rivera, J. D. Guiding principles: rebuilding trust in government and public policy in the aftermath of hurricane katrina. *Journal of Public Management and Social Policy* **12** (1), 37–47 (2006) .

[61] Kampen, J. K., De Walle, S. V. & Bouckaert, G. Assessing the relation between satisfaction with public service delivery and trust in government. the impact of the predisposition of citizens toward government on evalutations of its performance. *Public Performance & Management Review* **29** (4), 387–404 (2006) .

[62] American Community Survey 5-Year Data (2009-2019). URL https://www.census.gov/data/developers/data-sets/acs-5year.html. Accessed: 2021-05-23.

[63] Walls, M., Gerarden, T., Palmer, K. & Bak, X. F. Is energy efficiency capitalized into home prices? Evidence from three U.S. cities. *Journal of Environmental Economics and Management* **82**, 104–124 (2017). https://doi.org/10.1016/j.jeem.2016.11.006 .

[64] Im, J., Seo, Y., Cetin, K. S. & Singh, J. Energy efficiency in U.S. residential rental housing: Adoption rates and impact on rent. *Applied Energy*

205, 1021–1033 (2017). https://doi.org/10.1016/j.apenergy.2017.08.047 .

[65] NOAA. National Oceanic and Atmospheric Administration — Cooling and Heating Days (2004-2019). URL https://www.noaa.gov. Accessed: 2021-03-13.

[66] Sekhon, J. S. Multivariate and propensity score matching software with automated balance optimization: The matching package for R. *Journal of Statistical Software* **42** (7) (2011). https://doi.org/10.18637/jss.v042.i07 .

[67] Imai, K., King, G. & Stuart, E. A. *Misunderstandings between experimentalists and observationalists about causal inference*, 196–227 (2008).

[68] King, G., Lucas, C. & Nielsen, R. The balance-sample size frontier in matching methods for causal inference. *American Journal of Political Science* **61** (2), 473–489 (2017). https://doi.org/10.1111/ajps.12272 .

[69] Rosenbaum, P. R. *Overt bias in observational studies*, 71–104 (Springer, 2002).

[70] Rosenbaum, P. R. Sensitivity analysis for M-estimates, tests, and confidence intervals in matched observational studies. *Biometrics* **63** (2), 456–464 (2007). https://doi.org/10.1111/j.1541-0420.2006.00717.x .

[71] Athey, S. & Imbens, G. W. Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics* **226** (1), 62–79 (2022). https://doi.org/10.1016/j.jeconom.2020.10.012 .

[72] Callaway, B. & Sant'Anna, P. H. Difference-in-differences with multiple time periods. *Journal of Econometrics* **225** (2), 200–230 (2021). https://doi.org/10.1016/j.jeconom.2020.12.001 .

[73] De Chaisemartin, C. & d'Haultfoeuille, X. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* **110** (9), 2964–96 (2020). https://doi.org/10.1257/aer.20181169 .

[74] Miller, D. L. An introductory guide to event study models. *Journal of Economic Perspectives* **37** (2), 203–30 (2023). URL https://www.aeaweb.org/articles?id=10.1257/jep.37.2.203. https://doi.org/10.1257/jep.37.2.203 .

[75] Ham, D. W. & Miratrix, L. Benefits and costs of matching prior to a difference in differences analysis when parallel trends does not hold (2023). 2205.08644.

[76] Goodman-Bacon, A. Difference-in-differences with variation in treatment timing. *Journal of Econometrics* **225** (2), 254–277 (2021). https://doi.org/10.1016/j.jeconom.2021.03.014 .

[77] Baker, A. C., Larcker, D. F. & Wang, C. C. How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* **144** (2), 370–395 (2022). https://doi.org/10.1016/j.jfineco.2022.01.004 .

[78] Sun, L. & Abraham, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* **225** (2), 175–199 (2021). https://doi.org/10.1016/j.jeconom.2020.09.006 .

[79] Smart Cities Albany: Dataverse Repository (2022). URL https://doi.org/10.7910/DVN/SF1DRW. Accessed: 2022-12-27.

[80] Smart Cities Albany: Open Data GeoHub (2021). URL https://geohub.albanyga.gov. Accessed: 2021-12-23.

[81] Smart Cities Albany: GitHub Repository (2022). URL https://doi.org/10.5281/zenodo.5684354. Accessed: 2022-12-27.

Contents

Supplementary notes

Supplementary note 1

One exception is the HUD-administered Disaster Recovery block grant program, which provides resources to help communities recover after Presidentially declared natural disasters.

Supplementary note 2

We used deterministic, rule-based procedures to join data records based on entities that may or may not share a common identifier. This included several indexing methods, e.g., exact matching and stepwise linkage, which allowed us to standardise formats, achieve entity resolution, and de-duplicate records for storage efficiency. A key technical hurdle was the fact that data entry from HUD's nationwide Integrated Disbursement and Information System (IDIS) was often not digitised in spreadsheets (not in database format), and project names and address records were in non-standard and sometimes inconsistent formats. This prompted our cross-sector public-private-academic collaboration.

Supplementary note 3

The CDBG entitlement program is authorised under Title I of the Housing and Community Development Act of 1974, Public Law 93-383 (42 U.S.C. 5301 et seq.). The HOME program is authorised under Title II of the Cranston-Gonzalez National Affordable Housing Act (42 U.S.C. 12701 et seq.). Regulations are at 24 CFR part 92.

Supplementary note 4

Detailed HOME and CDBG participation and community statistics are available in the City of Albany, GA 2016-2021 Consolidated Plan. Interactive public statistics have been deposited to: https://storymaps.arcgis.com/stories/e9990189ea00432089286ffeb636d3fd and https://albanyga-albgis.opendata.arcgis.com

Supplementary note 5

To establish the CO_{2e} equivalencies for the monthly energy savings, we used emissions factors from the EPA Greenhouse Gas Equivalencies Calculator: https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator for a total of 4,716,398.45 kWh saved.

Supplementary note 6

The U.S. Department of the Treasury and the Internal Revenue Service (IRS) have designated Opportunity Zones in 18 States as of 2018, including 260 census tracts in the State of Georgia, where poverty rates are greater than 20 percent. Economic investment in opportunity zones receives special tax advantages such as deferments and capital gains tax incentives for investors. Qualified opportunity zones retain their designation for 10 years.

Supplementary note 7

The Cost-Effectiveness (CE) ratio was calculated for all participating square feet for project i in month j, and time period of expenditures k as follows, where ATE is the average treatment effect for the project group, d is the time period of savings. Total costs include the program costs (PC), excluding program income, and administrative costs (AC) by the project as reported to HUD.

$$CE_{ijk} = \frac{ATE \sum_{i=1}^{n} \sum_{i=j}^{m} sqft_{ij}\, d_{ij}}{\sum_{i=1}^{n} \sum_{k=1}^{p} (PC_{ik} + AC_{ik})}$$

The energy-relevant programs make up 361 of the 549 projects in the sample. For the cost-effectiveness analysis, we do not consider the 188 projects (160 in HOME and 28 in CDBG) unrelated to energy savings.

Supplementary note 8

For the back-of-the-envelope internal rate of return calculations, we assumed the lifetime savings equals the total fixed costs for each program. We also assumed a 30-year lifetime for installed energy efficiency technologies and held electricity rates and savings at constant 2021 levels.

Supplementary note 9

According to Rosenbaum and Rubin [1], the standardised percent bias (SB) is defined as:

$$SB = 100 \times \frac{\overline{X}_{treat} - \overline{X}_{control}}{\sqrt{(S^2_{treat} + S^2_{control})/2}}$$

where $\overline{X}_{treat}$ and S^2_{treat} are the mean and the variance of the treatment group, while $\overline{X}_{control}$ and $S^2_{control}$ are the mean and the variance of the control group.

Supplementary note 10

In our basic specification, we deployed a two-stage analysis to determine the causal effects of program participation. In the first stage, we implemented multivariate matching procedures to construct reasonable counterfactuals and to mitigate observational bias across conditioning variables. In the second stage, we implemented the usual two-way fixed effect estimator. For project i at the time period t, the two-way fixed effects (TWFE) regression model is:

$$log\left(\frac{kWh}{sqft}\right)_{it} = \beta^{FE} D_{it} + \Theta W_t + \alpha_i + \gamma_t + \varepsilon_{it}$$

We regress the logarithm of monthly electricity loads in kilowatt-hour per square foot $log\left(\frac{kWh}{sqft}\right)_{it}$ on a treatment dummy variable D_{it} coded as 1 for months in which CDBG or HOME projects started and stays treated until the end of the whole period of analysis, and 0 otherwise, before a project's implementation; the policy indicator variable for properties that never received treatment and were available for counterfactual analysis was coded as 0 for all the periods; and β^{FE} represents the TWFE estimator. We also account for time-varying weather controls (W_t represents the vectors of heating and cooling degree-days), time-invariant property characteristics, and time-fixed effects (α_i and γ_t, respectively).

Supplementary discussion

Comparison to other US cities. According to WalletHub research, Albany, GA, scores similarly to other 24 cities across the U.S. on the five following dimensions: affordability, economic health, education and health, quality of life and safety [2]. Considering 43 relevant metrics across 1,322 cities, Albany, GA, is ranked close to Camden, NJ; Fort Hood, TX; Pine Bluff, AR; and Wasco, CA. On affordability, including median household income, cost of living, homeownership rate, housing costs, and share of households with severe housing cost burden, it is also similar to Goldsboro, NC; Greenville, MS; and Monroe, LA. To further evaluate our field site, we compared Albany, GA, to national and regional averages with respect to population characteristics, housing stock, and electricity consumption.

Population characteristics. Our sample population consists of residential single- and multi-family households, both homeowners and renters. Similar to many small-to-medium-sized urban areas, as of 2019, Albany's population is flat to declining [3]. According to American Community Survey 5-Year Data, 2015-2019 [4], the total population in Albany is 72,130, with the average household size of 2.42 being comparable to the national average of 2.62, and 74.35% of the population is Black or African American. The median household income in Albany is $36,615, whereas the national median household income is $62,843 [4].

Housing stock. Aside from population characteristics provided by the U.S. Census Bureau, HUD programs take into account the age and condition of the housing stock of program recipients [5]. The median home value in Albany is $99,800, which reflects a blighted housing stock, as described by community members and leaders [4]. On average, Albany's housing stock of our study population is over 50 years old, which is higher than the national average; this property age is similar to nearly 15% of the total number of housing units across the U.S. [6].

Electricity consumption. Given the characteristics of Albany's population and housing stock, from a sustainability perspective, energy conservation strategies are especially relevant and needed. Based on the data received from the city, we estimated the average energy consumption in Albany to be 13,255 kWh per year per household, which is higher than the national average of 10,649 kWh per year per household [7]. We found that participating households also face high energy burdens. For example, eight of the 27 U.S. Census tracts in our sample population are considered to have "unaffordable" energy burdens: spending above 6-10% of household income on electricity, as documented in refs. [8–10].

Administrator selection. Some may wonder whether heads of households or landlords who are better informed or connected to administrative personnel gain disproportionate access to block grant funds, a source of potential unobservable bias. Based on interviews with City of Albany administrators, we assessed selection and decision-making processes for block grant disbursement. In summary, we found little evidence of administrator selection bias for three likely reasons. (1) According to public officials, program management is subject to audits and oversight at both the federal and local levels in order to "...make sure there was consistency in expenditures as well as regulatory requirements." Accountability is also achieved through community participation, including public hearings, which serve to fulfill federal requirements for citizen input. (2) Administrators report their efforts to reach more people with information about available funding, such as going to town halls to "...talk to them about how to make their homes more energy efficient for all residents not just senior citizens." We subsequently learned that most recipients of block grant funds are over the age of 62, an often overlooked demographic in dedicated energy efficiency campaigns. (3) Despite "word-of-mouth" being a common mechanism for sharing information in Albany, we learned that the administrators reach a substantial share (about half) of the eligible population. One administrator said, "For everyone who [knows about the program], you talk to someone who doesn't know about it."

Addressing Split Incentives. Many LMI households include renters in single or multi-family units. We know that if tenants pay for their own utilities, they have the incentive to conserve energy to reduce bills, but may face capital constraints or other barriers to invest in home upgrades. If landlords pay for the utilities for their rental properties, landlords cannot easily benefit from bill savings in individual units, so they may choose to delay or refrain from investing in home upgrades. This disconnect, commonly referred to as a split-incentives problem, is well-known in the residential sector [11]. It has been estimated that policy support to address split incentives, particularly among LMI renter populations, could save low-income residents between $4 and $11 billion dollars per year [12]. For example, one Albany resident shared, "... And then you rent a house in the city. And you have only three bedrooms and one bath, and your bill is close to $500. When you turn on your AC, all the air is going up through the roof and out the window sills. Because the landlord is not making sure his property is weatherized, [it] sucks money out of the community and is bleeding us dry." According to the City of Albany's 5-year consolidated plan, "substandard housing conditions in [sic] affordable units may make them unsafe or may lead to exceptionally high utility costs, negating savings in rent as compared to a more expensive unit elsewhere" [13].

LMI renters often face high energy costs when lack of weatherization, aging appliances or other efficiency measures in their rental units are dilapidated. Of note was the magnitude of the 32% energy savings for renters in city-owned properties in the Rental Rehabilitation program, which is at the high end or exceeds the performance of capital upgrades and incentive programs in residential and commercial buildings [14, 15]. In conversation with a Community Development Manager within the City of Albany's Department of Community and Economic Development, we learned that occupants in all city-owned properties pay their own utility bills under tenant-paid contracts. For example, “they have customers calling all the time with extremely large ... bills, the landlord won’t fix it. They think the [resident] is supposed to [fix] it.” Prior studies have shown that under tenant-paid contracts, households can have substantially lower consumption, particularly in response to temperature fluctuations [16]; however, barriers remain for low-income residents in city-owned properties.

As multifamily households (e.g., Apartment; Condominium; Duplex, Triplex, Quadplex) represent only 4.5% of participants in our study, we acknowledge that there is limited potential for renters to benefit from policy options such as contractual interventions, i.e., shifting lease contracts from owner-paid to tenant-paid contracts [17] or establishing green leases in which the cost of capital improvements are offset by increased rent to tenants [12]. We also know that when owners pay for utilities, they tend to command higher rent prices [18], which puts even more pressure on LMI energy efficiency participation. Regulatory interventions such as building codes, and other financing options, are designed to address barriers related to split incentives, but generally do not focus on specific principal-agent problems faced by LMI households in practice. For instance, one city official informed us that “tenants can fill out [the application for public assistance] but landlord must give approval.”

Overall, our findings illustrate that housing policies in Albany, GA, which also fund structural upgrades in multifamily homes can meaningfully address split incentive investment barriers, which simultaneously benefit LMI renters with some of the highest energy and cost burdens nationally.

Insights from administrators and residents. In addition to evidence related to program uptake, our interviews with Albany, GA, administrators and residents revealed three additional findings. First, we learned that public administrators communicate a shared commitment to their fellow residents through a deep public service motivation [19, 20]. We also observed that City administrators often shared several characteristics and values with the residents they serve. The representative bureaucracy literature in public administration often argues that that administrative personnel who reflect the community served can actively represent the interests of particular groups, which translates into substantive benefits for those represented [21–23]. For example, HUD requires at least 70% of CDBG funding to be allotted to LMI households, defined as 80% of the area median income (AMI) or below. However, officials in Albany’s Department of Community and Economic Development (DCED), which manages HUD funds in Albany, exceed the minimum targeting set forth by HUD, reporting that over 90% of their portfolio goes to LMI households.

Second, we found that the city of Albany’s bureaucratic structure enabled centralised decision-making over data ownership and access by having a Chief Information Officer jointly overseeing city and county data initiatives. This structure allowed for organisational agility in which information technology

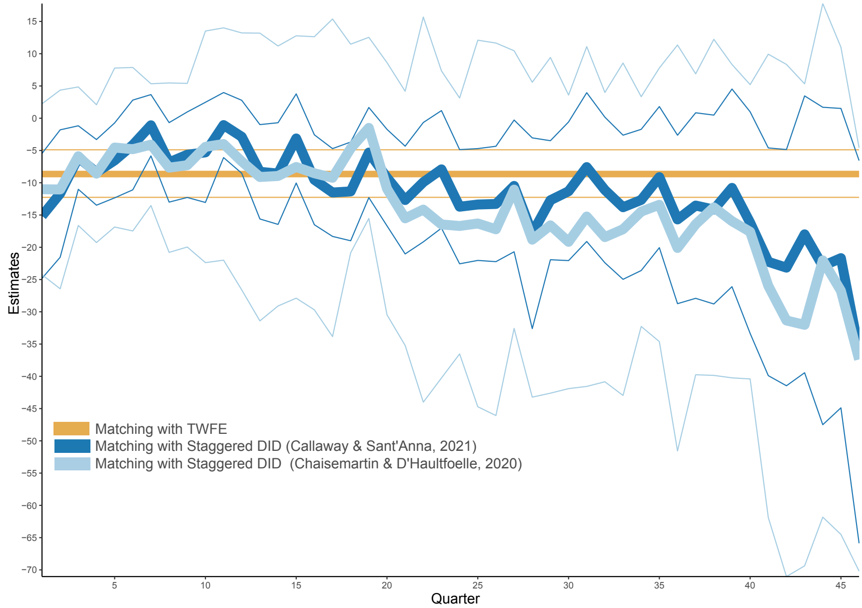
(IT) resources were centrally allocated to address data silos and data integration challenges across departments. Scholars have argued that such integrated access to data can uniquely address public pressure for information and greater transparency of public investments [24–26].

Third, from our resident interviews, we also uncovered some evidence of diverging perceptions about household energy use among participants. For example, one resident said, "What I do know is that the electricity bill is still over $200 a month and that's what it was before the [new] AC unit. So, I didn't see a change in my bill." Issues surrounding information provision and estimating resource use in the residential sector are well-documented [27–31]. Additional research is needed to understand potential perception gaps among residents regarding neighbourhood improvements.

Additional quotes from interviews.

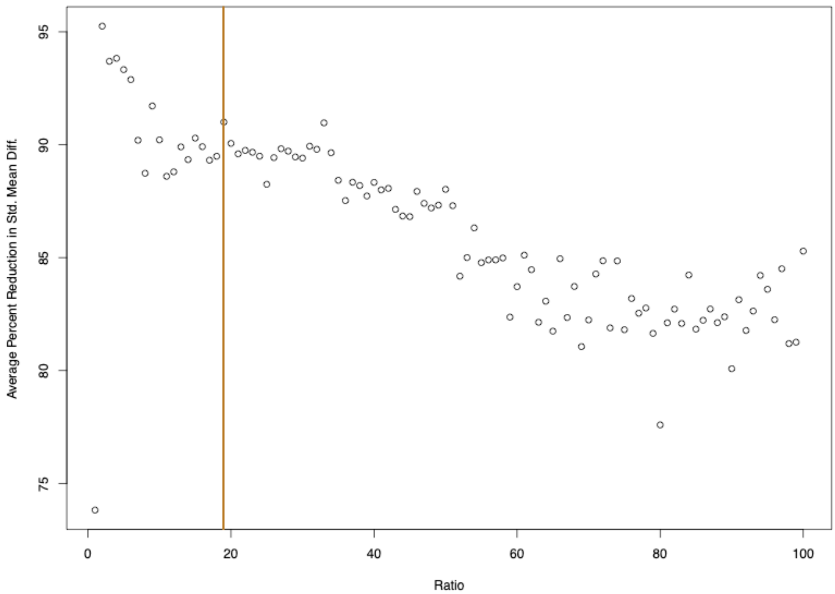
- **On shared commitment:** When asked what was the most important aspect of their job, one administrator answered, "... ensuring the most vulnerable populations have access to these funds and can partake in its benefits". A resident said that "I really do appreciate Albany. A lot of changes have been made, and I see us growing; and that's good also." When asked what motivates going to work everyday, an administrator said that it was "supporting the community you live and were born in." Another said that "we're in this together, we must work together."
- **On bureaucratic structure:** An administrator said that "We're IT for the city and the county...it's a group of us, who are cross-sectional, not all of them work for the technology department. But, our goal is to identify situations like [siloed housing and utility data] and then bring that group of people together; and see, is it possible to solve that problem with technology?" When asked how open data hubs facilitate interactions within a department, an administrator said that "Not so much within my department, but between us and other departments...This is a similar problem [that other cities across the US have;] a lot of departments, even though they're a part of a whole city, they work in silos; so a project that one department has really has a profound effect on a different department. But those 2 departments really don't know what's going on between the 2. So what we're using the [Open Data] Hub for... is a way to visualise what's happening around our city, and allow other people to see into some projects and some data that they never really access to before."
- **On consumer perceptions:** An administrator said that "...energy use and disproportionate percentages of income [are] being spent on energy for people in poverty, but how do you fix that? That is the big debate." A resident said that "Very concerned. Living on a $1500 income a month, and you're talking about the mortgage, light bill, personal items, that's pretty tight. That your light bill's over $200 a month, they're much concerned about it. I have to help my mom some months financially." Another resident said that "We paid $1500 in three months during the summer months. It

was \$500+ every month. And we had to try to come up with it. Because we can't operate without lights and electricity. But it's tough for retired people and people on social security but it was a blessing that I have a little retirement."

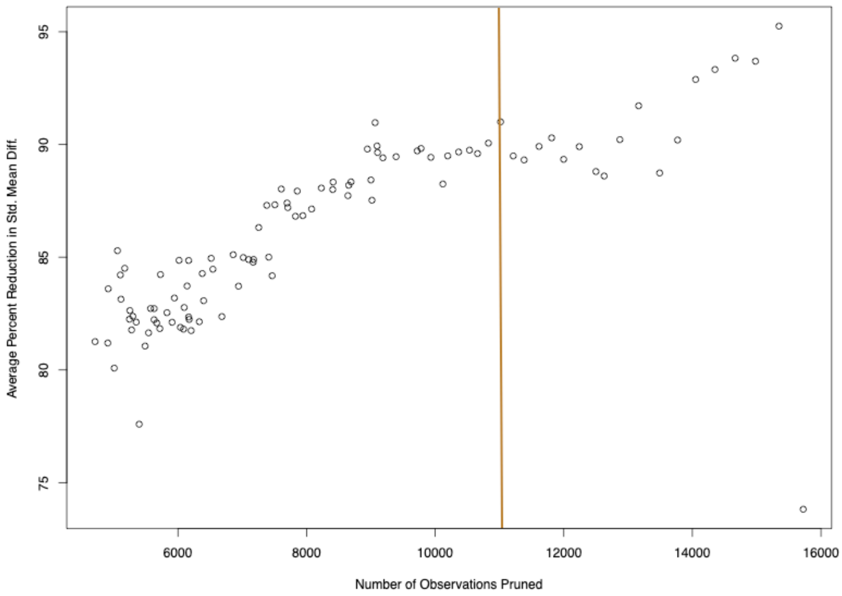


Supplementary Fig. 1 Comparison of matching models with TWFE and staggered DiD estimators.

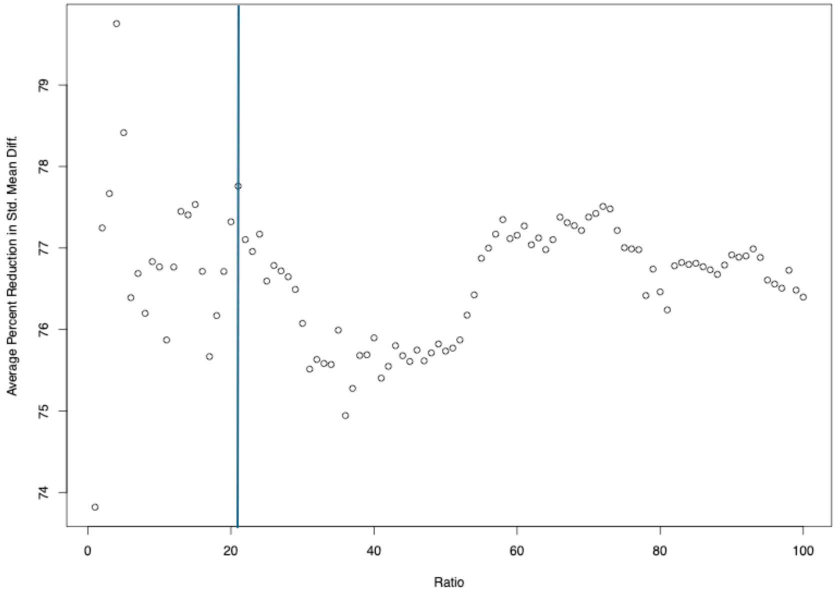
The figure compares the staggered DiD treatment effects with TWFE estimators after matching. The staggered DiD estimates suggest larger savings than more conservative TWFE approach. At the same time, both estimates are generally consistent with each other as the upper and lower confidence intervals largely overlap. The upper and lower colour-coded lines represent 95% confidence intervals.



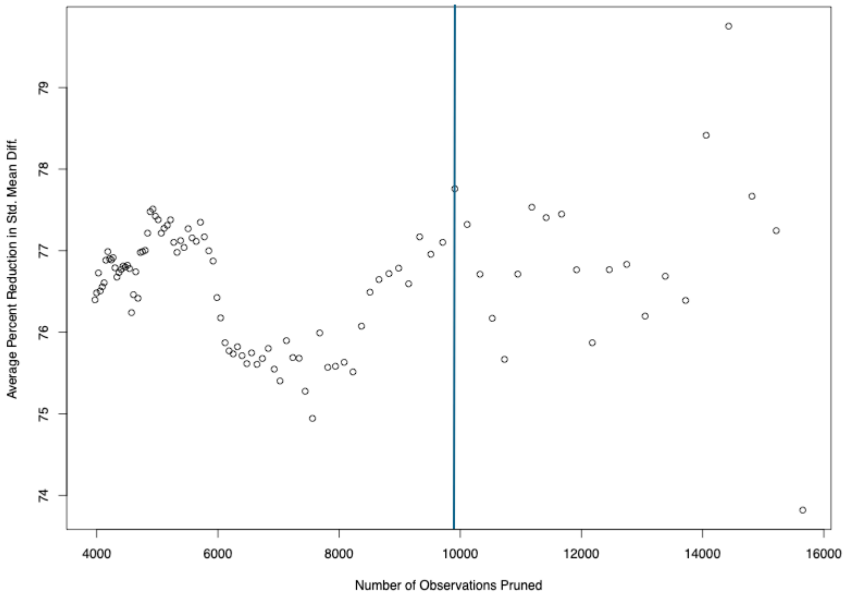
Supplementary Fig. 2 Bias reduction after genetic matching.
This figure plots the average percent reduction in standardised mean differences as a function of the matching ratio parameter. The optimal ratio of controls over treated households balances the need for saturation of potential counterfactuals with computational efficiency. The optimal ratio was found at 19:1 and depicted as an orange line.



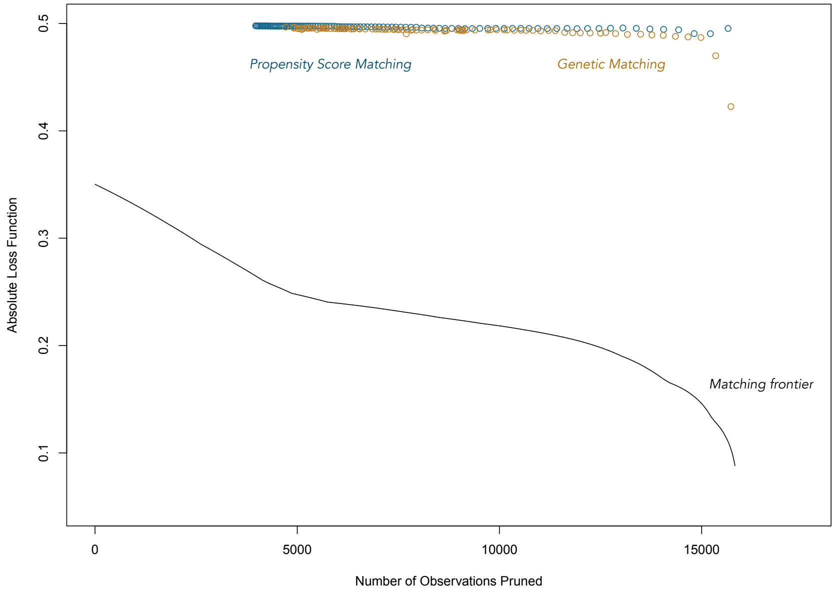
Supplementary Fig. 3 Bias reduction after genetic matching.
This figure plots the average percent reduction in standardised mean differences as a function of the number of observations pruned, derived from the optimal ratio of controls over treated households. The optimal ratio balances the need for saturation of potential counterfactuals with computational efficiency. The optimal ratio was found at 19:1 and the correspondent number of observations pruned is depicted as an orange line.



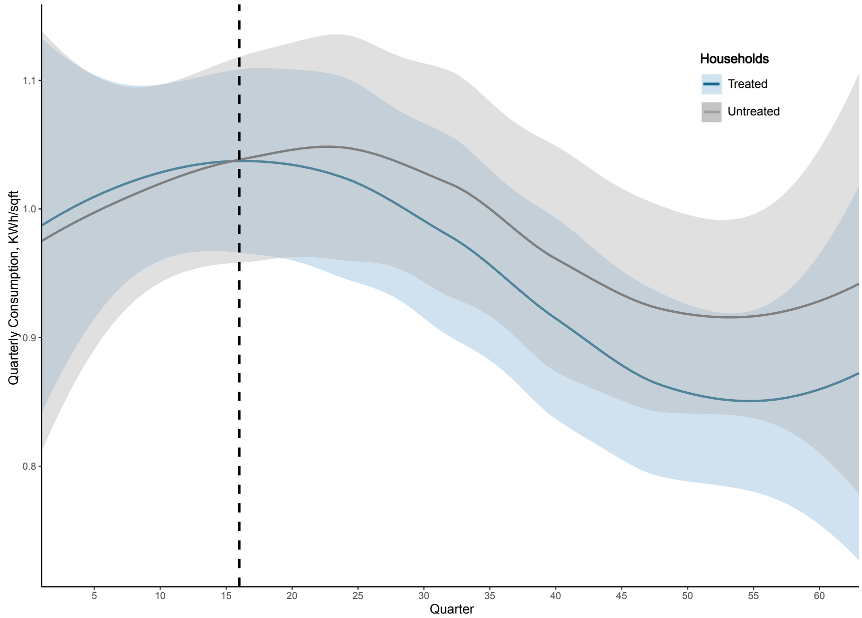
Supplementary Fig. 4 Bias reduction after propensity score matching. This figure plots the average percent reduction in standardised mean differences as a function of the matching ratio parameter. The optimal ratio of controls over treated households balances the need for saturation of potential counterfactuals with computational efficiency. The optimal ratio was found at 21:1 and depicted as a blue line.



Supplementary Fig. 5 Bias reduction after propensity score matching. This figure plots the average percent reduction in standardised mean differences as a function of the number of observations pruned, derived from the optimal ratio of controls over treated households. The optimal ratio balances the need for saturation of potential counterfactuals with computational efficiency. The optimal ratio was found at 21:1 and the correspondent number of observations pruned is depicted as a blue line.



Supplementary Fig. 6 Matching frontier.
This figure shows the matching frontier along the results of propensity score and genetic matching (visualised in blue and orange, respectively) and support the evidence that genetic matching outperforms propensity score matching.



Supplementary Fig. 7 Treated vs. untreated household trends. This figure shows trends of quarterly electricity consumption (kWh/sqft) pre and post housing policy implementation. The vertical dashed line depicts the period when the first housing project was initiated during October 2007. The trendlines serve as a visual guide for respective projects with the shaded areas representing mean values with upper and lower 95% confidence intervals.

Supplementary Table 1 Monthly energy savings by project, 2004-2019.

	No. of Projects	Genetic Matching Estimate (S.E.)	Genetic Matching Ratio: Controls/ Treated	PS Matching Estimate (S.E.)	PS Matching Ratio: Controls/ Treated	Without Matching Estimate (S.E.)
HUD-funded Projects	549	-5.03** (1.90)	9.30	-5.49** (1.89)	11.33	-4.32* (1.86)
CDBG Projects	349	-9.92*** (2.07)	14.62	-10.34*** (2.07)	17.83	-9.15*** (2.04)
Energy Efficiency	62	-12.93** (4.30)	82.31	-13.24*** (4.29)	100.34	-11.79** (4.28)
Emergency Repairs	268	-6.24** (2.20)	20.58	-6.69** (2.19)	25.09	-5.52** (2.18)
Rental Rehabilitation	22	-31.96* (16.18)	231.95	-32.37* (16.18)	282.77	-31.84* (16.17)
HOME Projects	200	6.38 (3.73)	25.52	5.79 (3.72)	31.11	6.94 (3.70)
Homeowner Rehabilitation	29	-10.46* (5.13)	175.97	-10.74* (5.13)	214.52	-9.30 (5.12)
Non-Energy Projects	160	15.13*** (4.03)	31.89	14.42*** (4.02)	38.88	15.53*** (4.00)
Placebo Tests Pre-Treatment		-2.55 (1.81)	9.30	-2.33 (1.80)	11.33	0.63 (1.76)
Treated Households		549		549		549
Control Households		5,103		6,221		16,131
No. of Observations		986,450		1,170,647		2,931,406

Notes: *$^{*}p < 0.0$; $^{**}p < 0.01$; $^{***}p < 0.001$. Standard errors are clustered at the household level by property ID. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as a percentage change. In this table, project savings are calculated using a two-way fixed effects estimator with and without matching procedures. Models without matching and bias reduction result in lower saving estimates. The non-energy projects include New Construction and Tenant Based Rental Assistance. The placebo tests for participating projects in the pre-treatment period indicate effects not significantly different from zero with all methods.*

Supplementary Table 2 Total quarterly energy savings for projects with staggered adoption, 2004-2019.

	Genetic Matching			PS Matching			Without Matching		
	Estimate (S.E.)	Lower 95%	Upper 95%	Estimate (S.E.)	Lower 95%	Upper 95%	Estimate (S.E.)	Lower 95%	Upper 95%
Two-Way Fixed Effects (TWFE)	-8.86*** (2.06)	-11.79	-4.35	-8.65*** (2.06)	-12.26	-4.89	-7.45*** (2.03)	-11.07	-3.69
Callaway & Sant'Anna, 2021	-10.99*** (3.20)	-17.26	-4.72	-10.90*** (3.32)	-17.41	-4.39	-11.51*** (3.07)	-17.53	-5.49
Chaisemartin & D'Haultfoeuille, 2020	-13.58* (7.37)	-28.03	-0.87	-13.07* (7.25)	-27.28	-1.14	-12.81* (6.52)	-25.59	-0.03
No. of Observations	327,560			391,142			994,151		

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. *Standard errors are clustered at the household level by property ID. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as percentage change. In this table, project savings are calculated by staggered difference-in-differences using Callaway & Sant'Anna [32] and De Chaisemartin & d'Haultfoeuille [33]. The projects with staggered adoption include Energy Efficiency, Emergency Repairs, and Homeowner Rehabilitation. Rental Rehabilitation was mostly implemented in one period and includes 20 projects in a large multifamily complex, therefore not suited for staggered DiD adoption.*

Supplementary Table 3 Annualised savings equivalencies using April 2021 Consumer Price Index (CPI).

Item and Group	Monthly Expenditure	Savings per 5% ATE	Savings per 32% ATE
Food	\$269.43	28%	179%
Household Furnishings and Operations	\$128.85	58%	374%
Apparel	\$127.23	59%	379%
Private Transportation	\$224.10	34%	215%
Professional Services	\$383.73	20%	126%
Recreation	\$125.20	60%	385%
Education and Communication	\$137.00	55%	352%
Durables	\$115.30	65%	418%

Note: For food expenditure, the annualised savings for a household range from nearly one-third of a month (28%) up to almost two month (179%) for a basked of goods.

Supplementary Table 4 Matching analysis with and without property value.

	With Property Value	Without Property Value	No. of Observations
All HUD-funded Projects (PSM)	-5.49** (1.89)	-5.59** (1.89)	1,170,647
All HUD-funded Projects (GenMatch)	-5.03** (1.90)	-5.99** (1.90)	986,450

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. *Standard errors are clustered at the household level by property ID. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as a percentage change. Data analysis was done using a two-way fixed effects estimator.*

Supplementary Table 5 Descriptive Statistics: means (standard deviations).

Variables	Treated	Non-Treated	*p*-value	National Average
Property characteristics				
Average Baseline Consumption, kWh/month	1,111.80	1,366.56	0.00	943.90 [34]
	(21.77)	(30.38)		
Property Size, sqft.	1,212.19	1,558.91	0.00	2,008.46 [6]
	(19.16)	(40.25)		
No. Beds	2.61	2.78	0.00	2.70 [3]
	(0.90)	(0.96)		
No. Baths	1.49	1.64	0.00	-
	(0.90)	(0.96)		
Property Age	50.53	54.81	0.00	45 [3]
	(4.45)	(4.28)		
Property Market Value, dollars	49,566.10	83,095.79	0.00	348,000.00 [35]
	(156.86)	(326.12)		
Property Assessment Value, dollars	20,026.43	33,238.33	0.00	240,000.00 [36]
	(102.85)	(206.26)		
Demographic characteristics				
Median Income, dollars	28,982.99	40,110.57	0.00	62,843.00 [3]
	(101.88)	(136.31)		
Female Head of the Household, %	46.68	42.47	0.00	27.70 [3]
	(3.47)	(3.54)		
Black Population, %	84.86	69.75	0.00	13.40 [3]
	(3.75)	(4.72)		
Neighborhood characteristics				
Population below Poverty Level, %	41.91	30.91	0.00	12.90 [3]
	(3.83)	(4.35)		
Gross Rent more than 35% of Household Income, %	48.17	42.09	0.00	39.40 [3]
	(3.14)	(3.64)		
Population on SNAP, %	37.12	27.55	0.00	12.38 [3]
	(3.37)	(3.96)		
Number of Households	549	16,131		

Notes: p-value for the two-sided t-test (95% confidence interval).

Supplementary Table 6 Rosenbaum's sensitivity analysis for unobserved confounders.

Gamma (Γ)	CI+ (upper bound)	CI- (lower bound)
1.35	-0.180004	-0.011615
1.40	-0.189627	-0.001678
1.45	**-0.19889**	**0.007922**
1.50	-0.207817	0.017204

Notes: α = 0.10. 95,689 matched pairs are based on nearest neighbor propensity score matching. At a critical Γ of 1.45, the difference between upper and lower bounds of the CIs includes zero.

Supplementary Table 7 TWFE estimates with different clustering.

	Spatial Clusters	Temporal Clusters	Genetic Matching
One-way Clustering (property level)	16,680	—	-5.03^{**} (1.90)
Two-way Clustering (property & year)	16,680	16	-5.03^{**} (1.94)
Two-way Clustering (property & month)	16,680	185	-5.03^{**} (1.98)

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. *Total number of observations is 986,450. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as a percentage change. Data analysis was done using a two-way fixed effects estimator.*

Supplementary Table 8 TWFE estimates with and without incomplete projects.

	Genetic Matching	PS Matching	Without Matching
With Incompletes	-5.03**	-5.49**	-4.32*
	(1.90)	(1.89)	(1.86)
Without Incompletes	-5.38**	-5.22**	-4.29*
	(1.93)	(1.93)	(1.90)
No. of Observations	986,450	1,170,647	2,931,406

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$. *Standard errors are clustered at the household level by property ID. The dependent variable is the monthly electricity consumption in kilowatt-hour per square foot, which has been log-transformed and multiplied by 100 for interpretability as a percentage change.Data analysis was done using a two-way fixed effects estimator.*

Supplementary References

[1] Rosenbaum, P. R. & Rubin, D. B. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician* **39** (1), 33–38 (1985) .

[2] WalletHub. Best Small Cities in America (2021). URL https://wallethub.com/edu/best-worst-small-cities-to-live-in/16581. Accessed: 2021-10-19.

[3] United States Census Bureau (2021). URL https://data.census.gov/cedsci. Accessed: 2021-11-14.

[4] American Community Survey 5-Year Data (2009-2019). URL https://www.census.gov/data/developers/data-sets/acs-5year.html. Accessed: 2021-05-23.

[5] HUD. CDBG Entitlement Program (2021). URL https://www.hud.gov/program_offices/comm_planning/cdbg. Accessed: 2021-11-14.

[6] Residential Energy Consumption Survey (2015). URL https://www.eia.gov/consumption/residential/data/2015. Accessed: 2021-11-14.

[7] U.S. Energy Information Administration (2021). URL https://www.eia.gov/. Accessed: 2021-08-09.

[8] LEAD. Office of Energy Efficiency and Renewable Energy: Low-Income Energy Affordability Data Tool (2021). URL https://www.energy.gov/eere/slsc/maps/lead-tool. Accessed: 2021-12-20.

[9] Charlier, D., Risch, A. & Salmon, C. Energy burden alleviation and greenhouse gas emissions reduction: Can we reach two objectives with one policy? *Ecological Economics* **143**, 294–313 (2018). https://doi.org/10.1016/j.ecolecon.2017.07.002 .

[10] Colton, R. Home energy affordability in New York: the affordability gap (2008–2010). *New York State Energy Research Development Authority (NYSERDA) Albany, New York* (2011). URL http://www.nyserda.ny.gov/-/media/Files/EDPPP/LIFE/Resources/2008-2010-affordability-gap.pdf .

[11] Gillingham, K., Harding, M. & Rapson, D. Split incentives in residential energy consumption. *The Energy Journal* **33** (2) (2012). https://doi.org/10.5547/01956574.33.2.3 .

[12] Bird, S. & Hernández, D. Policy options for the split incentive: Increasing energy efficiency for low-income renters. *Energy Policy* **48**, 506–514 (2012). URL https://www.sciencedirect.com/science/article/

pii/S0301421512004661. https://doi.org/https://doi.org/10.1016/j.enpol.2012.05.053, special Section: Frontiers of Sustainability .

[13] City of Albany Department of Community & Economic Development, M. 2016-2021 Consolidated Plan and 2016-2017 Annual Action Plan, City of Albany, Georgia, OMB Control No: 2506-0117 (2016).

[14] Asensio, O. I. & Delmas, M. A. The effectiveness of US energy efficiency building labels. *Nature Energy* **2** (17033) (2017). https://doi.org/10.1038/nenergy.2017.33 .

[15] Gillingham, K., Keyes, A. & Palmer, K. Advances in evaluating energy efficiency policies and programs. *Annual Review of Resource Economics* **10**, 511–532 (2018). https://doi.org/10.1146/annurev-resource-100517-023028 .

[16] Jessoe, K., Lade, G. E., Loge, F. & Spang, E. Spillovers from behavioral interventions: Experimental evidence from water and energy use. *Journal of the Association of Environmental and Resource Economists* **8** (2), 315–346 (2021). https://doi.org/10.1086/711025 .

[17] Elinder, M., Escobar, S. & Petre, I. Consequences of a price incentive on free riding and electric energy consumption. *Proceedings of the National Academy of Sciences* **114** (12), 3091–3096 (2017). https://doi.org/10.1073/pnas.1615290114 .

[18] Levinson, A. & Niemann, S. Energy use by apartment tenants when landlords pay for utilities. *Resource and Energy Economics* **26** (1), 51–75 (2004). https://doi.org/10.1016/S0928-7655(03)00047-2 .

[19] Ritz, A., Brewer, G. A. & Neumann, O. Public service motivation: A systematic literature review and outlook. *Public Administration Review* **76** (3), 414–426 (2016). https://doi.org/10.1111/puar.12505 .

[20] Vandenabeele, W., Brewer, G. A. & Ritz, A. Past, present, and future of public service motivation research. *Public Administration* **92** (4), 779–789 (2014). https://doi.org/10.1111/padm.12136 .

[21] Bishu, S. & Kennedy, A. R. Trends and gaps: A meta-review of representative bureaucracy. *Review of Public Personnel Administration* **40** (4), 559–588 (2020). https://doi.org/10.1177/0734371X19830154 .

[22] Bradbury, M. & Kellough, J. E. Representative bureaucracy: Assessing the evidence on active representation. *The American Review of Public Administration* **41** (2), 157–167 (2011). https://doi.org/10.1177/0275074010367823 .

[23] Sowa, J. E. & Selden, S. C. Administrative discretion and active representation: An expansion of the theory of representative bureaucracy. *Public Administration Review* **63** (6), 700–710 (2003). https://doi.org/10.1111/1540-6210.00333 .

[24] Lecy, J. D., Mergel, I. A. & Schmitz, H. P. Networks in public administration: Current scholarship in review. *Public Management Review* **16** (5), 643–665 (2014). https://doi.org/10.1080/14719037.2012.743577 .

[25] Kim, S., Krishna, A. & Dhanesh, G. Economics or ethics? Exploring the role of CSR expectations in explaining consumers' perceptions, motivations, and active communication behaviors about corporate misconduct. *Public Management Review* **45** (1), 76–87 (2019). https://doi.org/10.1016/j.pubrev.2018.10.011 .

[26] Pencheva, I., Esteve, M. & Mikhaylov, S. J. Big Data and AI — A transformational shift for government: So, what next for research? *Public Policy and Administration* **35** (1), 24–44 (2020). https://doi.org/10.1177/0952076718780537 .

[27] Fowlie, M., Greenstone, M. & Wolfram, C. Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *Quarterly Journal of Economics* **133**, 1597–1644 (2018). https://doi.org/10.1093/qje/qjy005 .

[28] Asensio, O. I. Correcting consumer misperception. *Nature Energy* **4** (10), 823–824 (2019). https://doi.org/10.1038/s41560-019-0472-5 .

[29] Attari, S. Z. Perceptions of water use. *Proceedings of the National Academy of Sciences* **111.14**, 25129–5134 (2014). https://doi.org/10.1073/pnas.1316402111 .

[30] Attari, S. Z., Poinsatte-Jones, K. & Hinton, K. Perceptions of water systems. *Judgment and Decision Making* **12.3** (2017) .

[31] Sterman, J. Risk communication on climate: mental models and mass balance. *Science* **322.5901**, 532–533 (2008). https://doi.org/10.1126/science.1162574 .

[32] Callaway, B. & Sant'Anna, P. H. Difference-in-differences with multiple time periods. *Journal of Econometrics* **225** (2), 200–230 (2021). https://doi.org/10.1016/j.jeconom.2020.12.001 .

[33] De Chaisemartin, C. & d'Haultfoeuille, X. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review* **110** (9), 2964–96 (2020). https://doi.org/10.1257/aer.20181169 .

[34] Residential Energy Consumption Survey — Energy Consumption (2005). URL https://www.eia.gov/consumption/residential/data/2005/index.php?view=microdata. Accessed: 2021-11-14.

[35] Federal Reserve Bank of St. Louis (2015). URL https://research.stlouisfed.org/publications/review/. Accessed: 2021-11-14.

[36] Zillow: United States Home Values (2019). URL https://www.zillow.com/home-values/. Accessed: 2021-11-14.