Understanding the residential energy efficiency financing coverage gap and market potential

Sydney P. Forrester*, Tony G. Reames

School for the Environment and Sustainability, University of Michigan, Ann Arbor, MI, United States

HIGHLIGHTS

• An energy efficiency financing coverage gap exists for moderate-income households.
• 12% of Michigan households fall into the energy efficiency financing coverage gap.
• Michigan counties’ coverage gaps ranged from 0% to 24%.
• Households with low incomes need higher credit scores for loan approval.

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ABSTRACT

Access to upfront capital remains a primary barrier in residential energy efficiency adoption. Government-sponsored programs exist for low-income households while traditional financing serves creditworthy households. However, there remains a coverage gap for those with moderate incomes too high to qualify for low-income programs, but without access to friendly capital. With limited research in this space, this study aims to: (1) develop a model to estimate the number of households in the coverage gap; and (2) explore their spatial distribution. For the state of Michigan, we used data from the US Census Bureau and approximately 12,000 green bank loans to estimate the energy efficiency financing coverage gap across the state’s 83 counties using a binomial mixed model. We found that credit score and income interacted to largely determine whether an applicant was approved. Households in the highest income quintile achieved a 50% chance of approval with a moderate credit score (662) while those in the lowest needed a very high credit score (715) for the same odds. Overall, this created an estimated 12% energy efficiency financing coverage gap of households statewide, with individual county levels between 0% and 24%. Broadly, understanding the market potential and spatial distribution of this coverage gap could allow impact-driven financiers such as green banks or community development financial institutions to expand programs that may offer alternative underwriting criteria. Expanding loan access to this underserved market can promote energy system improvements, policy goals, household living conditions, and an equitable clean energy transition.

1. Introduction

Globally, $138B was spent in 2018 on energy efficiency (EE) in buildings, which has the potential to reduce energy use intensity by over 3% annually [1]. Both direct and indirect benefits from EE have been widely researched [2–4]. Low-cost programs provide grid benefits through infrastructure investment deferral associated with reduced congestion, reduced peak load, and an overall reduction of electricity demand [5–7]. Beyond grid impacts, the benefits of EE for participating households result in improved health and comfort [8–12], monetary savings, and reduced vulnerability to future utility rate increases, supporting an equitable energy transition [10,13–15].

Acknowledging the wide range of benefits, many nations, both developed and developing, have implemented innovative funding and financing models for residential EE programs [16–18]. The United States (US) has made significant progress in residential EE with total energy consumption per household steadily declining over the last 30 years despite increases in the number and size of homes [19]. Across the US, 20 states have embraced mandatory EE standards with eight additional states adopting voluntary goals [20]. While the federal government has funded or incentivized energy conservation and efficiency efforts since the 1970s, a large amount of savings have come
from regional utility spending, which a forward-looking Berkeley Lab report predicts will increase 17% (low EE scenario) to 91% (high EE scenario) from 2016 levels to 2030 [21]. One key challenge that researchers anticipate in later years (2025–2030) is the ability to achieve deeper savings and higher penetration rates, which must be done by targeting traditionally underserved markets and combining efforts with complementary programs, such as on-bill financing and other green bank efforts [21]. Part of EE expansion is likely to come from the residential sector, where the Electric Power Research Institute found that proper incentives could result in a 25% increase in cost-effective EE potential through 2035 [22]. One source of increased residential EE investment has come from financing, where residential loans made up 77% of total EE lending by number and 64% by volume in 2014 [5]. Access to financing both enables and deepens sustainable energy technology adoption [23]. For instance, a Michigan study found that introducing financing led to a 127% increase in household EE investment from $4400 to $10,000 [24]. However, key addressing the key challenge of expanding EE into underserved markets will require access to capital across incomes and credit spectrums in order to include households that would greatly benefit from EE upgrades, but may not have the credit score or upfront capital to do so.

Low- and moderate-income (LMI) households fall into this underserved market due to programs being more expensive to administer and representing smaller project sizes [6,8]. This exacerbates existing inequities due to an inverse relationship between income and energy use intensity as a result of older, less-efficient housing stock and appliances [6,9,10,11,25]. To alleviate this burden for lower-income households, the U.S. Department of Energy has administered the Weatherization Assistance Program (WAP) since 1976 for income-qualified households to receive no- to low-cost EE measures. Households qualify if their income is either at or below 200% of the federal poverty level (FPL) or 80% of area median income (AMI), depending on the state [26]. Upgrades equate to annual savings up to $300 per home and indirect, non-energy benefits of near-equal value [8,26]. Utility-sponsored low-income EE programs employ similar income qualifications for participation and provide similar efficiency upgrades and retrofits.

Energy finance literature primarily focuses on commercial and industrial investments in scalable, large renewable infrastructure [23,27,28]. Although academic research on equity in EE financing for the U.S. residential sector is limited, there is understanding that financing is an important tool for mobilizing capital to encourage a successful energy transition [6,21,27]. The recent surge of energy justice literature pushes for equitable access to sustainable technologies, benefits, and affordable energy for all, including a special issue of Applied Energy [29]. Hall et al. (2018) look to financing to address social and economic disparities through six proposed principles to ‘just’ energy finance: (1) affordability; (2) good governance; (3) due process; (4) intra-generational equity; (5) spatial equity; and (6) finance resilience [27]. These six principles rest upon the principles of energy justice that address distributional, procedural, and recognition justice [30]. Green banks and community development financial institutions (CDFIs) are well positioned to play this role, having already expanded access and mobilized private capital by utilizing public funds to create loan loss reserves, credit enhancements, and other tools to lower the cost of capital [23]. Additionally, some programs collaborate with utilities to offer alternative underwriting criteria (e.g. utility bill repayment rather than credit score [61]) or bill neutrality to further overcome credit barriers and risk perception. Even so, LMI financing remains fairly nascent. Some argue that this customer segment should only be served by grant-based programs without payback, while others argue that financing, when paired with increased customer protections and reduced or neutral bill impacts, will allow dollars to go further and benefit more households [6]. Due to the finite nature of grants, these funds will continue to go to more vulnerable low-income households and may be a better option compared to financing. However, moderate-income customers that do not qualify for federal or utility low-income programs would likely stand to benefit from financing.

There have been many studies that bring attention to various “coverage gaps” in order to expand services to larger portions of society to promote health and/or equality (e.g. retirement income [31] or childhood vaccinations [32]). The most recognized application is within the health care context, where the “Medicaid coverage gap” is defined as those making too much money to qualify for Medicaid, but not enough to receive marketplace subsidies, creating significant, additional burden for LMI families [33]. While we find no current literature that applies the coverage gap concept to EE financing, practitioners have identified the importance and difficulty in engaging moderate-income households. As in the case of the Medicaid coverage gap, the lower bound is defined by the respective government program’s income qualifications. As a result, low-income households may have access to, and benefit more from, grant-based sustainable energy funds. On the other end of the spectrum, higher-income households may have the upfront capital or creditworthiness to either directly pay for the upgrade or gain friendly capital to do so. Nevertheless, we argue that there remains a non-negligible, moderate-income population that may be excluded from an affordable energy transition due to earning an income just above low-income program cutoffs, but not enough to make improvements on their own or secure access to friendly capital (Fig. 1).

Due to this lack of research and limited understanding of the EE financing coverage gap and its market potential, this study aims to first develop a model to estimate the number of households in the coverage gap and secondly to explore the spatial distribution of these households. We examine these aims in the U.S. state of Michigan using anonymized EE loan data from September 2010 to January 2018 via Michigan Saves and the Census’ Five-Year 2017 American Community Survey. These estimates will offer insight into the market potential for alternative financing mechanisms and may assist green banks in leveraging or expanding existing programs to equitably increase moderate-income households’ access to EE. More broadly applied to other states, programs could include on-bill financing and those that use alternative underwriting criteria for loan qualification or features like bill neutrality. The remainder of the paper is structured as follows: Section 2 describes the study area; data and statistical methodology; Section 3 presents study results; and Section 4 concludes with policy implications, limitations, and areas of future research.

2. Material and methods

2.1. Description of study area

EE adoption varies widely throughout the US by region due to various factors such as policy and climate. On one end, the West and Northeast have more mature markets and larger EE spending, driven primarily by state legislatures. Similarly, Midwest expenditures are concentrated in Illinois, Michigan, Ohio, and Minnesota where there also exist state-specific targets [21]. Michigan’s Public Act 342 of 2016 set utility efficiency goals at 1% of electricity sales and 0.75% of natural gas sales as well mandating EE programs for low income residential customers [34].2 Due to old homes and a colder climate, Michigan households consume 38% more energy and spend 6% more than the average US home, underlining the value of EE’s potential savings and home comfort improvement [10,35,36]. Funds for residential efficiency adoption generally come from the government, utility programs, and/
or through green bank financing. Michigan mobilized $111 M of federal WAP funds to serve an annual average of 1,648 low income homes between 2010 and 2017 [37]. Simultaneously, Michigan Saves acts in a complementary manner as a green bank for the state, serving various income levels in residential, commercial, multi-family, and public sector markets. For comparison, Michigan Saves facilitated $191.3 M of investment and $172.1 M of financing from 2009 to 2018. Of that, 73% of all investment and 72% of all dollars went to their residential Home Energy Loan Program (HELP), saving over 19,000 homes an average of $525 per year [38]. Public dollars go only toward building a loan loss reserve, which mobilizes private dollars by reducing lender risk [39]. In turn, this allows for more inclusive underwriting criteria and lower interest rates that fall between 4.25% and 7% (3–5 percentage points lower than what a lender would offer for a comparable, unsecured loan product) [40]. Michigan Saves aims to expand access further through alternative financing. In partnership with the Holland Board of Public Works, Michigan Saves began an on-bill repayment program in 2016, using 12 months of on-time, utility bill payment history in lieu of traditional underwriting criteria. By offering alternative financing programs, Michigan Saves hopes to better reach underserved customers and to scale or replicate the program in other communities [41]. Better understanding the market potential and where the coverage gap may lie would help target programs, allowing for more efficient use of funds. This, in turn, would increase impact through more households served. While the example carried through this study is specific to Michigan, each state likely has their own coverage gap and would benefit from additional underwriting criteria. By offering alternative financing programs, Michigan Saves hopes to better reach underserved customers and to scale or replicate the program in other communities [41]. Better understanding the market potential and where the coverage gap may lie would help target programs, allowing for more efficient use of funds.

2.2. Data

Table 1 details the data sources for this study. We analyzed 13,083 anonymized Michigan Saves residential HELP loan applications across 81 of Michigan’s 83 counties from September 2010 to December 2017 (see Table A.1) [40]. Of those, 61% of applicants received loans and data on savings and repayment were gathered. 1,107 applicants were removed due to missing FICO scores, leaving 11,975 data points. Application criteria includes census tract, self-reported income, credit score, debt to income ratio, and loan amount requested. The data then include a flag indicating whether or not the applicant was approved. All income data were adjusted to 2016 values from the year indicated on each respective application date to ensure consistency across datasets. Overall, the applicant pool skewed higher than state averages in terms of both FICO and income. Compared to a state average FICO score of 678 [42], applicants had an average FICO score of 700. However, the majority of approved applicants had FICO scores above 720 while the majority of those denied had scores of 640 and below (Fig. 2). This highlights the overwhelming importance of FICO score in loan approval and the potential for alternative financing in expanding opportunities to a large number of households that may otherwise be able to prove ability to repay loans.

While applicants’ average income of $73,231 skewed higher than both the state household average of $50,803 and the owner-occupied household average of $62,251, applicants’ incomes were fairly evenly distributed among their respective tracts’ income quintiles, with the exception of a lower representation of the lowest quintile (Fig. 3). This trend is more pronounced for those approved, and reversed for those denied. This indicates that those applying for residential HELP loans may be socioeconomically similar to their neighbors, but come from tracts with incomes above average. From a different angle, looking at applicants’ AMI or FPL may indicate what percentage of the population may be low-income (less than or equal to 80% of AMI or 200% FPL) or moderate-income (80–120% of AMI or 200–300% of FPL). By these measures, LMI households made 49% of all applicants, 41% of those approved, and 62% of those rejected (Fig. 4). This indicates that there is indeed interest in EE loans for LMI households, but they may be significantly under-represented in the applicant pool.
To define the coverage gap, this paper considers the time span of Michigan Saves' loans, were used to identify the Community Survey (ACS) 5-year estimates, generally representative of rejected disproportionately, further illustrating this financing coverage and those denied by tract-specific household income quintile.

Fig. 3. Distribution of total Michigan Saves HELP applicants, those approved, and those denied by tract-specific household income quintile.

County data from the U.S. Census Bureau 2012–2016 American Community Survey (ACS) 5-year estimates, generally representative of the time span of Michigan Saves’ loans, were used to identify the number of households in the 17 income bands sectioned out by the Census Bureau. To define the coverage gap, this paper considers household incomes greater than 200% FPL (to be consistent with Michigan WAP criteria), but without disposable income to pay for EE upgrades upfront. To determine which households met the income qualification for WAP, we used county-level data from Fisher, Sheehan, and Colton’s Home Energy Affordability Gap model for 2016 which details the number of households below 200% of FPL for each county in the U.S. The mean density of households below 200% FPL across Michigan’s 83 counties was 38.28% with a range of 17.3–51.7%.

2.3. Modeling the energy efficiency financing coverage gap

To find the coverage gap by county, this study takes all households in Michigan and subtracts those in the lower and upper bounds (Eq. (1)). Households in the coverage gap represent customers that could benefit from efficiency upgrades, but do not have access due to barriers to financing and disqualification for federal and/or utility assistance. This information may help in targeting areas for financing programs from green banks or CDFIs that ease access through alternative underwriting criteria, bill neutrality, or such programs as low-interest on-bill financing.

Eq. (1): Energy efficiency coverage gap

\[
\text{Households}(HH)_{\text{coverage gap}} = HH_{\text{county total}} - HH_{\text{lower bound}} - HH_{\text{upper bound}}
\]

Lower bound: For the purposes of this study, households at or below 200% of FPL were determined to be beyond the lower bound of the coverage gap due to Michigan’s qualifying income criteria for the federal Weatherization Assistance Program [26]. Consequently, in order to best represent the lower bound, information on the number of households at or below 200% FPL by county were used directly [43].

Upper bound: The upper bound for this study was defined as those households most likely to have access to friendly capital through currently available financing mechanisms. In our study, this would include households that would be approved for Michigan Saves’ residential HELP program. Defining the upper bound was done in three parts. First, we used multiple linear regression models on the dataset in order to understand how variables impacted whether an applicant was approved or not, and at what level each impact had. Second, tests were run on these models side-by-side to select the best predictive model. Lastly, the selected model was used on a dataset generated using census data on county-level income distribution for the entire state to ultimately come up with an estimate of households that would likely be approved for a traditional EE financing program.

First, each regression on the Michigan Saves HELP dataset considered county, tract, FICO score, debt to income ratio (DTI), income, and whether or not they were approved. Each numeric variable was scaled and centered for analysis across all models, while county and tract were used to account for spatial random effects. The three modeling methods ultimately considered were: (1) Binomial mixed model; (2) Non-linear General Algebraic Modeling optimization; and (3) Random Forest machine learning (see Table B.1).

Secondly, to validate and compare each model against the others, the data were randomly split 80/20 into training and test sets, respectively. Each model, created with the training set, then predicted upon the test set whether an applicant would be approved. Predicted results were then compared to actual results. The first baseline test was to ensure that each model's accuracy (i.e. the number of correct assignments within a 95% confidence interval) was always greater than could be achieved via random guessing, quantified as the "no information rate". All models’ lowest bound of accuracy within a 95% confidence range was above 80%, well exceeding the no information rates (see Table B.2). Once through the baseline test, each model’s predictive power was compared using their accuracy, a confusion matrix, and a receiving operating characteristic (ROC) curve. Ultimately, the binomial mixed model was selected due to its significantly higher level of interpretability, simplicity, area under the ROC curve, and speed. Its predictive accuracy was marginally smaller than that of the others, but still boasted a value of 81.2% (between 79.5% and 82.7% with a 95% confidence interval). Outputs of the comparative tests are detailed in Appendix B (Table B.2). The binomial mixed model incorporated an applicant’s county as a random effect; centered and scaled FICO and income, respectively; and a FICO/income interaction effect (Eq. (2)). While each fixed variable had a positive, significant effect (Table 2), there was little correlation between income and FICO, and were consequently treated separately. Since all effects had a significant, positive relationship to approval, if an applicant had both a high income as well as a high FICO score, they were more likely to be approved than a similar applicant with only one or the other. It is also important to note here that we omitted DTI due to the fact that these data were only available for 47% of applicants, and since we were unable to find adequate DTI data statewide upon which we could run a predictive model. More detailed characteristics of the binomial model are further elaborated upon in Appendix C (Table C.1).

Eq. (2): Predictive binomial mixed model for i applicant in j county

\[7A \text{ The } 2016 \text{ ACS 5-year estimates split the number of households into 17 annual household income groups (in } \$1000): < \$10, \$10–\$15, \$15–\$20, \$20–\$25, \$25–\$30, \$30–\$35, \$35–\$40, \$40–\$45, \$45–\$50, \$50–\$60, \$60–\$75, \$75–\$100, \$100–\$125, \$125–\$150, \$150–\$200, \$200–\$500, > \$500. \]

\[8\text{ The Home Energy Affordability Gap also utilized ACS five-year averages from 2012 through 2016, so results are consistent with the rest of the data.} \]
Lastly, to estimate the number of households statewide that would likely be approved for existing lending, and thus fall above the coverage gap, we used the five-year ACS 2016 county data to create a predictive dataset upon which to run our predictive model. Using the given number of households within 17 income ranges and an average FICO score of 678, the test set included the upper and lower bound for each income range, and average FICO for each county. Run through the predictive model, the output was a single column of loan approval probability \( p_{approval} \) for each income range \( i \) within each county \( j \).

These numbers were then multiplied by the number of households in each income range to get the total estimated number of likely approved households in each income range via traditional green bank financing. Summed across all 17 income ranges, the total represented each county’s estimated number of households above the coverage gap (Eq. 3).

### Results and discussion

#### 3.1. Regression output

Probability of loan approval via traditional green bank financing was highly dependent on FICO score, income, and the interaction of the two. All had positive relationships (e.g. higher FICO and/or higher income led to a higher probability of approval) with low levels of correlation between independent variables (Table C.2).

Putting it all together, each county’s coverage gap was calculated by subtracting out households below the lower bound of the coverage gap [i.e. those with incomes at or below 200% FPL that would qualify for WAP] and above the upper bound (i.e. those likely to be approved for Michigan Saves’ HELP) (Eq. 1). To get the statewide number, we divided the total number of households in the coverage gap by the total statewide number of households.

\[
\text{Households}(HH)_{\text{coverage}} = \sum_{i} p_{\text{approval}}(\% \times \text{HH}[\#])
\]  

(3)

Eq. (3): Estimating the number of each county’s households above the coverage gap (i.e. likely to be approved via traditional green bank financing)

\[
p_{\text{approval}}(\%) = \beta_0 + \beta_0 \text{FICO} + \beta_1 \text{Inc} + \beta_1 \text{Inc}_i \text{FICO} + \epsilon
\]  

(2)

Fig. 4. Distribution of total Michigan Saves HELP applicants, those approved, and those denied by area median income (AMI), defined at the core-based statistical area or, secondarily, the county level as well as by federal poverty level (FPL) defined for a 3-person family. Those at 80% of AMI or below as well as those at 200% of FPL or below may be characterized as low-income while those between 80% and 120% AMI as well as 200% and 300% FPL may be characterized as moderate-income.

#### Table 2

Binomial mixed model variables’ impact on whether an applicant gains approval, by scale and significance.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>j County (N = 83)</td>
<td>N/A (random effect)</td>
<td></td>
</tr>
<tr>
<td>FICO Household’s FICO score</td>
<td>2.18</td>
<td>( p-value &lt; 0.001 )</td>
</tr>
<tr>
<td>Inc Median Monthly Income</td>
<td>0.70</td>
<td>( p-value &lt; 0.001 )</td>
</tr>
<tr>
<td>FICO/Inc Interaction term</td>
<td>0.58</td>
<td>( p-value &lt; 0.001 )</td>
</tr>
</tbody>
</table>

\( p_{\text{approval}}(\%) = \beta_0 + \beta_0 \text{FICO} + \beta_1 \text{Inc} + \beta_1 \text{Inc}_i \text{FICO} + \epsilon \)  


11 83 counties by 18 income values and FICO scores resulted in a predictive set of 1494 rows by 3 columns (one for each variable).
to a variety of factors such as household density, urbanization level, social norms and networks, prevalence or effectiveness of contractor/financier networks, marketing, utility territory, etc.

3.2. Distribution of the energy efficiency financing coverage gap

Results estimate that 457,731 of Michigan’s 3,860,394 households fall into the EE financing coverage gap, approximately 12% of all households statewide.

Exploring the spatial distribution of these households at the county-level, represented in number of households, Fig. 6a illustrates the coverage gap in a way that may be helpful for green banks or community development financial institutions to expand alternative financing programs. Macomb and Oakland Counties in southeast Michigan had the largest number of households in the coverage gap, 78,192 and 75,700 households, respectively. This is mainly due to the fact that these counties have the third and second largest number of households in the state, respectively. On the other hand, Wayne County, which includes the City of Detroit, has the largest number of households statewide, but far more income-qualified households for government-sponsored programs. Consequently, Wayne has fewer households in the coverage gap.

Fig. 6b represents the proportionality of the coverage gap as a percentage of total households. This figure helps to better understand the spatial distribution of moderate-income households in the larger context of energy justice literature. A county’s larger coverage gap could be due to a smaller low-income population, a smaller higher-income population, or a combination of the two. For example, in Fig. 6b, six counties (Monroe, Macomb, Livingston, Eaton, Washtenaw, and Barry) had a coverage gap of 20% or higher (listed from highest to lowest). While all counties had a percentage of households that qualify for green loans similar to that of the statewide average, the average number of households that income-qualify for federal assistance (17–29%) was far lower than the median value of 39%. Important to note here, Macomb was the only county amongst the highest coverage gap by both number and percentage of households.

Fig. 5. Modeled interaction plot between applicant FICO score and annual income impacts on approval probability, segmented by (a) statewide mean incomes by quintile and (b) by federal poverty level. Dashed line marks 50% chance of being approved.
Houghton County, in Michigan’s Upper Peninsula (northwest corner of the state), was the only county estimated to have no coverage gap due to slightly more households qualifying for traditional green lending than the state average along with far more households qualifying for federal assistance than average.

The average coverage gap for an individual county was 10.1% of all households with a standard deviation of 5.2 percentage points (Fig. 7). While county-level coverage gaps ranged from 0% to just over 24%, the majority of counties had a coverage gap between 5% and 10% (Fig. 8).

While this paper focuses on the state of Michigan to illustrate the EE financing coverage gap, the ideas and framework presented here could be replicated elsewhere to encourage other impact-driven financiers.
(e.g. green banks or CDFIs) to consider necessary strategies for expanding access to financing into an underserved market. The EU has pointed to revolving funds’ self-sustainability and success in mobilizing private dollars through public funds [16]. Across the world, similar low-interest, revolving loans exist in countries such as the UK, Germany, France, Japan, and others in order to increase access to capital, support environmental and social policy goals, and increase EE adoption [17,18,45,46]. Sarkar and Singh discuss western EE program models’ relevance to developing countries and conclude that revolving funds can be effective, but only if flexible and aware of the specific market enough to effectively address the communities’ needs [18]. Conceivably, using available program data to model and better understand the extent of the EE financing coverage gap at various locations could improve program targeting and extend capital to underserved markets in a localized manner. In the US, green banks currently exist in various states such as Connecticut, New York, California, Rhode Island, a Maryland county, and Hawaii [47]. These banks similarly use their capital to leverage $3-$6 in private funds for each public dollar spent and are able to reduce lender risk and increase access through credit enhancements, loan loss reserves, aggregation services, and more [47]. Furthermore, for places without green banks, there have been multiple examples of CDFIs doing similar work on a more local level such as Clean Energy Works Oregon, which has aimed to close the coverage gap for moderate-income households by using a point system that takes into account multiple criteria in addition to credit score such as utility historical and current delinquency as well as length of bill payment history [48]. With automatic pre-approval for certain scores, rejection rates fell to 12% while maintaining a low default rate [48]. On the other end of the coverage gap, low-income households across the US have access to state administered WAP funds and may have similar, additional program opportunities from their local utility. Between states, while there are large differences in consumer behavior, average age of households, climate, energy usage, and availability of funds, moderate-income households across the country likely fall into different-sized coverage gaps. A Berkeley Lab report states that public resources and business-as-usual market activity cannot close the EE coverage gap for moderate-income households without innovative programs and access to friendly capital [48]. The report validates our finding that moderate-income customers are rejected at a higher rate than households with higher incomes, but that they remain a good avenue for impact-driven financing due to relatively high levels of home ownership, reducing the split-incentive that is more prevalent with renters. Conceivably, if moderate-income financing were to prove successful in multiple parts of the country, EE investment would increase to support various state policies and encourage an equitable energy transition.

4. Conclusions

Access to energy efficiency has increased with green banks and other programs that offer low interest rates. Even so, there are households that cannot take advantage of programs with cut-offs based on FICO, debt-to-income, and other traditional underwriting criteria alone. Households in this financing coverage gap are less able to access capital for energy efficiency investments. Consequently, without targeted programs, these households may not be able to realize the savings and other non-energy benefits of energy efficiency. In this study, we developed a model to estimate the number of households in the coverage gap and explored the spatial distribution of these households at a state and county level in the U.S. state of Michigan using anonymized energy efficiency loan data from September 2010 to January 2018 as well as publicly available socio-economic data. Results estimated that 12% of Michigan households fell within this gap.

Loan approval was largely dependent on the interaction between income and FICO score in addition to each predictor separately. For loan approval, higher income households were able to have lower credit scores than lower income households (Fig. 5). This finding illustrates the challenge for households in the coverage gap with moderate incomes but lower FICO in accessing capital. While this study was carried out for Michigan, other regions are also likely to have coverage gaps when it comes to residential financing of sustainable energy projects. Though some program administrators may consider 12% of households to be relatively small, this represents a non-negligible portion of a population with unrealized benefits at the household and energy system level. Regions with low levels of energy efficiency adoption or without impact-driven financing programs that offer lower rates may have coverage gaps far higher than Michigan. Understanding the spatial distribution of the coverage gap would allow administrators to target programs, lowering costs and increasing access. Responsible program expansion would likely include non-predatory alternative financing mechanisms. For example, program administrators may be able to target areas with many underserved households to create programs that offer credit enhancements, bill neutrality, alternative underwriting criteria (e.g. utility repayment in lieu of FICO scores), and more. Broader impacts from expanded access to friendly capital, statewide as well as across the globe, would include improvements in the larger energy system, efficiency and other policy goals, household living conditions, and an equitable clean energy transition.

4.1. Limitations

Due to the specific and unique nature of this study, it is difficult to determine if results and conclusions are consistent with what may be found in other locations. In order to best guide alternative financing implementation, we must acknowledge some limitations of this study due to data availability.

First and most importantly, the regions for which FICO scores were available (i.e. zip code) did not align with spatial boundaries of census and Michigan Saves’ data. While we tried to create county- and tract-specific FICO values from Michigan Saves’ dataset, we were unable to do so due to the fact that some counties’ data were too sparse and that the applicant pool’s scores skewed far higher than the state average, likely due to households only applying if they believed their FICO score to be good enough for approval12. When we tried imputing data or creating a probabilistic model, the predictions resulted in very similar numbers. Ultimately, the statewide average was applied to each county, but the study would greatly improve through use of more granular numbers at the tract or county level.

12 The average FICO score across all Michigan Saves applicants was 700, while the statewide average is 678.
A second limitation was the treatment of identifying single-family, owner-occupied homes. The coverage gap described in this paper represents all occupied households in each county and does not address the split incentive and other barriers that renters experience. Future research could strengthen this study by considering homeowner-occupied homes separate from renter-occupied homes. Additional considerations could include different treatment of homes by number of units in the structure.

Finally, it is important to note here that there are other factors that may disqualify or hinder a household from receiving weatherization assistance, as described in the introduction. At a national level, an estimated 39.5 million income-eligible households remain unserved [49]. In Michigan, funds are finite and prioritized for households that receive cash assistance from the Department of Human Services or Supplemental Security Income; or to households with members over the age of 60, under the age of 18, and/or with disabilities (MDHHS 2018). Housing conditions such as presence of asbestos may also disqualify a household until problems are remedied. Unfortunately, with census data aggregated to the tract level, it was not possible to pair income, number of household members, their ages, and/or their disability status by household and this study assumed 200% federal poverty level as the lower boundary of the coverage gap. Instead of working at the county level, data gathered at the household level, aggregated up, would allow for a more accurate representation of a county and statewide coverage gap.

CRediT authorship contribution statement

Sydney P. Forrester: Formal analysis, Investigation, Methodology, Visualization, Writing - original draft, Writing - review & editing. Tony G. Reames: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Table A.1.

Table A.1

<table>
<thead>
<tr>
<th>Year</th>
<th>Applicants</th>
<th>Approved</th>
<th>Issued</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>177</td>
<td>85</td>
<td>82</td>
</tr>
<tr>
<td>2011</td>
<td>1447</td>
<td>852</td>
<td>761</td>
</tr>
<tr>
<td>2012</td>
<td>2332</td>
<td>1356</td>
<td>1242</td>
</tr>
<tr>
<td>2013</td>
<td>1847</td>
<td>964</td>
<td>859</td>
</tr>
<tr>
<td>2014</td>
<td>1467</td>
<td>900</td>
<td>795</td>
</tr>
<tr>
<td>2015</td>
<td>1755</td>
<td>1116</td>
<td>931</td>
</tr>
<tr>
<td>2016</td>
<td>1736</td>
<td>1106</td>
<td>973</td>
</tr>
<tr>
<td>2017</td>
<td>2316</td>
<td>1590</td>
<td>1236</td>
</tr>
<tr>
<td>Total</td>
<td>13,077</td>
<td>7969</td>
<td>6879</td>
</tr>
</tbody>
</table>

Appendix B. Model comparison and selection process

Models all had the same dependent variable of loan approval probability. In the dataset used to create this model, values were either 0 for rejection or 1 for approval. Results of the predicted dataset were produced as a value between 0 and 1 to indicate probability [%] of approval.

The three model types considered were binomial mixed model regression, machine learning random forest, and GAMS (General Algebraic Modeling System). The models utilized the same variables: FICO (centered and scaled); Income (centered, scaled, and adjusted to 2016 values); and County (random effect for Binomial and GAMS). The three models were then compared side-by-side for predictive performance using a confusion matrix and Receiving Operating Characteristics (ROC) curve. A confusion matrix compares the test set’s true answers with the predicted answers to quantify the number of true positives, true negatives, false positives, and false negatives. An ROC curve plots the probability of getting a true positive against the probability of a false positive. A larger area under the curve indicates that there is a better chance of predicting true positives as well as true negatives. The models’ 95% confidence interval for accuracy summarizes the number of correct guesses. A baseline test for binary models is to compare this with a “no information rate” (NIR) i.e. the rate that one could achieve through random guessing. To be considered at all, any model predicting onto a binary response must have accuracy above the NIR, which was the case for all three. Ultimately, despite the binomial mixed model’s marginally smaller accuracy, it was selected for reported results due to its significantly higher level of interpretability, simplicity, area under the ROC curve, and speed (see Tables B.1 and B.2).
Table B.1
Summary of three models considered for predicting loan application approval for a household.

<table>
<thead>
<tr>
<th>Model</th>
<th>Benefits</th>
<th>Challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binomial Mixed</td>
<td>Accounts for clustered random effects</td>
<td>Assumes linear relationships between dependent and independent variables when creating the combination effect of predictors</td>
</tr>
<tr>
<td>Random Forest</td>
<td>Highly accurate</td>
<td>Fairly uninterpretable</td>
</tr>
<tr>
<td>GAMS</td>
<td>Accounts for non-linear relationships between dependent and independent variables through smoothing</td>
<td>Complex, time-consuming Risk of over-fitting</td>
</tr>
<tr>
<td></td>
<td>for clustered random effects</td>
<td>Fairly interpretable</td>
</tr>
</tbody>
</table>

Table B.2
Comparative model tests for accuracy and performance.

<table>
<thead>
<tr>
<th>Model</th>
<th>Area Under ROC Curve</th>
<th>Accuracy</th>
<th>95% Confidence Interval for Accuracy</th>
<th>No Information Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binomial Mixed</td>
<td>0.8857</td>
<td>82.00%</td>
<td>80.41% 83.52%</td>
<td>66.22%</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.7978</td>
<td>82.92%</td>
<td>81.35% 84.41%</td>
<td>72.90%</td>
</tr>
<tr>
<td>GAMS</td>
<td>0.8938</td>
<td>84.96%</td>
<td>83.47% 86.37%</td>
<td>75.40%</td>
</tr>
</tbody>
</table>

Appendix C

Summary of binomial mixed model and correlation of fixed effects (see Tables C.1 and C.2).

Table C.1
Results of binomial mixed model.

Fixed Effects

<table>
<thead>
<tr>
<th>Name</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Z Value</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.84133</td>
<td>0.05165</td>
<td>16.290</td>
<td>&lt; 2e−16</td>
</tr>
<tr>
<td>Income [2016 $]</td>
<td>0.70337</td>
<td>0.04453</td>
<td>15.795</td>
<td>&lt; 2e−16</td>
</tr>
<tr>
<td>FICO</td>
<td>2.17643</td>
<td>0.04348</td>
<td>50.056</td>
<td>&lt; 2e−16</td>
</tr>
<tr>
<td>FICO/Income Interaction</td>
<td>0.57649</td>
<td>0.06611</td>
<td>8.721</td>
<td>&lt; 2e−16</td>
</tr>
</tbody>
</table>

* All predictors centered around mean and divided by standard deviation.

Table C.2
Correlation of fixed effects.

<table>
<thead>
<tr>
<th>Correlation of Fixed Effects</th>
<th>Intercept</th>
<th>Income</th>
<th>FICO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income</td>
<td>0.191</td>
<td>0.262</td>
<td>0.451</td>
</tr>
<tr>
<td>FICO</td>
<td>0.173</td>
<td>0.451</td>
<td>0.451</td>
</tr>
<tr>
<td>FICO/Income Interaction</td>
<td>0.132</td>
<td>0.451</td>
<td>0.451</td>
</tr>
</tbody>
</table>

Appendix D

See Fig. D.1 and Table D.1.
Fig. D.1. Random Effects (centered intercepts) by County for Predictive Binomial Mixed Model (Positive values indicate higher loan approval probability).

Table D.1
Incorporation of random effects by county.

<table>
<thead>
<tr>
<th>Name</th>
<th>Groups [#]</th>
<th>Intercept Variance</th>
<th>Intercept Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>County</td>
<td>81</td>
<td>0.0443</td>
<td>0.2108</td>
</tr>
</tbody>
</table>

References
