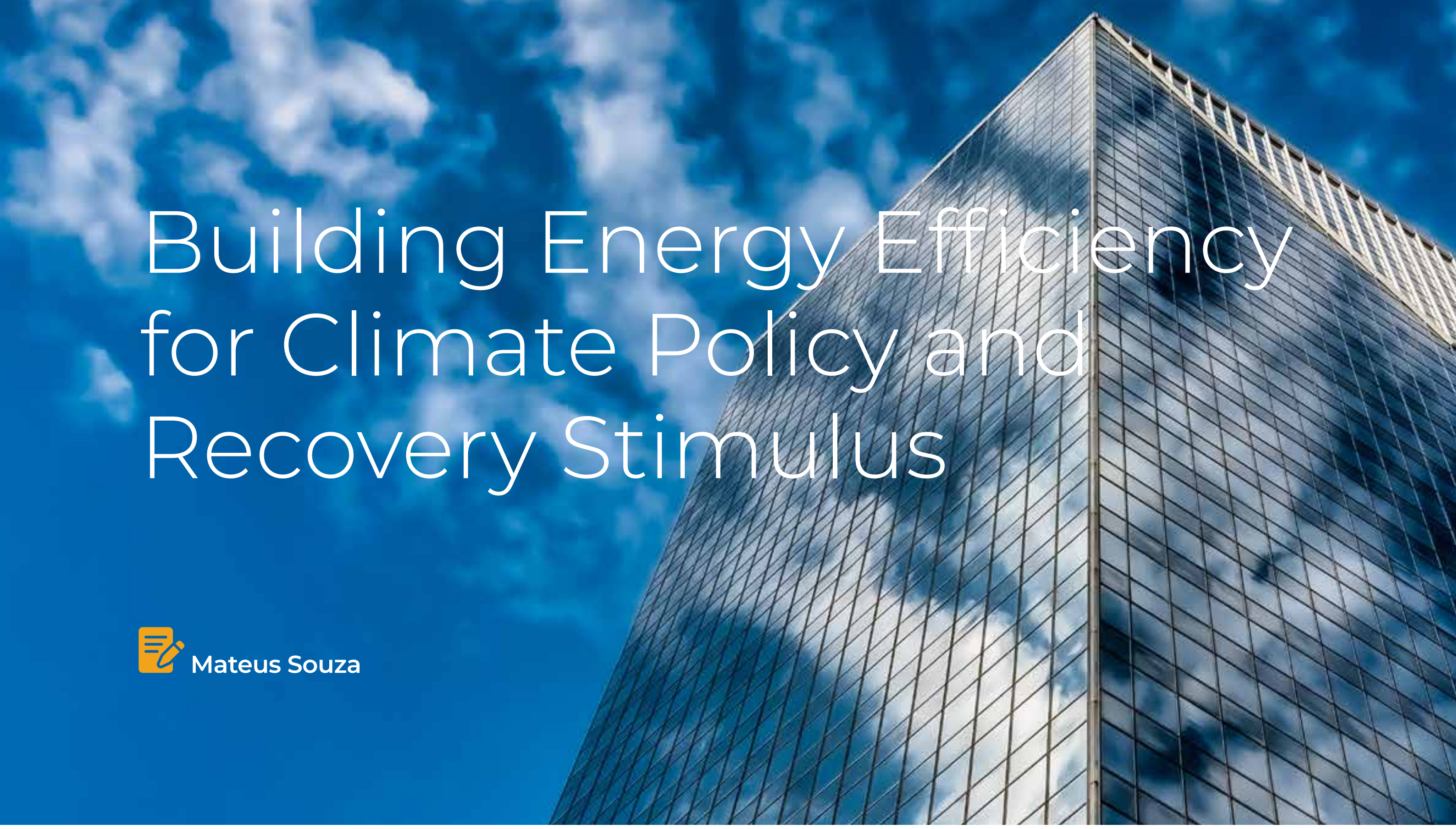


Building Energy Efficiency for Climate Policy and Recovery Stimulus

Mateus Souza

Improving the energy efficiency of buildings is often viewed as one of the most promising strategies for climate policy. In addition to avoiding carbon emissions, retrofit and renovation programs can lower households' energy bills, improve air quality within homes, and may create jobs. Given all these potential benefits, renovation projects are taking a central role in economic stimulus packets for COVID-19 recovery, both in the EU and in the US. However, because of recent evidence that energy savings from these programs often do not meet expectations, some economists have started to question if they are in fact cost-effective strategies for carbon abatement, compared to available alternatives.

EnergyEcoLab team member, Mateus Souza, along with coauthors Peter Christensen, Paul Francisco and Erica Myers, dive deep into this issue in a forthcoming paper at The Review of Economics and Statistics (REStat). The paper dissects this common "wedge" between expected and realized savings from energy efficiency programs**.** The same coauthors, plus Hansen Shao, have also published a working paper showing that machine learning tools can be used to help improve funding allocation within these programs.

Decomposing the wedge

To better understand the wedge, the team studied the Illinois Home Weatherization Assistance Program (IHWAP), which is the Illinois implementation of the largest residential energy efficiency program in the United States. The program is intended to reduce energy bills for thousands of low-income households in the US, by improving the heating, ventilation, and air conditioning (HVAC) systems in their homes. In the REStat paper, the team analyzes detailed program information, including data on housing structure and demographics collected during energy audits for more than 9,800 homes served by the program. Monthly energy billing data was also available for those homes. Using a novel machine learning-based approach, the paper investigates the importance of three channels that have been proposed to explain the wedge: 1) systematic bias in ex ante engineering measurement and modeling of savings, 2) workmanship, and 3) the rebound effect (savings may be offset in case households increase the intensity of HVAC usage once the system becomes more energy efficient).

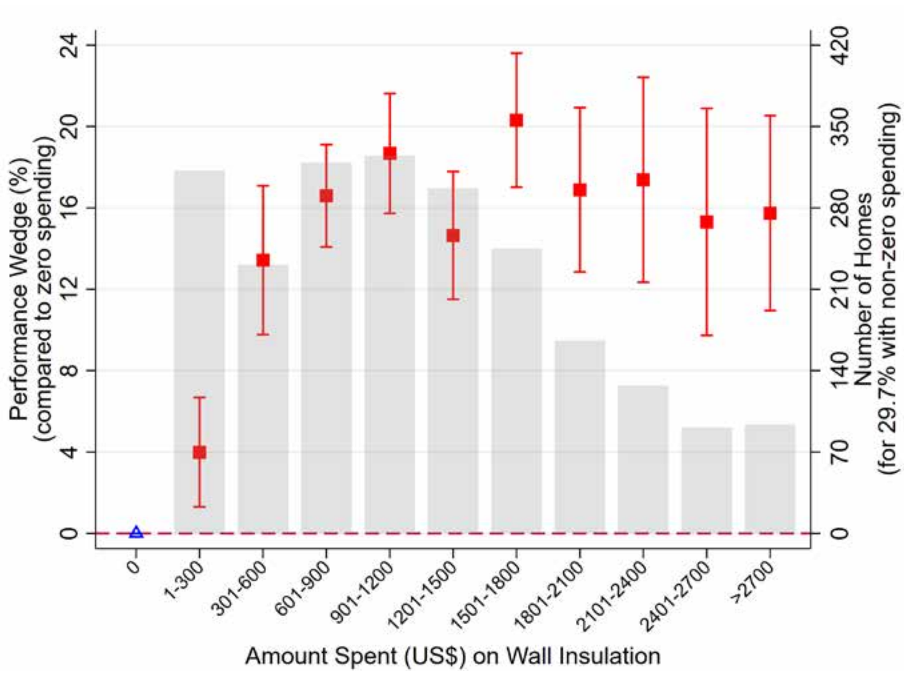
Results suggest that **bias in model projections is one of the primary contributors to the wedge.** Up to 41% of the wedge

can be explained by discrepancies between projected and realized savings in five major retrofit categories: air sealing, furnace replacement, wall insulation, attic insulation, and windows. Results are particularly striking for wall insulation, as shown in Figure 1. The red squares are point estimates of how the performance wedge increases depending on expenditures in that measure, compared to homes that received zero wall insulation spending. The whiskers represent 95% confidence intervals. The figure shows, for example, that the wedge is approximately 20 percentage points higher for homes with wall insulation expenditures between $1,501 and $1,800.

Heterogeneity in workmanship is also an important factor in explaining the wedge. Results suggest that the wedge could be reduced by up to 43% if all workers performed at top levels. This implies that there exist potential gains from reforms to improve workmanship, changing worker incentives, training, etc. On the other hand, only a modest portion of the wedge may be explained by behavioral factors such as the rebound effect. Using data on the realized relationship between outdoor air temperature and energy consumption, the authors estimate that a standard rebound effect can account for up to 6% of the wedge.

The final section of the paper analyzes the cost-effectiveness of the program. The authors compare the energy-related benefits of the program versus the retrofit costs. They find that, on average, each home served by the program is associated with private net benefits of $234, and social net

Figure 1 – Increased Performance Wedge by Spending on Wall Insulation



The paper dissects this common “wedge” between expected and realized savings from energy efficiency programs

A natural follow-up question is whether it is possible to identify the high-return projects before they are actually implemented

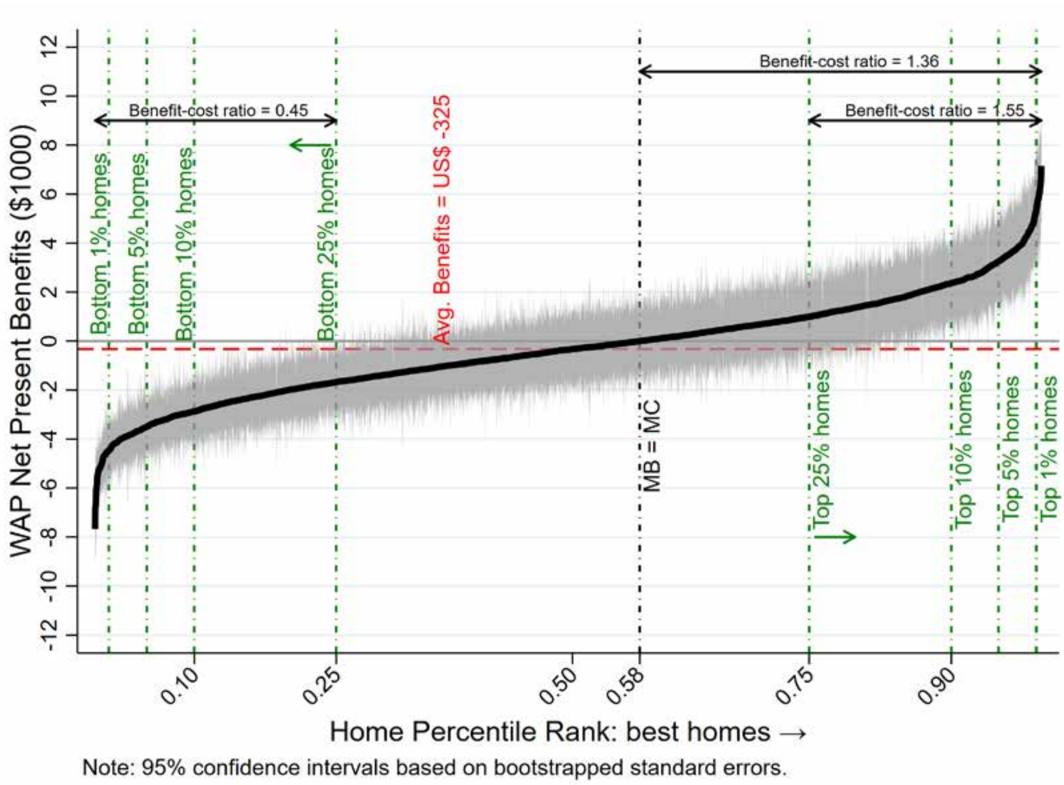
benefits of -$324. Although average net benefits are close to zero, disaggregated estimates reveal significant heterogeneity, such that approximately 42% of homes generate positive energy-related net benefits, as shown in Figure 2. Therefore, certain types of projects are highly cost-effective, suggesting a potential role for targeting in this context. That is the subject of a follow-up paper from the same team of coauthors.

Potential gains from targeting

Within this context of substantial heterogeneity in net benefits, a natural follow-up question is whether it is possible to identify the high-return projects *before* they are actually implemented. The authors carry out another analysis with data from the Illinois Home Weatherization Assistance Program, but now using information available only *before* program implementation. The idea is to mimic the role of a program implementer who is trying to predict the magnitude of net benefits prior to performing the retrofits. To maximize the total predicted net benefits from the program, the implementer would then choose to treat only those homes (or even individual measures within homes) that have positive expected returns. This consists of an *ex-ante* prediction/targeting exercise, which differs substantially from an *ex-post* evaluation performed with information available many months after the renovations.

As a first step, the authors show that, within this ex-ante framework and data-rich setting, **it is possible to accurately predict household energy usage with machine learning techniques.** On average, the predictions are statistically indistinguishable from true energy consumption, both pre- and post-retrofit. With those tools it is therefore also possible to obtain accurate predictions of the ex-ante savings. ML predictions are compared against projections from an ex-an-

Figure 2 - Net Present Benefits for Each Home in the Sample



te engineering model that currently guides funding allocation decisions within the program. Results show that the ML strategy significantly outperforms the engineering model and could have a drastic impact on program cost-effectiveness. In the IHWAP sample, targeting high-return interventions based **on the ML predictions can dramatically increase net social benefits, from negative to $1.23 per dollar invested.**

Conclusions and future work

Thanks to recent advances in information and data technologies, retrofit programs can readily incorporate ML-based strategies to help select among candidate projects. Energy efficiency programs are often sponsored by utilities that have recently developed the data infrastructure to store, query, and serve household billing data. It would be straightforward to integrate predictions from ML models to those infrastructures. Although ML may be computationally demanding, these models would only need to be occasionally updated. Once the results are obtained, they can be fed into the back end of the softwares that help with funding allocation decisions.

The importance of considering and implementing these types of tools continues to grow as energy efficiency remains central to climate policy discussions. Worldwide energy efficiency investments are expected to continually increase, reaching $220 Billion per year by 2025. Optimal allocation of these funds may be crucial in order to achieve ambitious climate goals. Future work within this context has yet to explore, for example, the distributional implications of targeting investments based solely on energy or climate-related benefits. Analyses of health and potential job creation impacts of these programs also seem mostly missing in the economic literature •

The importance of considering and implementing these types of tools continues to grow as energy efficiency remains central to climate policy discussions

Further reading

Christensen, P.; Francisco, P.; Myers, E. and Souza, M. (2021). "Decomposing the Wedge between Projected and Realized Returns in Energy Efficiency Programs." *The Review of Economics and Statistics.*

Christensen, P.; Francisco, P.; Myers, E.; Shao, H. and Souza, M. (2021). "Machine Learning can Increase the Impact of Energy Efficiency Programs." *E2e Working Paper 47.*

Souza, M. (2019). "Predictive Counterfactuals for Treatment Effect Heterogeneity in Event Studies with Staggered Adoption." SSRN Working Paper; EEL Discussion Paper 107.