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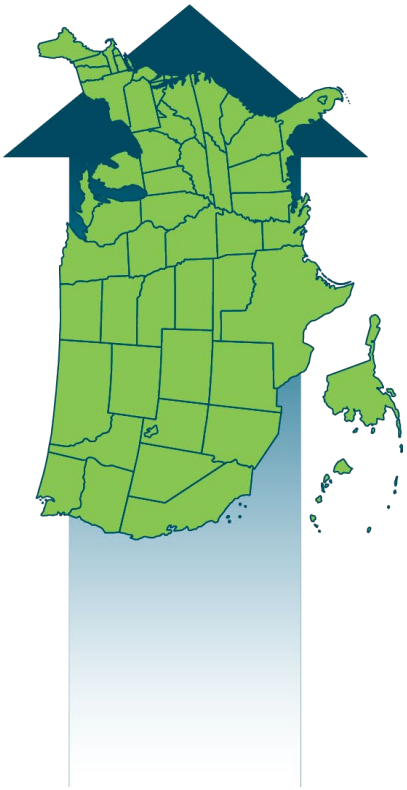

Long-Term Performance of Energy Efficiency Loan Portfolios

March 2022

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Executive Summary

This report reviews and documents the financial performance of four large and long-running residential energy efficiency financing programs. The analysis presented will inform potential capital providers, lenders, and program administrators and help them assess the likely outcomes and risks associated with energy efficiency lending. Anecdotally, performance of energy efficiency lending is generally understood to be strong, but data on energy efficiency loan performance has not been readily available. The data made available in this report significantly expand the public evidence base.

This report reviews loan performance data from four programs:

- The Connecticut Green Bank (CGB)'s Smart-E Loan program, which began issuing loans in 2013;
- The Keystone HELP program run through the Pennsylvania Treasury, which began issuing loans in 2006;
- The Michigan Saves loan program, which began issuing loans in 2010; and
- The New York State Energy Research and Development Agency (NYSERDA)'s loan programs, which began issuing loans in 2010.

Loan and borrower characteristics

The average loan across the four studied portfolios (52,511 energy efficiency-only loans) has the following characteristics:

- A principal amount of $9,137;
- A loan term of 121 months (just over ten years);
- An average seasoning (i.e., time since a loan was issued) of 4.5 years;
- An interest rate of 5.0%;
- A monthly payment amount of $93; and
- Is unsecured.[1]

While there is some variation across programs, in general the loans are relatively similar along these parameters.

Borrowers in these programs have relatively high credit scores, concentrated in the 660-780 range with an average of 740. The average borrower lives in a census tract with a median household income between 80% and 100% of the median income in its metropolitan statistical area. Borrower characteristics are also comparable across the four programs.

Loan performance

Our data document each pool's delinquency and loss status as of a specific date (March 2020 for NYSERDA and Smart-E, December 2019 for Michigan Saves, and September 2017 for Keystone HELP). Across the four portfolios:

- The 30-day delinquency rate – the share of outstanding loan dollars that are at least 30 days delinquent – is 1.57% (the 60-day delinquency rates is 0.62%, and the 90-day delinquency rate is 0.21%).

[1] In some on-bill lending programs (including both Michigan Saves' and NYSERDA's on-bill programs), nonpayment could result in disconnection of the participant's power service. Although some may refer to disconnection as "security" for these loans since it could incentivize repayment, technically secured loans carry the potential loss of some form of collateral (e.g., a car or a home); this both incentivizes repayment and also helps to make the lender whole in case of a loss. Disconnection would not help make a lender whole after a loss. On-bill loans comprise only a small subset of the loans in the portfolios.

- Losses (charge offs) are highest early in loan lifetimes and decline later, a common finding for consumer loans. The pooled portfolios lost 2.1% of the principal by year 2, 3.3% by year 4, 4.5% by year 6, and 5.1% by year 8.

Regression analysis identifies features of loans and borrowers that are associated with strong loan performance:

- Borrower credit scores stand out: all else equal (e.g., same interest rate, loan age, and borrower income), increasing borrower credit score by 100 lowers the odds that a given loan is 30 days delinquent by 1.06 percentage points and the odds that a given loan is charged off by 5.81 percentage points.
- Income metrics (the income of the census tract in which the borrower lives, as well as household income available for one portfolio) are also associated with loan performance; however, this association is not nearly as strong as that with credit score, demonstrating that credit score is a better predictor of loan performance than income.

Performance compared to other financial products

The delinquency and loss rates of loans in the studied energy efficiency loan portfolios are low compared with unsecured consumer loans and are comparable to the rates for prime auto loans, which are secured by the vehicles (see Figure ES1). This strong performance may be supported by utility bill savings resulting from the financed efficiency projects or also may in part reflect differences in borrower and loan characteristics between the efficiency loans and comparators. Regardless, the data provide the most comprehensive evidence to date that lenders and capital providers can expect energy efficiency loans—at least those from well-designed and administered programs such as those studied here— to perform well.

These findings show that financial institutions can market energy efficiency improvements to their customers and lend them the money they need for those projects at low risk, while creating a more efficient building stock. The data show that households from low- and moderate-income areas participate in these programs and that high-credit borrowers in these areas repay at a strong rate, suggesting efficiency financing could support policy goals related to equitable access (e.g., Justice 40 goals and Community Reinvestment Act compliance requirements). This analysis can inform the design of credit enhancement mechanisms, such as loan loss reserves, at the federal or state level—for example, by setting loan performance expectations to help size financial outlays — that could help encourage financial institutions to increase energy efficiency lending.

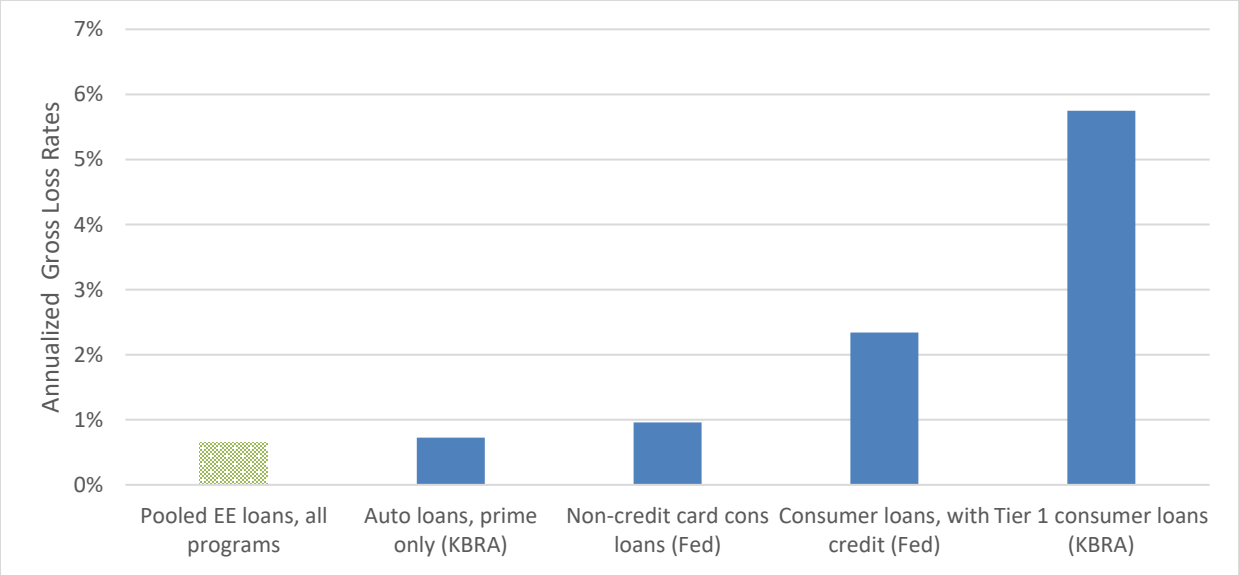

Figure ES1. Delinquency rates, energy efficiency loans, and comparators

1. Introduction

This report presents a detailed analysis of energy efficiency loan performance data from four large and long-running residential programs. Although smaller-scale energy efficiency financing programs have operated for many years, several larger programs were operating by 2010. These programs have now accrued enough historical data to be of sufficient volume and maturity for substantive analysis.

Energy efficiency stakeholders have long theorized that borrowers in energy efficiency loan programs may have low delinquency and loss rates. These loans might perform strongly because the projects being financed reduce energy consumption and save borrowers money, leaving them with additional resources to repay the loans. Another explanation may be because the types of households that participate in these programs may be low risk in ways that traditional loan underwriting may not capture. For example, these households are investing in their properties, thereby demonstrating that they value them, and are identifying and pursuing relatively small savings opportunities, thereby demonstrating their careful attention to their expenditures (Zimring et al. 2013). The analysis presented here is a first step toward testing this theory.

Capital market stakeholders are generally unfamiliar with energy efficiency loans.[2] Prior to this report, no comprehensive, loan-level analyses of the financial performance of energy efficiency loans were publicly available. If lenders and capital providers lack data regarding the true risks of these loans, they may ration credit (Palmer et al. 2012), offering less desirable terms than they would if they had better information. This report provides investors, lenders, and program administrators with data regarding the attributes of energy efficiency loans and their performance.

Section 2 reviews the four energy efficiency programs studied and presents a detailed description of the loan portfolios. Section 3 reviews the performance of these portfolios in terms of delinquency rates, charge-off rates, and prepayment. Section 4 compares their performance to that of other financing asset classes to put the report's findings in context. Section 5 concludes.

2. Studied energy efficiency loan portfolios

Berkeley Lab obtained loan-level data for four residential energy efficiency financing portfolios: Keystone HELP, Michigan Saves, the New York State Energy Research and Development Authority's (NYSERDA) On-bill Recovery Loan and Smart Energy Loan programs, and the Connecticut Green Bank's Smart-E Loan program.

All of these programs except for Keystone HELP make loans for both energy efficiency and solar projects. Because this report addresses loans for energy efficiency, loans that included solar PV were excluded. Furthermore, loans made for the two technologies may not perform comparably. Berkeley Lab will address the performance of solar loans in these portfolios in future work.

In total, the data include 52,511 loans. Due to occasional missing data, some data elements presented in this report have fewer observations.

For three of the portfolios, Berkeley Lab was able to obtain data from program inception through the end of 2019 or beginning of 2020 (see Table 1 for specific dates for each portfolio). Notably, all data sets end before the financial impacts of the Covid-19 pandemic began.

[2] This differentiates energy efficiency loans from solar loans, which are more established in securities markets.

Table 1. Description of the loan portfolios studied

Program	State	Years of data	Total non-PV loans
Keystone HELP	PA	February 2006—September 2017	14,753
Michigan Saves	MI	October 2010—December 2019	16,042
NYSERDA	NY	December 2010—March 2020	18,556
Smart-E	CT	May 2013—March 2020	3,160

Figure 1 shows the different program volumes by vintage, i.e., the year in which each loan was made.

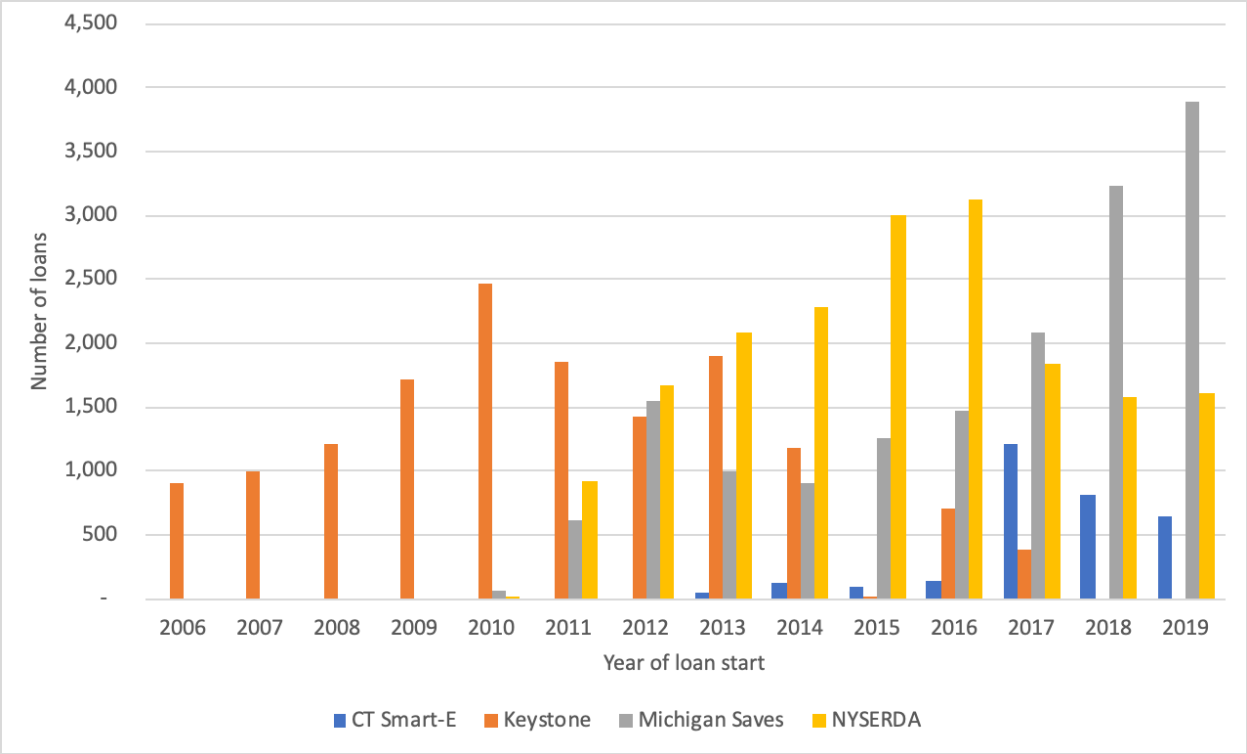

Figure 1. Loan volumes by program and vintage

For Keystone HELP, data were only available on loan status as of September 2017. Since this program began in 2006, this still represents 11 years of program loans. Keystone HELP is also the one program analyzed with significant activity prior to the 2008 recession, and thus has navigated an economic cycle. The other programs began after the recession. The Michigan Saves and Smart-E programs made the bulk of their loans in the last three years of the analysis period.

2.1. Program overviews

The loan portfolios included in the analysis come from four energy efficiency loan programs: the Connecticut Green Bank's Smart-E Loan program, Pennsylvania's Keystone HELP program, Michigan Saves' programs, and the Green Jobs, Green New York programs (comprised of the On-bill Recovery Loan and Smart Energy Loan) of the New York State Energy & Research Development Authority (NYSERDA). See Table 2.

Table 2. Program portfolios included in this analysis

Program	Smart-E	Keystone HELP	Michigan Saves	Green Jobs Green New York
Program administrator (PA)	Connecticut Green Bank (CGB) and Inclusive Prosperity Capital (IPC)	AFC First[a]	Michigan Saves	NYSERDA
Description of PA	Quasi-governmental green bank increasing flow of private capital to markets that energize the green economy	Private energy efficiency financing company	Nonprofit green bank funding clean energy	State authority advancing clean energy innovation and investments
Lender (entity extending program loans)	13 local financial institutions[b]	AFC First[a]	7 local financial institutions[b]	NYSERDA
Underwriting criteria	CGB/IPC ask lenders to use their standard practice: FICO (min. 640 or 580), Debt-to-income (DTI) (max. 50% or 45%), no bankruptcy in last 4 to 7 years, income verification[c]	Min. credit 640 Max. DTI 50% (42% for loans >$25K), no bankruptcy for 5 years	Min. credit 600 Max. DTI 50%, no bankruptcy for 12 months; for on-bill, 12 months on-time utility bill payment	Min. credit score 540 Max. DTI depends on credit score, no bankruptcy for 2 years, 12 months on time mortgage payments
Loan underwriter	13 local financial institutions[b]	AFC First[a]	7 local financial institutions[b]	Slipstream
Structure (on- vs off-bill, secured[d] or unsecured)	Unsecured, off-bill loans	Unsecured, off-bill loans	Unsecured, on- and off-bill loans	Unsecured, on- and off-bill loans
Credit enhancements (CE) to lenders (does not include CEs for secondary market loan sales)	Loan loss reserve (second loss, at the portfolio level)	Loss reserves were provided through various Pennsylvania state agencies and grants	Loan loss reserve, and utility capital from one publicly-owned utility	None
Source of capital	Local financial institutions	Pennsylvania Treasury, AFC First, securitization proceeds, local bank loan pool	Local financial institutions, municipal utility capital (for Holland on-bill program)	Regional Greenhouse Gas Initiative funds[e], securitization proceeds
Federal funds used	American Recovery and Reinvestment Act (ARRA) funds for loan loss reserve and interest rate buydowns at different points in the program	ARRA funds provided loss reserves and rate buydown funds for some of the program years	ARRA funds provided the loan loss reserve	None

[a] The program administration changed in 2015 upon AFC First's acquisition by Renew Financial. AFC First was also lender and underwriter for the program. The National Energy Improvement Fund (NEIF), a successor run by AFC First's management, is now providing administration services for a portion of the portfolio.
[b] For residential program participants.
[c] Participating lenders can use standard or credit-challenged term sheets; underwriting thresholds depend on which is used.
[d] In some on-bill lending programs (including both Michigan Saves' and NYSERDA's on-bill programs), nonpayment could result in disconnection of the participant's power service. Although some may refer to disconnection as "security" for these loans since it could incentivize repayment, technically secured loans carry the potential loss of some form of collateral (e.g., a car or a home); this both incentivizes repayment and also helps to make the lender whole in case of a loss. Disconnection would not help make a lender whole after a loss.
[e] See: https://www.rggi.org.

2.2. Descriptive statistics

This section describes several characteristics of the studied efficiency loan program portfolios: four properties of the loans themselves (loan tenors, principal amounts, monthly payment amounts, and interest rates) and two characteristics of the participants (incomes and credit scores). Each of the characteristics could impact loan repayment performance; Section 3 explores their relationships with loan performance.

2.2.1. Loan characteristics

Figure 2 summarizes the principal amounts of loans issued by each program. The amounts participants are borrowing through these portfolios is concentrated in the $5,000 to $10,000 range (see averages and medians in Table 3).

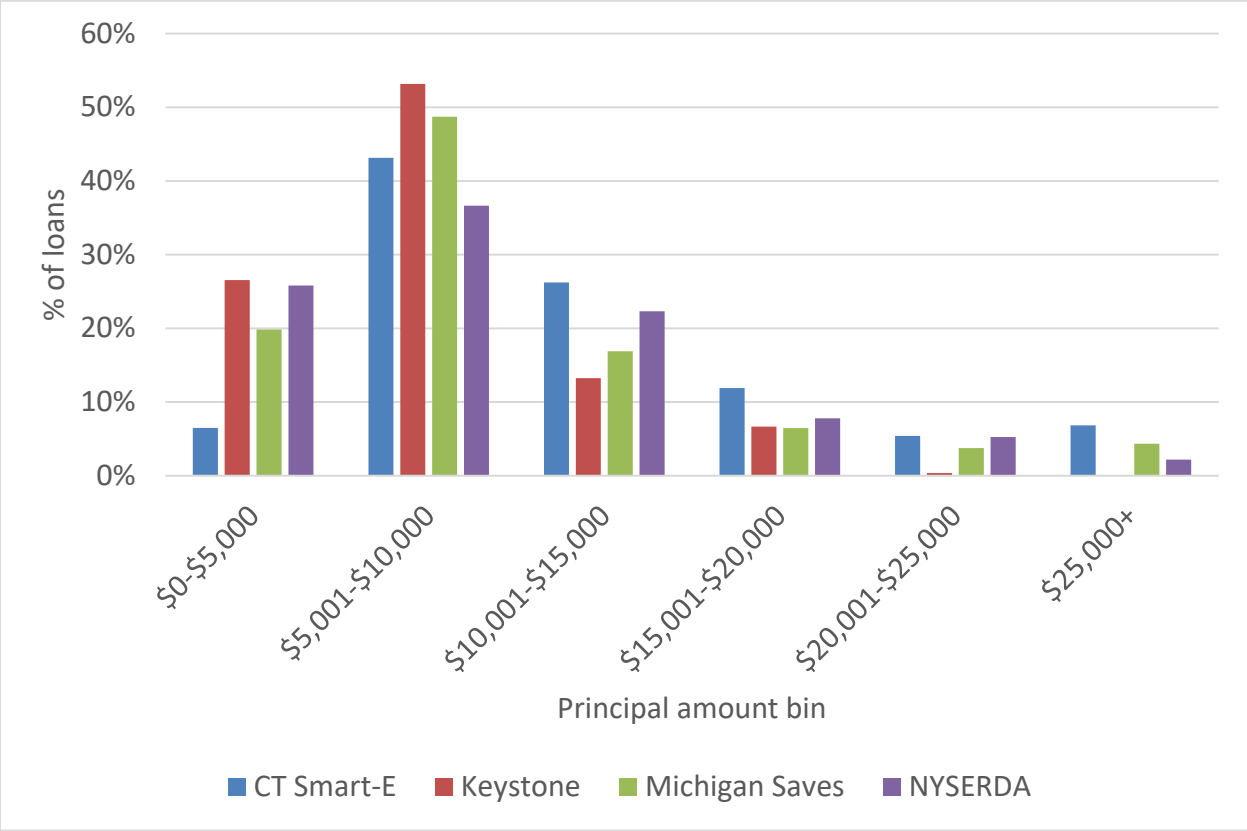

Figure 2: Participation by principal amount bin

Table 3. Average and median principal amounts, monthly payments, terms, and interest rates

	Smart-E	Keystone	Michigan Saves	NYSERDA	All programs
Average principal amount	$12,239	$7,594	$9,679	$9,366	$9,137
Median principal amount	$10,094	$7,000	$7,801	$7,971	$7,661
Average monthly payment	$160	$90	$101	$76	$93
Median monthly payment	$139	$80	$85	$65	$80
Average term (months)	92	93	100	166	121
Median term (months)	84	120	120	180	120
Average interest rate	3.5%	6.7%	5.1%	3.8%	5.0%
Median interest rate	4.5%	7.0%	5.0%	3.5%	5.0%

Maintaining loan program data to facilitate performance analysis

To expand the public evidence base on the performance of energy efficiency loans, Berkeley Lab approached a number of energy efficiency loan programs for this analysis. The four programs that shared data were very cooperative, and several other programs were willing but ultimately unable to share.[3]

A common issue that makes data access challenging is that all the necessary loan data are often not maintained by a single entity. It is common for different entities to perform different functions – e.g., project approval, loan origination/underwriting, loan servicing. In some cases, the data on each function reside in different systems. While there is generally some common identifier (such as a loan ID) that could be used to associate the data, the level of effort to do so can be significant. By proactively integrating these systems where possible to maintain consolidated data for analysis, program administrators can help educate and motivate capital providers and lower the cost of capital for these programs in the future.

Moreover, some programs – including Michigan Saves, Smart-E, and many others – partner with local lenders (most often credit unions and banks) that make their own loans and maintain their own data. Michigan Saves and the Connecticut Green Bank demonstrate that some programs gather and consolidate data from multiple lenders to enable analysis. Where possible, other programs that use many local lenders can help facilitate additional analysis by gathering their loan data in one central system.

Finally, most if not all programs do not maintain their data in a manner that easily enables time series analysis. This report studies delinquency and charge-off rates at one moment in time for each program. Programs that can assemble and maintain a monthly time series of loan status could support more detailed and powerful statistical analysis.

Berkeley Lab's report *Energy Efficiency Finance Programs: Use-case Analysis to Define Data Needs and Guidelines* provides recommendations on maintaining data to facilitate loan performance analysis; see SEE Action Network (2014a).

Monthly payments demonstrate the ongoing cash flow burden that a loan presents for participants. Figure 3 presents monthly loan payments for each program. Across the portfolios included in the study, monthly payments mostly fall into the $51 to $100 per month range. The distribution of monthly payment sizes between Michigan Saves and Keystone varies little. Compared to the other portfolios, the NYSERDA portfolio has a higher share of

[3] The four programs analyzed are among the largest and oldest in the U.S. There are dozens of other energy efficiency financing programs in the U.S., but few programs offer the high-volume, long-term data (and were willing to share their data), that the four programs provided.

loans with monthly payments under $50 per month (37%). The CT Smart-E portfolio has a higher share of loans with monthly payments above $150 per month (44%). Smart-E principal amounts and area median incomes are also higher than other programs, suggesting that (1) Connecticut is likely the highest-cost market and (2) Connecticut borrowers may qualify for larger loans due to their incomes.

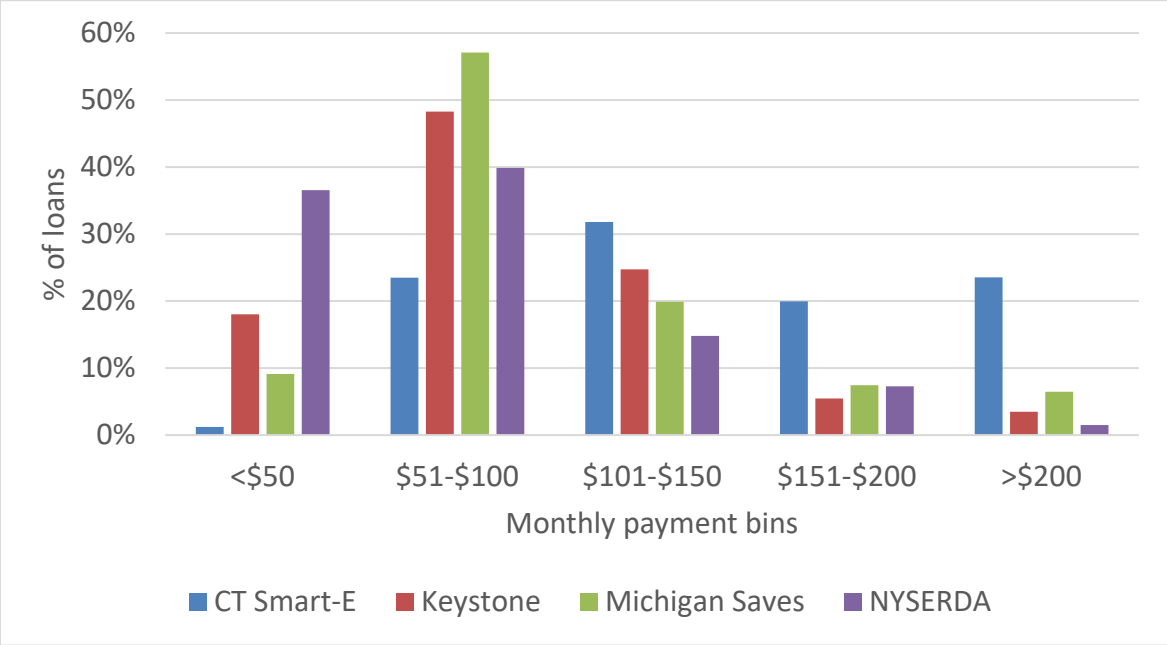

Figure 3. Participation by monthly payment amount

Loan term (or tenor) refers to the amount of time until a loan matures. Longer term loans are riskier for lenders but result in lower monthly payments for borrowers because the repayment is spread over a longer period. Programs generally offer a limited number of terms (e.g., five years, seven years) and the terms offered may change over time. Program administrators provided terms for each loan. Loan terms for Keystone, Michigan Saves, and CT Smart-E are almost entirely ten years (120 months) or less, with terms for over half of loans in each of those portfolios falling between 61 and 120 months. NYSERDA is the outlier: 84% of their loan terms are 15 years (180 months), which explains the relatively small monthly payments for NYSERDA loans in Figure 3. The median loan term across all four portfolios is ten years (120 months) (see Table 3).

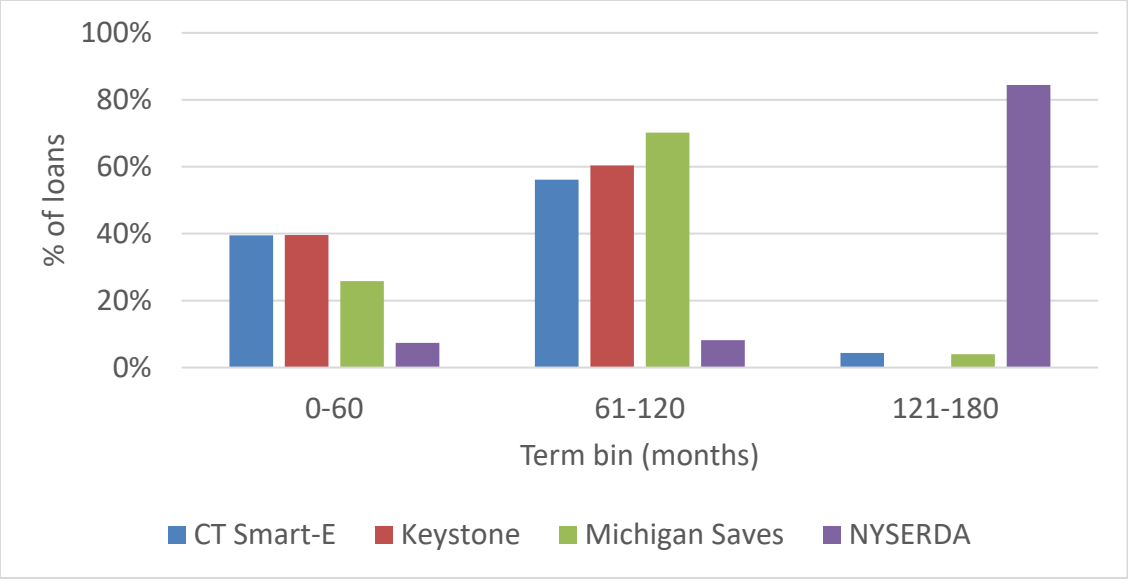

Figure 4. Share of portfolio participants with different loan terms

Another factor that impacts payment amounts is the interest rate charged on a loan. Interest rates vary within and across the four programs. Rates ranged from a low of 0% to a high of 8.99%. Most fall between 4% and 6% with most NYSERDA loans at 3.49% or 3.99% (see Figure 5). Several factors explain the differences in interest rates across programs:

- Credit enhancements: Programs that benefit from more generous credit enhancements (such as larger loan loss reserves) can charge lower interest rates.
- Lender requirements: Different lenders require different returns to participate in these programs. "Pure" private capital providers generally require higher returns than mission-driven lenders, and programs that lend public or utility customer dollars have more freedom to set their own rates.
- Timing: Prevailing market interest rates have been low since the Great Recession, but were at times much higher in the past; this in part explains the higher interest rates charged by Keystone HELP.
- Promotional rates: The Smart-E program offered very low interest rates for a period of time to attract interest in the program, which explains the large share of Smart-E loans in the first bin.

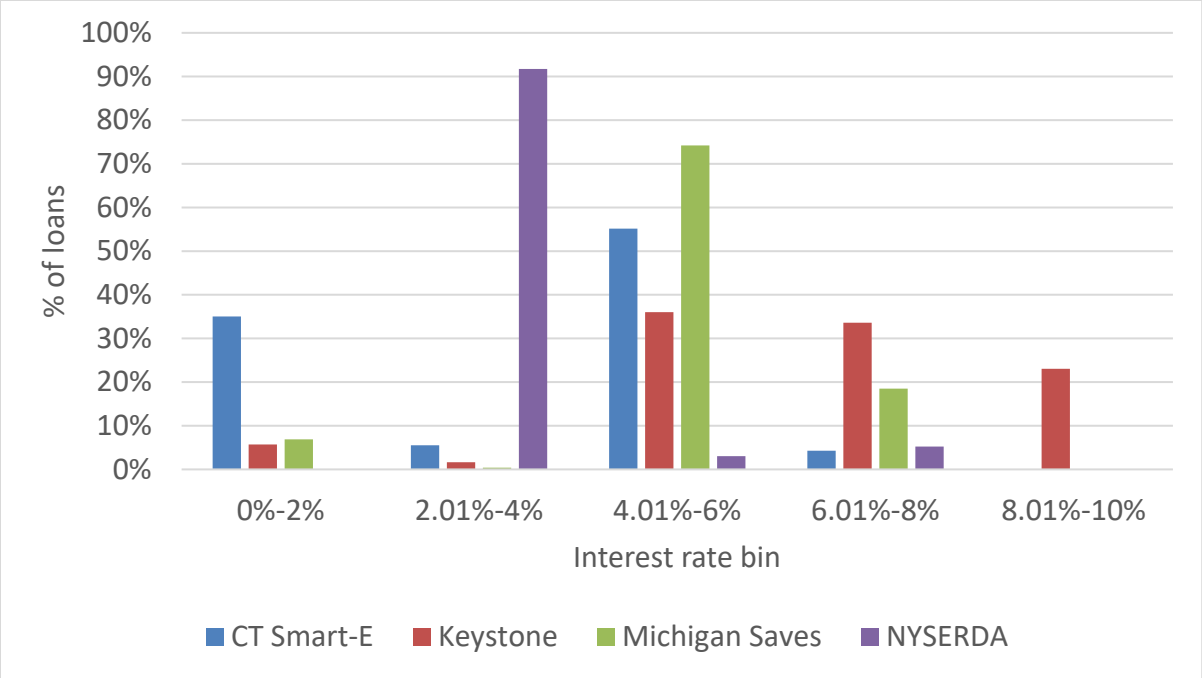

Figure 5. Participation by interest rate

2.2.2. Borrower characteristics

Participant income could impact repayment performance since households with more income have more financial resources available to make loan payments. Each program collected participant income data differently. Keystone HELP did not have participant income data (and this portfolio is therefore not included in any analyses that use income data). NYSERDA reported a debt-to-income-ratio, but not a household-level income metric. The Connecticut Smart-E Loan program reported a ratio of the median income of a household's census tract to the area median income (AMI). Only Michigan Saves reported actual household income. However, every program except Keystone HELP reported the census tract in which each borrower lives. Berkeley Lab therefore was able to calculate a common metric – the ratio of median census tract income to AMI – for all programs except Keystone HELP (see Table 4).[4] Note that this metric describes the income of the census tract in which the home resides but is not a household-level value.

Overall, about two-thirds of participants in these programs are from census tracts where incomes are 80% of the AMI or higher. The greatest share of participants falls into the 80%-100% AMI bin (see Figure 6). The three portfolios have a similar distribution across the AMI bins. Overall, across programs the majority of borrowers are from census tracts with median incomes less than the median income of their statistical area.[5] Relatively few

[4] To assess the impact of income across programs in a consistent fashion, Berkeley Lab calculates census tract AMI bands for each program. This metric is the ratio of census tract-level median household income estimates from the American Community Survey (ACS) to area median income as defined by the Department of Housing and Urban Development (HUD). This method is consistent with Smart-E's in the use of census-tract level median household incomes, but differs in the source of the area median income. Smart-E used ACS Metropolitan and Micropolitan Statistical Areas, which provided full geographic coverage for Connecticut. New York and Michigan, however, have tracts that are outside these two types of statistical areas. The HUD area median incomes address this gap and provide county-level incomes alongside statistical area data incomes. This analysis matches HUD and ACS vintages to the year of loan issuance to account for changes in tract and area incomes over time.

ACS income data can be found at https://www.census.gov/programs-surveys/acs/data.html. HUD income data can be found at https://www.huduser.gov/portal/datasets/il.html. In this analysis, HUD and ACS incomes are aligned by data release year. HUD data draw on three-year old ACS estimates for each data release (e.g., 2018 HUD data is based on 2015 ACS data). Given that the ACS incomes cover five years (e.g., 2014-2018 for the 2018 release), they still overlap with the window of HUD incomes.

[5] To see participant incomes by AMI broken into income bins used for the purposes of the Community Reinvestment Act, see Appendix B.

borrowers (10-15%) in each program live in census tracts with median incomes below 60% of area median; between 30 and 40% of borrowers in each program live in census tracts with median incomes below 80% of area median.[6]

Table 4. Average and median borrower characteristics. (Keystone HELP did not have sufficient data to determine income metrics.)

	Smart-E	Keystone	Michigan Saves	NYSERDA	All programs
Median tract income	$89,858		$63,425	$68,593	$67,152
Median AMI	$95,260		$72,842	$75,736	$74,507
Median tract income / median AMI	92.6%		88.8%	85.3%	87.5%
Average tract income	$93,210		$67,478	$77,529	$74,134
Average AMI	$98,042		$72,637	$87,404	$81,262
Average tract income / average AMI	95.2%		93.0%	87.3%	90.8%
Average FICO	739	751	741	729	734
Median FICO	741	754	744	740	745

[6] Definitions of low-income households and areas vary, so there is no single way to characterize the share of borrowers in these programs that are low- and moderate-income (LMI). In the energy sphere, the Low-Income Home Energy Assistance Program uses a household-level eligibility criterion of 60% of state median income, and the Weatherization Assistance Program also relies on this criterion in some states. 10-15% of households in the data meet this definition per area (as opposed to state) median income. HUD considers households with incomes less than 80% AMI to be low income and those less than 50% to be very low income for rental housing assistance programs and the HOME program (see https://www.hud.gov/topics/rental_assistance/phprog and https://www.huduser.gov/portal/datasets/home-datasets/files/2021-HOME-IncomeLmts-Memo.pdf). The Community Redevelopment Act (CRA) designates less than 80% AMI as moderate income and less than 50% as low income. Per Appendix B, 5-8% of borrowers in each program live in census tracts considered low income by the CRA or very low income by HUD, while about 30-40% would be considered either low- or moderate-income by CRA and low income by HUD.

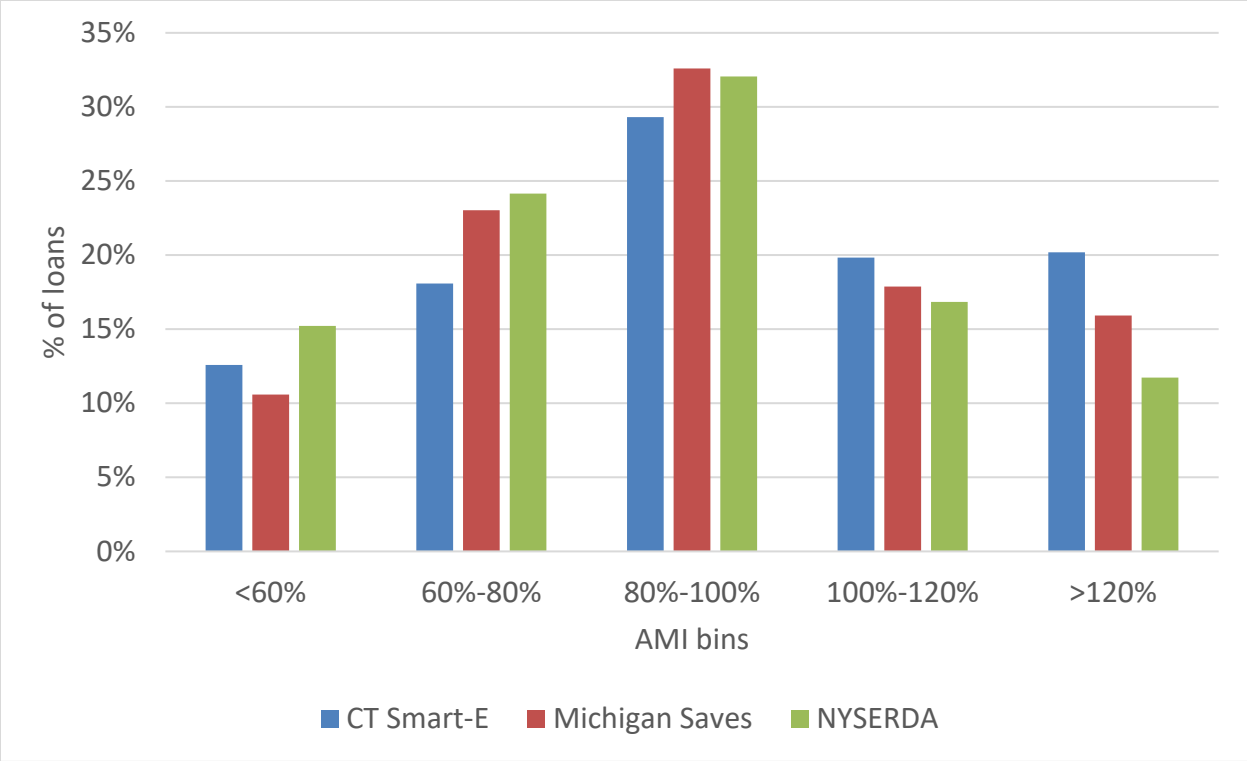

Figure 6. Participant incomes (by AMI bin) for three portfolios

A credit score is a number designed to measure a consumer's creditworthiness, i.e., it is used to predict the likelihood that a borrower will fully repay their loan. The most commonly used credit score is the Fair Isaac Corporation (or FICO) score which ranges from 300 to 850, higher numbers suggesting the borrower is more creditworthy (see Figure 7 for more).[7] Across the four portfolios, most credit scores are high: the average credit score is 734 with a median credit score of 745. Importantly, these programs are only available to homeowners, who as a customer segment have higher credit scores than renters (Li 2016). These scores suggest that the likelihood that borrowers participating in these programs repay their loans in full is high.

[7] Although Berkeley Lab believes that most of the reported scores are FICO scores, Michigan Saves identified one lender that reported Vantage Scores instead. It is possible that other lenders did so as well.

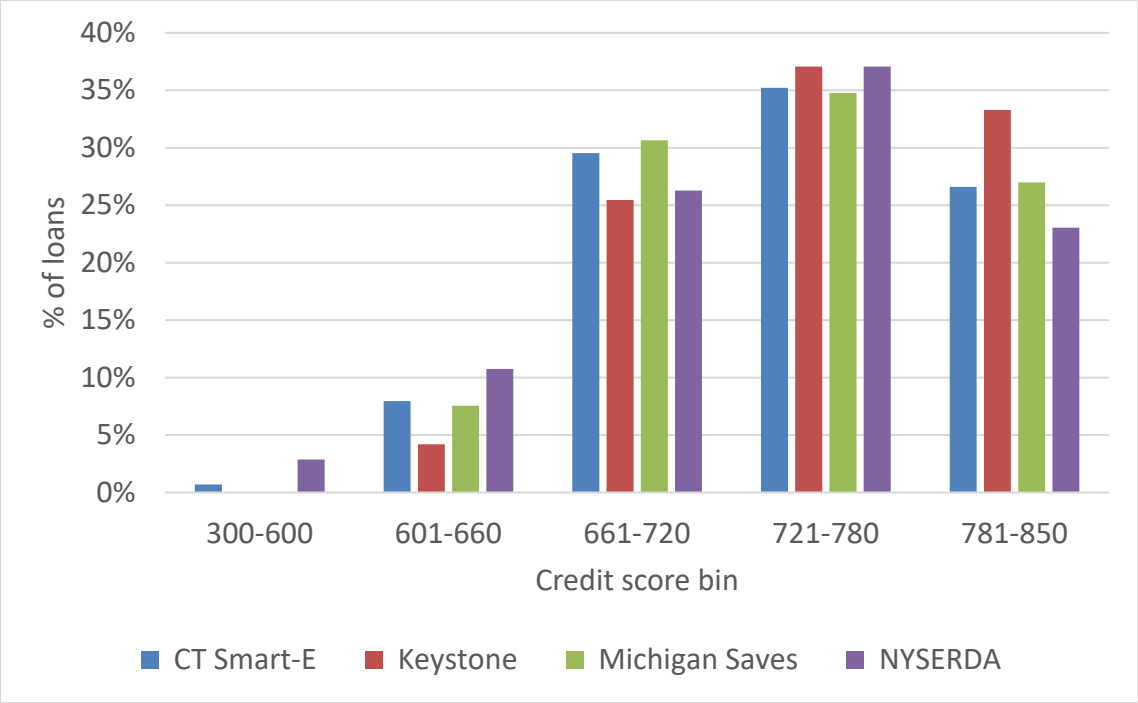

Figure 7. Participation in four efficiency financing programs by credit score bin

3. Performance analysis

3.1. Methodology

To analyze the data from all portfolios, each loan is assigned a status as either paid-off, delinquent, charged off, or current.

The definition of **charge-offs** can vary across loan providers, depending on how they decide when to declare a loan as a loss.[8] Such determinations may be made if the loan becomes seriously delinquent, but also for other reasons (e.g., bankruptcy, death of a borrower, etc.). Many lenders automatically declare a loan as charged off if it reaches a certain delinquency status, often 120 days. This study considers a loan charged off if either (a) the program identified a loan as charged off or (b) the loan was 120 days or more delinquent. This definition of charge-off is consistent with those used by comparator products later in this study (auto loans and consumer loans – see Section 4), to the extent that they specify clear definitions.

Loan providers generally report **delinquencies** in bins that denote the number of days that have passed without payment since a payment due date (e.g., 30, 60, 90, 120 days). Since the definition of charge-off covers loans 120 days or more delinquent, delinquent loans are those that have not been paid 30-120 days after the payment due date.

Customers may pay their loans off at or before the original maturity date. A loan is **paid-in-full** if a program identifies it as such or the remaining balance is zero.

[8] When a lender declares a loan to be charged off, it declares the loan as a loss on its accounts and often transfers collection responsibilities to a collection agency. If the collection agency reports to credit bureaus, the loan will now appear as a charge-off on a borrower's credit report. The borrower is still obliged to repay the loan.

A loan is **current** if it is neither charged off, delinquent, nor paid-in full. Current loans are actively in repayment but not in any form of distress.

Delinquency rates presented in this report are the share of active (not charged off and not paid off) loans that are 30-120 days behind on payments. The **delinquency rate** can be expressed both in terms of the total remaining balance of loans that are delinquent and the number of delinquent loans.

$$Delinquency\ rate_{dollars} = \frac{\sum Remaining\ balance_{loans\ delinquent\ 30-120\ days}}{\sum Remaining\ balance_{\ loans\ not\ charged\ or\ paid\ off}}$$

$$Delinquency\ rate_{count} = \frac{Count\ of\ loans_{loans\ delinquent\ 30-120\ days}}{Count\ of\ loans_{loans\ not\ charged\ or\ paid\ off}}$$

For example, if a loan portfolio has $1,000,000 in outstanding principal balance from 1,000 active loans and 60 of those loans with a total of $50,000 in outstanding principal balance are 30-120 days delinquent, then the portfolio would have a dollar-based delinquency rate of 5% ($50,000/$1,000,000) and count-based delinquency rate of 6% (60/1,000).

The **cumulative gross loss rate**[9] is the total dollars charged off after some number of years for loans originated at least that long ago (but not past their term) as a share of the original balance of those loans. The cumulative gross loss rate can be calculated for each year of seasoning (i.e., how much time has passed since the program issued the loan). Loans that have seasoned for five years, then, are part of the loss rate for years one through five but not for years after five.

$$Cumulative\ gross\ loss\ rate = \frac{\sum Dollars\ charged\ off_{\ loans\ originated\ at\ least\ X\ years\ ago}}{\sum Principal\ Amount_{\ loans\ originated\ \ at\ least\ X\ years\ ago}}$$

In the hypothetical portfolio with $1,000,000 in outstanding principal balance from 1,000 loans, assume that the original loan pool was 1,050 loans (i.e. 50 have already charged off). If the original principal balance of those 1,050 loans was $2,000,000 and the 50 which were charged off totaled $40,000, then the cumulative gross loss rate would be 2% ($40,000/$2,000,000).

Regression analyses determine the drivers of delinquency and charge-off and unpack differences in performance across the portfolios (see Section 3.2.3 for details).

3.2. Findings

3.2.1. Delinquency and loss analysis

Figure 8 presents 30-120-day delinquency rates for each program. The sample sizes in this figure differ from those in Figure 10 because the delinquency rate calculation only considers current loans and excludes any paid-off or charged-off loans. Overall, the 30-120-day delinquency rate for loans in the four portfolios is 1.57%.

NYSERDA delinquency rates for the On-Bill Recovery Loan – an on-bill loan – are much higher than those for its Smart Energy Loan product, explaining its high overall delinquency rate. Due to the structure of the program, any delinquency on a utility bill also results in a delinquency on the on-bill loan. When NYSERDA on-bill loans – which are somewhat atypical – are removed from the pool, the 30-day delinquency rate drops to 1.14% Notably, NYSERDA on-bill *loss* rates are not higher than those of the off-bill Smart Energy Loan, indicating that most of these delinquencies do eventually cure. Section 3.2.3.3 discusses this issue further. As also noted in Section 3.2.3.3, the difference in delinquency rate between Smart-E loans and the lower-delinquency programs is not statistically significant (Smart-E has the smallest loan count of the programs in this study).

[9] As discussed in Section 4, most loan performance indices look at net losses, e.g., losses minus recoveries (any monies recovered after a loan is charged off). Because no recovery data was available for these portfolios, this analysis reports gross losses instead of net losses.

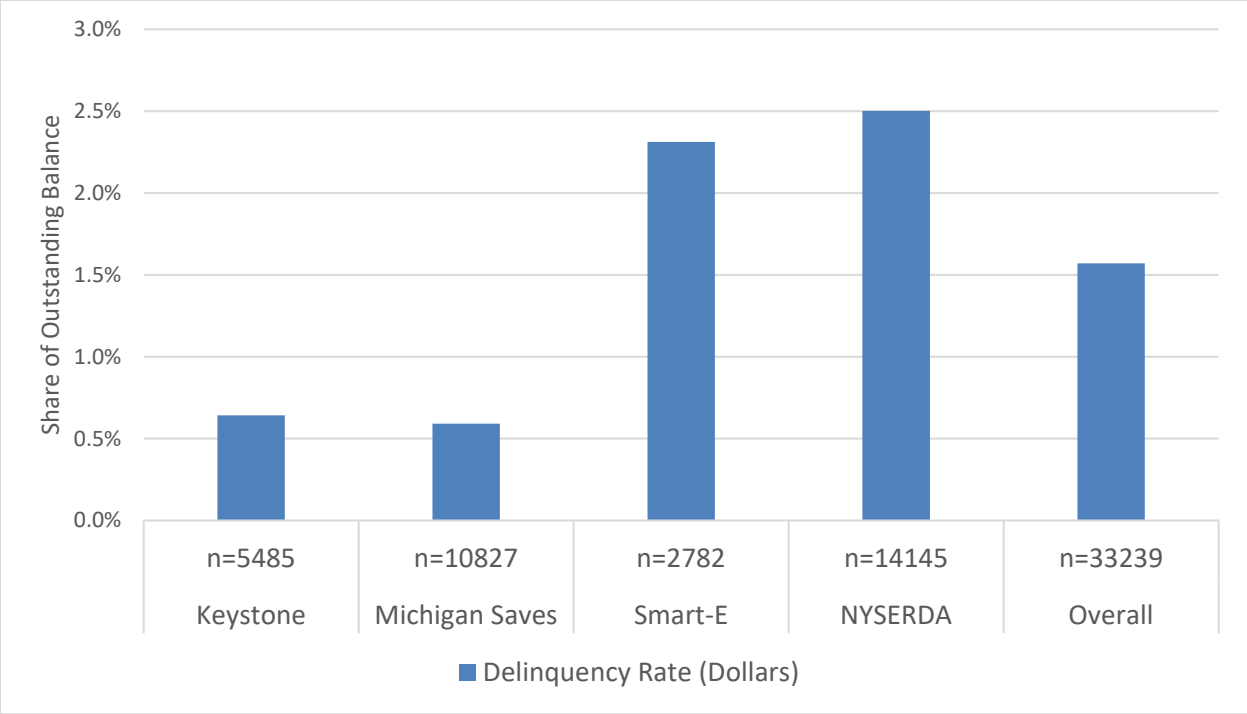

Figure 8. 30-120-day delinquency rates by program

To understand how losses depend on loan seasoning, Figure 9 presents cumulative gross loss rate over time for each program with respect to years of loan seasoning. Each data point in this figure shows the cumulative gross loss rate since initial loan closing. Since the loss rates are cumulative, they increase over time for all four portfolios. The loss rates are sensitive to both vintage effects and small loan pools. The number of loans that have seasoned eight years, for example, is much smaller than the number that has seasoned two. This figure addresses this issue by excluding loan vintages with total principal amounts under $5M, which is why some curves do not extend as far as others. Vintage effects, such as higher loss rates for loans issued before the 2008 financial crisis could affect Keystone loans in particular.

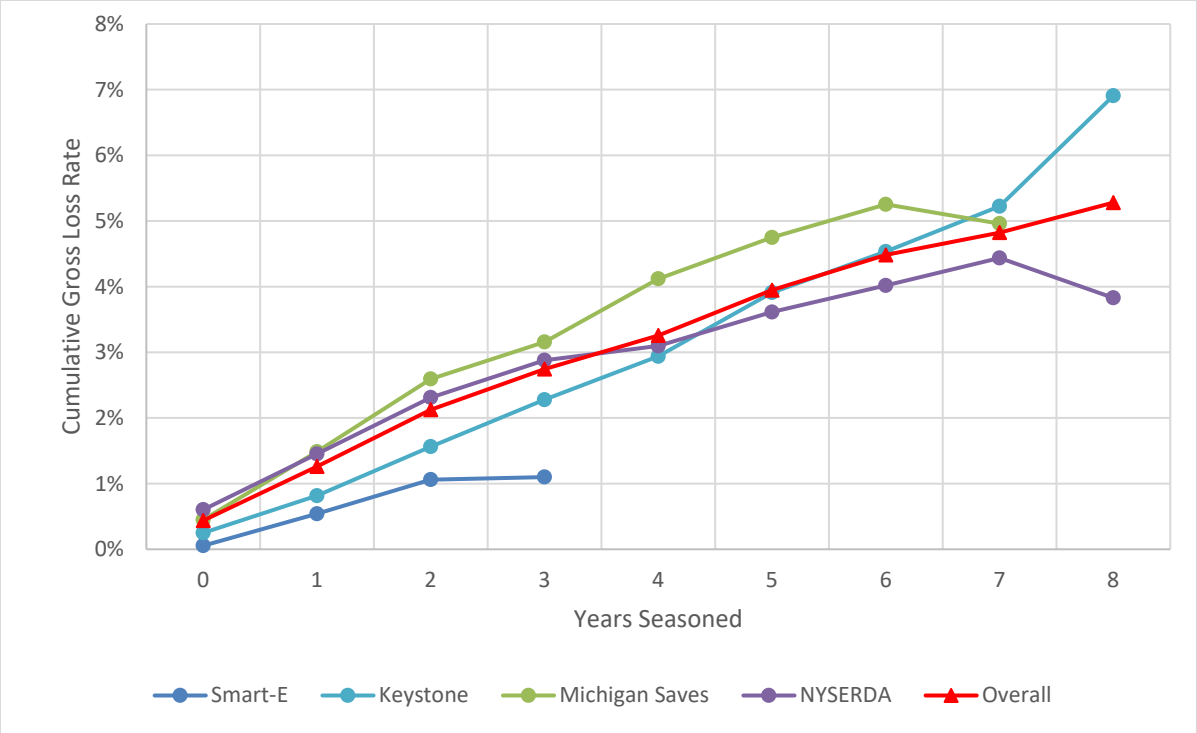

Figure 9. Cumulative gross loss rates by program and years of seasoning

Close examination of Figure 9 shows that more losses occur in the early years after loan issuance than in later years. For example, looking at the overall cumulative loss curve, losses in year 8 are 5.3%. If the loss rate was constant over time, losses in years 2, 4, and 6 would be 1.3%, 2.6%, and 4.0% respectively. In fact, those loss rates are 2.1%, 3.3%, and 4.5%, showing that the loss curve is somewhat concave (bowed downward). This behavior is visually apparent for all the individual portfolios except Keystone, which again may be affected by vintaging (i.e., a loan's issue year) effects of the financial crisis – meaning that loans with a good deal of seasoning (which are the ones that date to before the crisis) have higher loss rates than if the financial crisis had not occurred. Since a large share of the more seasoned loans in the pooled portfolios are Keystone loans (consistent with Figure 9), this may also affect the latter years in the overall curve.

Figures 10 and 11 show the relationship between loan performance and credit score across the pooled portfolios. Figure 10 shows how delinquency rates decline as credit score increases; Figure 11 demonstrates how cumulative gross loss rates increase as credit score declines. Loans to customers in the highest credit score bin have one-third of the delinquencies of the combined portfolios as a whole. Figure 11 shows a similar relationship between cumulative gross losses and credit score: the higher the credit score, the lower the losses. Differences are apparent in the first year of seasoning and grow as the loans mature. After three years of seasoning, loans issued to customers with the lowest credit scores (300-600) have cumulative gross loss rates more than 21 percentage points higher than customers with the highest credit scores (781-850). For loans issued to customers in the two highest credit score bins, cumulative gross losses are less than 5% after eight years.

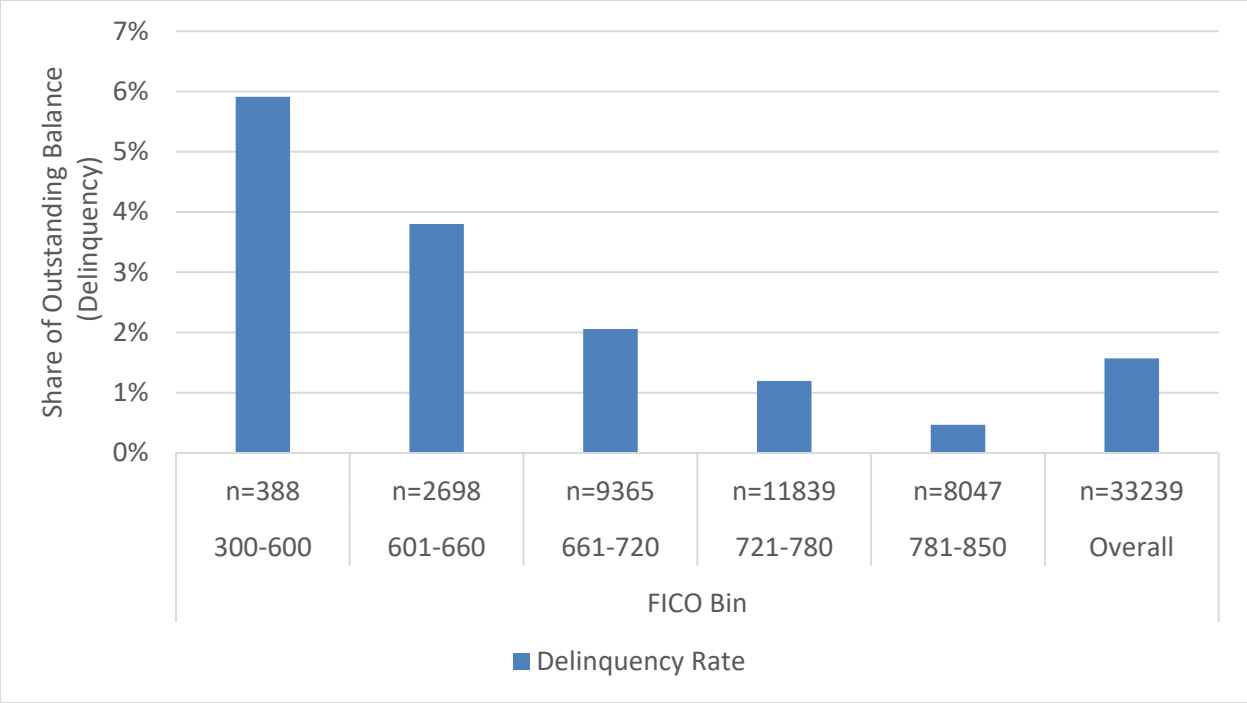

Figure 10. Delinquency (share of outstanding loans) by credit score bin

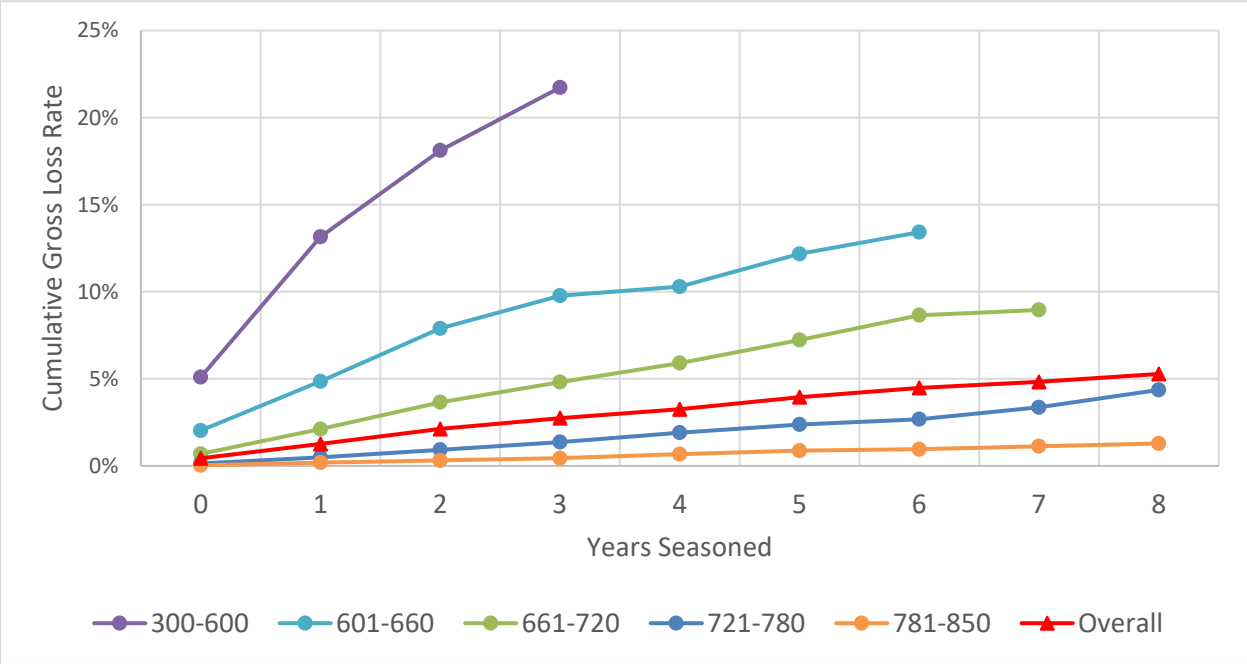

Figure 11. Cumulative gross loss by credit score bin

Loan performance does not show the same degree of sensitivity to census tract income, as shown by AMI bands in Figures 12 and 13. Delinquency and loss rates decline as income increases, but not to as great an extent as they do with credit score increases. For example, delinquency rates in the lowest credit score bin (300-600, Figure 10) are about 12 times higher than the delinquency rates in the highest credit score bin (781-850), but delinquency rates in the lowest AMI band (0-60%, Figure 12) are only 1.9 times as high as in the highest AMI band (>120%). As shown

in Figure 13, cumulative gross loss rates are highest in the lowest AMI band (0-60%) but are only higher than the loss rate in the highest AMI band by five percentage points after five years.[10]

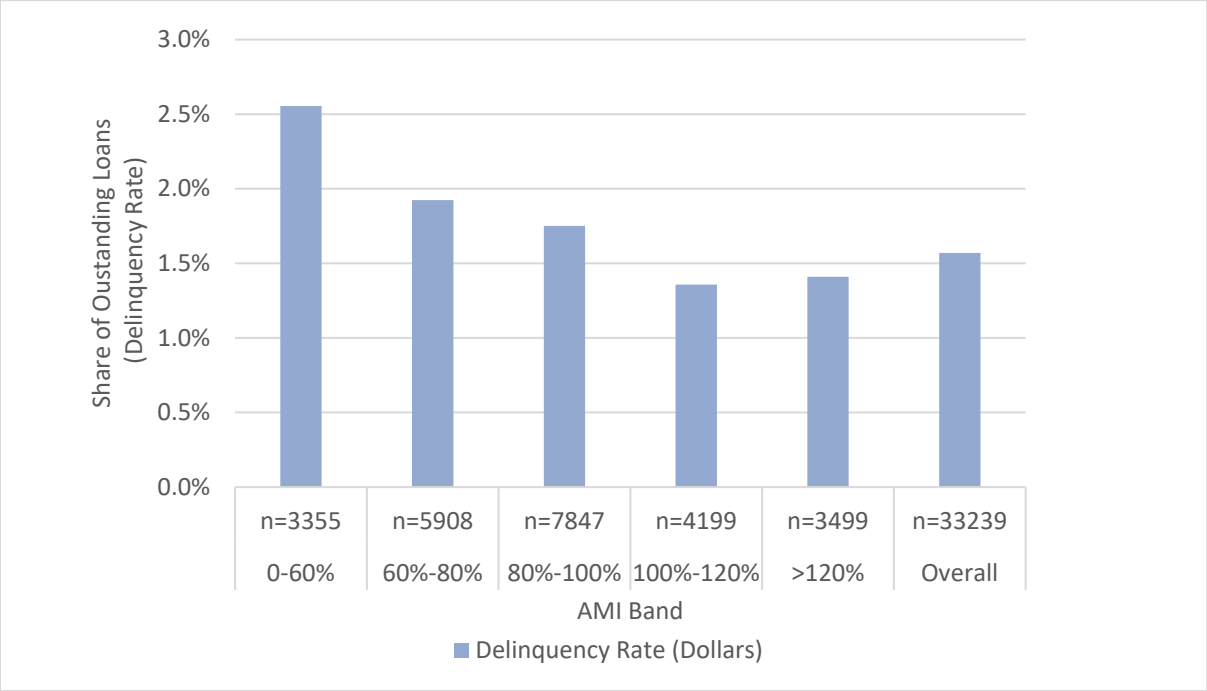

Figure 12. Delinquency (share of outstanding loans) by program and AMI band

[10] The cumulative gross losses by income band do not include loans from Keystone due to the lack of census tract data in that dataset. Since Keystone has some of the oldest loans in the dataset, its absence in this figure contributes to the loss rates not extending to year eight as they do for most credit score bins in Figure 11.

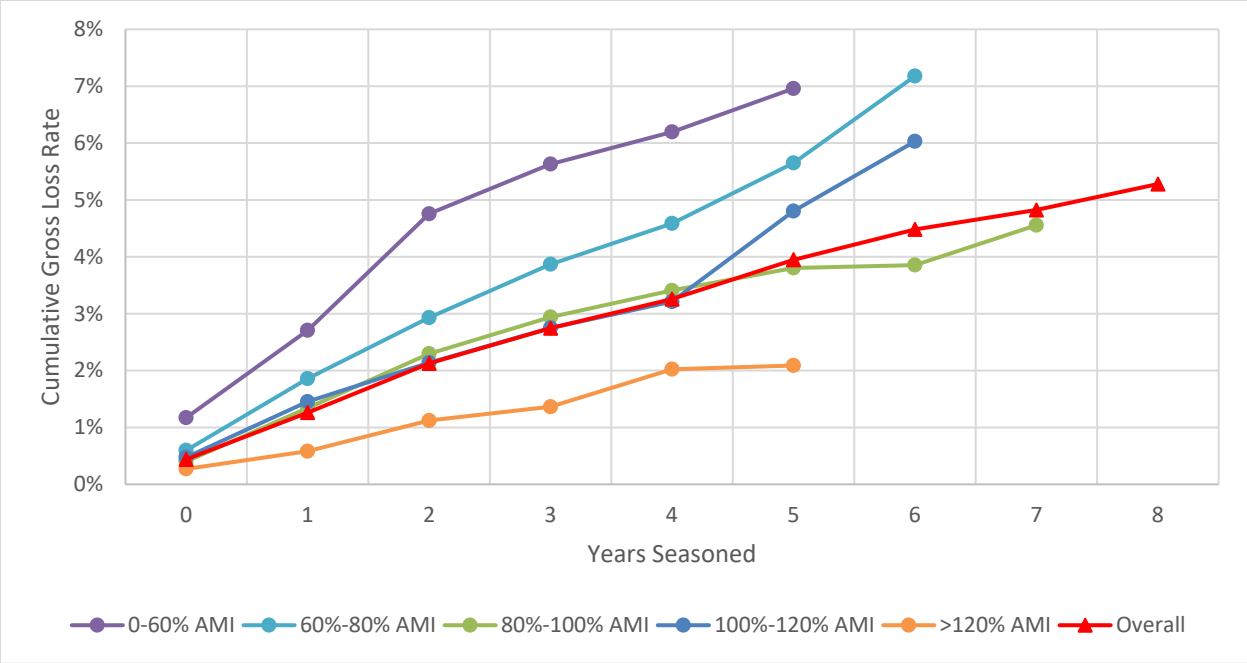

Figure 13. Cumulative gross loss rates by AMI band

The relationship between income and credit, and implications for programmatic lending

It is commonly believed that high-income households also have high credit scores. In fact, there is generally a small positive correlation between income and credit score, but this correlation is lower than might be expected. In the pooled data, the correlation[11] between the median household income of the census tract where borrowers live and their credit scores is only 0.11 – meaning that census tract median income explains only about 11% of the variation in credit scores and vice versa. Moreover, this low correlation does not appear to be due to use of a census tract-based income. In Michigan, the correlation between census tract median income and credit score is similar at 0.10; the correlation between household income and credit score is considerably *lower*, at 0.015.

These findings do not suggest that income *per se* is not important to understanding loan performance. All the programs in this analysis generally include a debt-to-income threshold in their loan underwriting. (The partial exception is NYSERDA, which allows higher than traditional DTI ratios with satisfactory mortgage payment history under its "Tier 2" underwriting option, and in January 1, 2019 eliminated maximum DTI ratios for applicants with FICO scores greater than 780). Rather, the findings suggest that, *for households that pass the debt-to-income screens implemented by the programs* (see Table 2), income matters relatively little – and less than credit – for understanding delinquencies and losses. These DTI ratios may screen out many low-income households; this analysis does not explore whether alternative DTI thresholds could be set.

This report finds that credit score predicts delinquencies and charge-offs far better than income. Figures 10 through 13 demonstrate this finding in the raw data, and the regression analysis in Section 3.2.3 confirms that the association between performance and credit is much stronger than that between performance and income. These findings suggest that lenders can expect strong payment performance from households in lower-income areas that (1) have strong credit and (2) meet debt-to-income screens similar to those in these programs. Many households in the data fit this description. Of participating households in census tracts below 100% AMI, 48% had credit scores above 740 – similar to the share of participating households in census tracts above 100% AMI with credit scores above 740 (56%).

[11] "Correlation" refers to Pearson's correlation coefficient.

3.2.2. Prepayment

This section briefly discusses prepayment rates in the studied portfolios. Prepayment occurs when a borrower pays the loan in full prior to the scheduled loan maturity.[12] All values in this section exclude Smart-E loans, since Smart-E program data did not include the date loans were prepaid.

Most loans in the studied portfolios are still active. Among loans that have come to term (loans whose scheduled maturity was prior to the end date of each portfolio's dataset), borrowers reach about 70% of the loan term on average before paying in full. This average combines loans prepaid at various points in the term with loans carried to the full term. It should be noted that the average term of these loans is 56 months; most of these loans are Keystone loans with five-year terms. These loans are not representative of the larger pool of loans since very few longer-term loans or loans from other programs have come to term.

The cumulative prepayment rate is the share of the original loan balance that has been prepaid after a period of time. For example, the cumulative prepayment rate for loans that have seasoned for at least three years is the value of loans that has been fully prepaid through those three years as a share of original balance for those loans. In the pooled loans, after three years, about 17% of the original loan balance has been fully prepaid. After six years, that cumulative prepayment rate is about 32%. The data do not provide enough information for us to include partial prepayments in these calculations, so the figures above are underestimates of the true prepayment rate in these portfolios.

3.2.3. Regression analysis

This regression analysis builds on the high-level program, credit, and income trends in the previous section by parsing the impact of the various determinants of loan performance discussed above. The logistic regression measures the change in the likelihood of delinquency and charge-off depending on borrower and loan characteristics: principal amount, income bin, credit score, loan seasoning, interest rate, and which program issued the loan. The regression demonstrates the impact of each factor while holding all the others constant. See Appendix A for more details on the regressions.

Our analysis splits out two subprograms in NYSERDA, On-Bill Recovery and Smart Energy, to account for differences in program design and customer characteristics in these programs. Note that the regression models presented here include income as a variable, and therefore exclude Keystone HELP due to lack of income data. When removing income and adding Keystone HELP back to the analysis, results for the other variables are similar to those presented here. For regression tables, see Appendix A.

3.2.3.1 Credit score regression results

Credit score stands out as a consistent, statistically significant predictor of delinquency and charge-off. Higher credit scores are associated with lower chances of delinquency and charge-off for every portfolio. Considering Figure 10, this is not a surprise.

The association between credit score and charge-off is larger than the association between credit score and delinquency (see Table A-1). For charge-offs, a 100 point increase in credit score is associated with a 5.81 percentage point decrease in the chances a loan is charged off.[13] A 100-point increase in credit score is associated with only a 1.06-percentage point reduction in the chance of delinquency. Still, both relationships have strong statistical significance.[14] Program-specific regressions show similar impacts; while the magnitude of the

[12] Lenders generally prefer for loans to be carried to term. If a loan is prepaid, then the investor will not receive part of the interest payments that they may have been expecting.

[13] The term 'percentage point' is used to distinguish a *difference* in percentages from a "percent of a percent" change; "percentage points" refers to the former. For example, a change from 1% to 2% is a change of one percentage point.

[14] Note that the positive correlation between borrower credit score and loan performance is not unique to energy efficiency loans.

relationships varies somewhat, in all cases higher credit scores are associated with lower chances of delinquency and charge-off, and in all cases the relationships are statistically significant at conventional levels of significance.

3.2.3.2 Income regression results

Across all portfolios combined, relative to loans in the 0-60% AMI band, the chance of charge-off decreases for loans in the three highest income bands (80-100% AMI, 100-120% AMI, > 120% AMI). These differences are statistically significant. Holding all else equal, households in the > 120% AMI band have a charge-off rate 1.98 percentage points lower than those in the < 60% AMI band. When examining delinquency, loans in the two highest income bands (100-120% AMI, > 120% AMI) show statistically significantly lower rates of delinquency than loans in the lowest income band. Both the high-income bins show a rate lower by 0.50 percentage points relative to the rate in the <60% AMI band (see Table A-2).

In single-portfolio regressions, the impacts of income on charge-off were often, but not always, statistically significant. The impact of income on delinquency were almost never statistically significant. This difference between pooled and single-portfolio results suggests that the scale of the study – in these regressions (which do not include Keystone HELP), about 25,000 loans – is important to demonstrate a relationship between income and loan performance, especially in the case of delinquency. When pooling the programs, the relationships emerge; however, single portfolios do not have adequate sample size to clearly demonstrate them. This stands in contrast to credit score, where associations with both delinquency and charge-off are clear and large even in single-portfolio regressions.

One possible explanation for the relatively weak relationship between income and loan performance (also shown in Figure 12) is that the income variable is based on the median income of the census tract, rather than the income of the household itself. Census tract income is a blunt signal of actual household-level income. However, the data do not suggest that use of census tract incomes, rather than household incomes, is consequential for these results. For Michigan Saves – the one program with available household-level income data – the correlation between household income and census tract median income is relatively weak (0.20). However, the relationships between household income and charge-off/delinquency are not clearly different than those using census tract median incomes. Regression analysis on the Michigan Saves data shows that household incomes – like census tract median incomes – are associated with charge-offs, with a $10,000 increase in income decreasing the chance of charge-off by 0.26 percentage points. Household income is not a statistically significant predictor of delinquency in the Michigan Saves data. Both results are similar to the results of regression analysis on the Michigan Saves program using census tract incomes.

3.2.3.3 Program regression results

The regression analysis generally confirms the differences in overall program delinquency and loss rates presented in Section 3.2.1. Connecticut Smart-E has the lowest charge-off rates when controlling for the other factors discussed in this section, and NYSERDA's Smart Energy loans have the highest.[15] Smart-E and both NYSERDA programs have the highest delinquency rates, while Keystone and Michigan Saves have the lowest. It is beyond the scope of this study to consider program-specific features that might explain these differences in performance. Overall, while some of these differences are statistically significant, they are relatively small in magnitude.

3.2.3.4 Other regression results

In addition to credit score and income, the regression analysis also estimates the impact of principal amount, interest rate, and seasoning on loan performance. This section reviews only the results for regressions on the combined portfolios.

[15] This study observes higher chances of delinquency in NYSERDA's on-bill loans relative to its Smart Energy loans, consistent with the findings in Deason (2015) several years earlier in the program's lifespan. However, Deason (2015) did not study charge-offs. The results in this report show that NYSERDA's on-bill loans are not charged off more often than its Smart Energy loans; in fact, controlling for other factors, they are charged off less often, though the difference is not statistically significant.

Principal amounts have a statistically significant association with charge-offs, but not with delinquencies. Even for charge-off, the effect is relatively small: a $10,000 increase in principal amount only increases the chance of charge-off by 0.46 percentage points.

A 1-percentage point increase in interest rate increases the chance of charge-off by 2.29 percentage points for all programs combined. Interest rate does not have a statistically significant impact on delinquency.

Loan seasoning does have clear associations with loan performance. A loan's chance of charge-off *increases* by 0.76 percentage points for each year it has seasoned, while the chance of delinquency *decreases* by 0.11 percentage points for each year of seasoning. Seasoning can only increase the chances a loan becomes charged off, since charge-off can occur only once. On the other hand, loans can and do go in and out of delinquency. The fact that the relationship is reversed for delinquency suggests that borrowers who have trouble repaying their loans tend to get in trouble relatively quickly – which is consistent with the shape of the loss curves in Figures 9, 11, and 13.

4. Comparators

A key purpose of this research is to help assess whether energy efficiency loans perform differently than other comparable financial products. Observers have long theorized that energy efficiency loans may carry a performance premium. If so, there may be a number of potential reasons:

- These loans generate their own cash flow (through energy cost savings) to help service the debt.
- Participating borrowers have particular characteristics that make them likely to repay, whether easily observable (e.g., credit scores) or not (e.g., adoption of energy efficiency measures may be a sign that a borrower tends to be frugal or pay close attention to costs, so these products might select for borrowers with an otherwise unobservable tendency to repay reliably).
- Participants see clean energy improvements as an investment in their home and treat that investment similar to the way they would a loan that is secured by the home.
- Borrowers may seek these loans out because they believe they are doing something beneficial for the environment and would see failing to make payments as undermining their good deed.
- Program structures and safeguards (e.g., careful contractor vetting and approval as well as well-executed project approval and underwriting processes) help forestall predatory lending and otherwise avoid abusive lending practices that may be present to a greater extent in other loan pools.

To contextualize these results, this section compares the delinquency and charge-off performance of the energy efficiency loans in this study with several indices of loan performance. These comparisons cannot specifically determine whether efficiency loans carry a performance premium relative to otherwise similar non-efficiency loans, but they do help situate their performance relative to better-known asset classes.

4.1. Methodology

The analysis first identifies several relevant comparator financial products. There is no one perfect comparator to residential energy efficiency loans. In a sense, energy efficiency loans are a specialized type of home improvement loan; however, most home improvement loans are for more expensive renovation projects and may be secured by the home. Instead, Berkeley Lab chose general consumer loans and auto loans as comparators.[16] Consumer loans are broadly similar to energy efficiency loans in that they are generally unsecured loans made to individuals, although consumer loans are made without regard to dwelling ownership (or rental) status. While different types of consumer loans (and consumer loans to different customers) vary substantially, in general these loans have similar principal amounts on shorter terms (and therefore higher monthly payments), and carry considerably

[16] While mortgages are another potential comparator, the fact that mortgages are secured by the home, and the much longer loan terms of many mortgages, make them less suitable for comparison.

higher interest rates than the studied energy efficiency loans.[17] Auto loans differ in that they are secured by the vehicle, meaning that one might expect somewhat stronger repayment performance. Average auto loan amounts and monthly payments are higher than residential energy efficiency loans and average terms are shorter, while interest rates are similar for new cars and higher for used cars. Average credit scores for new car loan borrowers are similar to the energy efficiency loan borrowers, while average credit scores for used car borrowers are considerably lower.[18] Most importantly, both consumer loans and auto loans have very large markets and are well-characterized by public loan indices.

Comparator loan performance data comes from three sources:

- Data maintained by the Federal Reserve ("Fed"). The Fed data[19] cover loans reported by brick-and-mortar banks, including credit card loans as well as non-credit card personal loans.
- Loan performance indices maintained by Kroll Bond Rating Agency (KBRA). The KBRA Marketplace Consumer Loan indices cover securities comprised of loans made by online lenders (often known as FinTech loans), separated into three tiers by the average credit quality served by each lender. The analysis uses data for Tier 1 loans in the KBRA index, which include deals with average credit scores from 710 to 740 (and are therefore the appropriate comparator for energy efficiency loans). KBRA also reports two auto loan indices, one for prime auto loans and one for non-prime auto loans. While there is no universal division between the two, non-prime loans are generally loans to borrowers with credit scores in the mid-600s and below. The analysis therefore focuses on the prime auto loan index.
- Loan data sampled from credit reports by TransUnion. While TransUnion data cover auto loans, bankcard loans, and unsecured personal loans, the analysis only includes their data on unsecured personal loans here. TransUnion usefully subdivides these loans further by type of lender (e.g., banks vs. credit unions), providing greater resolution on personal loans than the other indices.

The comparisons focus on the same two performance metrics used elsewhere in this report: 30-day delinquencies and cumulative gross losses. All indices define 30-day delinquencies in the same way that this report has defined them.

In terms of losses, earlier sections of this report show loss curves over time. For most comparators the data to support these curves are not available, though KBRA helpfully supplied us with the requisite data for two of their loan indices. Most comparators instead report an annualized loss rate, which indicates the share of the portfolio that would be expected to be lost in a year. Annualized losses are readily calculated for large portfolios that can be assumed to be at "steady state," meaning that loans of many different maturities are present and the overall seasoning of the portfolio is not changing significantly over time. In the energy efficiency loan data, this is not the case: the majority of loans are still relatively unseasoned. In this situation a common ratings agency practice is to "gross up" cumulative losses to the loss rate expected at loan maturity. However, few loans in the portfolios studied here have reached maturity (nearly none in some portfolios). Instead of attempting to forecast losses at maturity, the annualization method employed here divides losses at the time they are observed by the average seasoning of the loans. This method essentially assumes losses occur at a constant rate over time, which is not consistent with Figure 9; however, there is no ready alternative. Since loss rates do decline somewhat with seasoning, this method likely overestimates the loss rates in a mature portfolio of these efficiency loans.

Even setting aside this difference in annualization method, this annualized loss calculation differs from the comparators in two other respects:

[17] See the following sources regarding unsecured consumer loans: https://www.lendingtree.com/personal/personal-loans-statistics/; https://www.fool.com/the-ascent/research/personal-loan-statistics/; https://fred.stlouisfed.org/series/TERMCBPER24NS; https://www.chamberofcommerce.org/personal-loan-statistics.

[18] See https://www.experian.com/content/dam/noindex/na/us/automotive/finance-trends/state-of-auto-finance-q2-2021.pdf for data on auto loans and auto loan borrowers.

[19] See https://www.federalreserve.gov/releases/chargeoff/

- Gross rather than net charge-offs. KBRA reports net charge-off rates that include revenues from recoveries.[20] This analysis could not access data on recoveries from energy efficiency loans, as discussed above, so the calculated charge-off rates are gross rates. Since gross charge-off rates are an upper limit on net charge-off rates (only reached if recoveries are zero), these rates may be overestimates of the net charge-off rates from the programs studied. Thus, this report's comparisons to net charge-off indices may underestimate the true relative performance of energy efficiency loans included in this report.

- Berkeley Lab annualizes charge-offs differently. The Fed and KBRA indices draw from a large volume of loans and calculate loss rates solely within the month or quarter that are reported, then multiply (by 12 or 4, respectively) to extrapolate those losses to annual values. The energy efficiency loan pools are much smaller, resulting in a good deal of random variance month-to-month and year-to-year. Therefore, as discussed in Section 3.2.1, the method used here annualizes in the reverse direction: it calculates the net loss rate of each portfolio across its entire lifetime, and then annualizes that value by dividing by the average seasoning of each portfolio.

4.2. Findings

The Fed data are reported quarterly, while KBRA indices are calculated monthly. To generate the comparators to the energy efficiency loan data, Berkeley Lab averages the rates reported by each index in the months/quarters of each of the four program datasets (see Table 1).

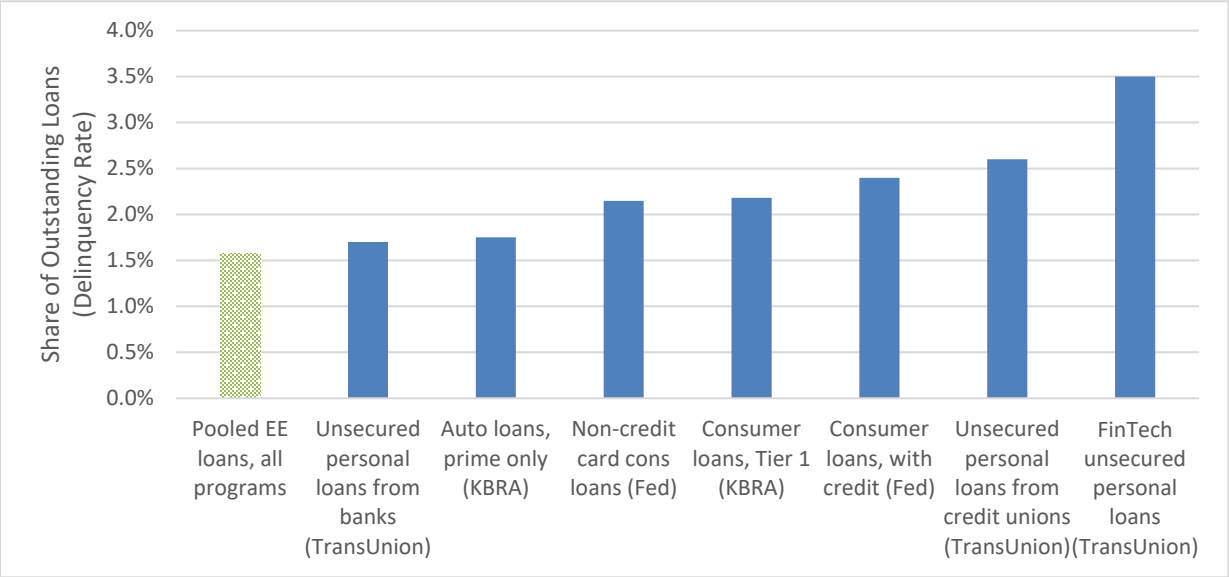

Figure 14. Delinquency rates, energy efficiency loans and comparators

The pooled 30-day delinquency rate across all four energy efficiency loan portfolios is lower than all comparators, including secured prime auto loans (see Figure 14). The energy efficiency loan delinquency rate is 1.57%, a fair bit lower than the 2.15% rate of non-credit card consumer loans (from the Fed data), as well as the 1.75% rate for unsecured personal loans from banks and the 2.6% rate for unsecured loans from credit unions.

Figure 15 presents the equivalent data for charge-offs (gross charge-offs for the energy efficiency loans; net charge-offs for comparators) for two KBRA indices for which KBRA shared data on losses over time to facilitate this analysis. The comparator loss rates in this graphic are principal-weighted averages of KBRA's loss rates by annual

[20] Recoveries are money that a lender has been able to recover from a loan that has been charged off, e.g., through a collection agency or sale of the vehicle in the case of auto loans.

loan vintage from 2006-2019, in the case of auto loans, and from 2016-2019 for consumer loans (as the index began in 2016).

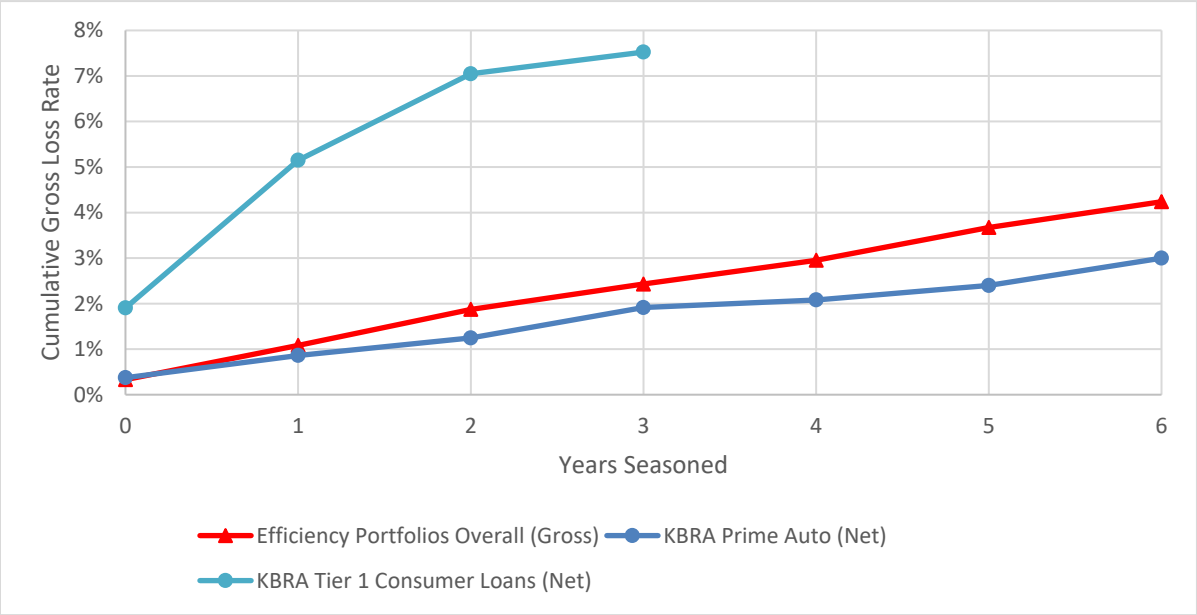

Figure 15. Cumulative loss rates for, energy efficiency loans (gross), KBRA Prime Auto (net), and Tier 1 Consumer Loans (net)

Losses for energy efficiency loans are comparable to prime auto losses and are much lower than Tier 1 consumer loan losses, despite the fact that the energy efficiency loan losses are gross rather than net. After three years of seasoning, the pooled energy efficiency loans have a cumulative gross loss rate of 2.4%, while the KBRA prime auto loans and Tier 1 consumer loans have cumulative net loss rates of 1.9% and 7.5% respectively.

Finally, Figure 16 shows a comparison between the annualized loss metric for the energy efficiency loans – again, an imperfect metric as described above – and annualized loss rates for comparators. In the same manner as the delinquency comparisons, the comparator loss rates are calculated by averaging the rates reported by each index in the months/quarters of each of the program datasets. Given this annualization method, one could argue that comparator rates should in some way average delinquency and loss rates across the portfolios' lifetimes. In practice, with the notable exception of the 2008/09 recession (which affected only early loans in the Keystone program), comparator delinquency and loss rates have been very stable during the period of observation, so the simple approach suffices.

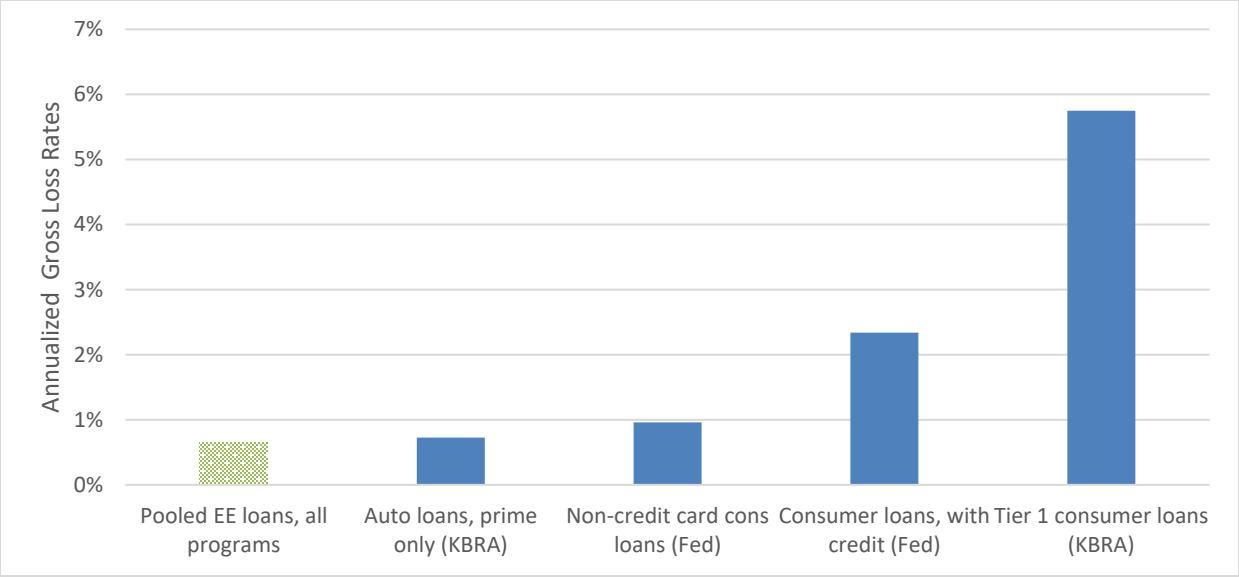

Figure 16. Annualized loss rates, energy efficiency loans and comparators

In this comparison, charge-off rates for the pooled energy efficiency portfolios are lower than those for all comparators including prime auto loans, despite the fact that the energy efficiency loan charge-off rates are gross rather than net. The pooled energy efficiency loans have a gross annualized charge-off rate of 0.65%, while prime auto loans show 0.73% and the Fed data on non-credit card consumer loans shows a net annualized charge-off rate of 0.96%. The fact that the energy efficiency loans show slightly lower annualized losses than auto loans in Figure 16, but slightly higher losses in Figure 15, likely relates to differences in the construction of the comparators in terms of their performance over time; overall, loss performance of the studied efficiency loans is very similar to that of prime auto loans.

5. Conclusions

This report documents and analyzes four large and (in most cases) long-running energy efficiency loan programs to characterize their financial performance. The energy efficiency loans in this analysis exhibit strong repayment performance, outperforming other creditworthy unsecured consumer loans and performing comparably to prime auto loans.

Taking the four studied energy efficiency portfolios together, the overall 30-day delinquency rate of these loans is 1.57%. Losses are highest early in loan lifetimes and decline later, a common finding for consumer loans. The pooled portfolios lost 2.1% of the principal by year 2, 3.3% by year 4, 4.5% by year 6, and 5.1% by year 8.

Regression analysis on loan-level data shows that credit scores are strongly associated with loan performance, for both 30-day delinquency and charge-off. Income is also correlated with loan performance; however, this effect is not as strong as the effect of credit score. Other features of the loans – like loan amounts and interest rates – have small effects on charge-off rates and no clear relationship with loan delinquency. These results are in line with the findings of other loan-level analyses of energy efficiency loan and solar PV financing performance (Deason 2015; Deason, Leventis and Murphy, 2021).

One implication of these regression findings is that borrowers from low-income areas who have strong credit and pass household-level debt-to-income screens are likely to repay loans or other extended financing at a reasonable rate. Such borrowers are not uncommon. Lending to low- and moderate-income households requires careful consideration of factors unique to these borrowers. See Leventis et al. (2017) for discussion of energy efficiency financing for low- and moderate-income households.

When pooled across all four studied programs, energy efficiency loans outperform their most logical comparators – creditworthy unsecured consumer loans – and overall perform comparably to prime auto loans, which are secured. This is despite the charge-off comparisons between loans analyzed in this report and these other products that disadvantage the energy efficiency loans in two senses: this analysis does not include data on recoveries after charge-off, and in some cases the annualization methods employed likely slightly overestimate the charge-off rates these programs would achieve when more fully seasoned. These findings are the most comprehensive evidence yet that energy efficiency loans perform strongly relative to other similar forms of lending.

Our results fall short of proving a relationship between financial performance and either the projects financed by these programs or the customers of the programs. To do this properly would require loan-level data for the comparators as well, to adequately control for other potentially relevant differences. While the energy efficiency loan data are granular, the comparison indices are highly aggregated. Although Berkeley Lab carefully reviewed and discussed the definitions of the metrics these indices draw on, some inconsistencies in definitions and reporting surely exist. Some of the indices considered as comparators do not provide any information on the average creditworthiness of the borrowers; the relatively high credit scores in the energy efficiency programs (or other factors Berkeley Lab cannot observe in the comparators) may or may not explain some of the differences in performance between the energy efficiency loans and the comparators.

Regardless of the explanation, the data speak for themselves: the loans made by these four programs, in aggregate, have performed well. These loans were made by four carefully designed and carefully administered programs, and one should not assume that other energy efficiency loans would necessarily perform as well if program design and administration differ. Nevertheless, when considering these programs and other similar programs, capital providers might wish to take note of this performance. A useful heuristic for capital providers might be that these energy efficiency loans perform more like prime auto loans than like unsecured consumer loans. If energy efficiency loans reliably exhibit stronger performance than other similar loans – as these results suggest – capital providers and lenders should offer better terms (lower interest rates, longer tenors, or both) on these products as their performance is further proven.

This analysis demonstrates that financial institutions can market efficiency upgrades to their customers and provide them with the capital they need to make such improvements at low risk, increasing the efficiency of their homes in the process. Furthermore, our data show that some households from low- and moderate- income areas take up energy efficiency loans, and that high-credit borrowers in these areas repay financing at a strong rate. Thus, energy efficiency lending can help support policy goals related to equitable access to capital, such as the Biden Administration's Justice 40 goals and Community Reinvestment Act compliance requirements.

6. Areas for future work

This study presents the most comprehensive evidence on energy efficiency loan performance that is publicly available to date. That said, additional work could advance understanding of energy efficiency loan performance further. Additional work on loan performance could include:

- Studying additional energy efficiency loan portfolios to expand sample size and test how generalizable the results of this study are.
- Accessing loan-level data on comparator loans and including those loans in the dataset. This would permit controlling for factors (for example, credit scores) that may systematically differ between the loans in this analysis and comparator loans, more directly revealing whether the energy efficiency loans carry a performance premium.

- Adding household incomes, or estimates of same, for additional programs to the data to see if household income has a notably different relationship with loan performance than census tract metrics. (As discussed in Section 3.2.3.2, results thus far suggest that this may not yield very different results.)

- Studying whether realized energy savings materially affect loan performance. Deason (2015) found that *projected* savings were not a statistically significant predictor of delinquency in early NYSERDA loans. However, projected savings do not always correspond to actual savings.

Above and beyond loan performance itself, additional research to support potential program administrators looking to offer or expand residential energy efficiency lending programs could include:

- Assessing the size of the addressable market for these products.

- Considering the most cost-effective way to offer financial support to expand programs offering these loans, likely through various forms of credit enhancement (such as loan loss reserves, subordinate capital, or loan guarantees). Zimring et al. (2013) outlines some preliminary considerations in this regard. This analysis could inform the design of a support facility (for example, a national loan loss reserve or state-level facility) by leveraging the energy efficiency loan data analyzed here to set performance expectations for different types of borrowers, thereby helping to size required financial outlays to expand lending.

- Estimating the potential impact of such financial support, or of other types of support to programs, on the availability and uptake of energy efficiency loan products and on deployment of energy efficiency measures.

- Identifying programmatic design elements and credit enhancements that might be best able to extend capital for energy efficiency to markets that are currently underserved by existing financing options. This effort could help to promote equitable access and tailor suitable loan products (or other financing products) to underserved households. Leventis et al. (2017) reviews a number of key considerations in this regard. The analysis in this paper could serve as a starting point for understanding the level of credit enhancement needed to reach lower-income or low-credit borrowers.

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Appendix A: Regression results

The table below summarizes the regression results used in Section 3.2.3. The average marginal effects for credit score, seasoning, interest, and principal amount all measure the change in likelihood of the outcome variable (e.g., charge-off) for a unit increase in each variable. For categorical variables like AMI band or program, the average marginal effects represent the change in likelihood for some outcome relative to some base case. For the four AMI bands in the table, the base case is the 0-60% AMI band. For program comparisons, Michigan Saves serves as the base case.

Table A-1. Regression output for all loan portfolios combined (n=51,041)

	30-120 Day Delinquency			Charge-off		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P Value**	**Average Marginal Effects**	**Standard Error**	**P Value**
Credit Score	-1.06E-04	8.09E-06	2.06E-39	-5.81E-04	1.76E-05	8.82E-240
Seasoning (Days)	-3.12E-06	5.77E-07	6.20E-08	2.07E-05	1.01E-06	4.71E-93
Interest Rate	-5.87E-02	3.36E-02	8.00E-02	2.29E-01	6.45E-02	3.75E-04
Principal Amount ($)	4.29E-08	6.72E-08	5.23E-01	4.61E-07	1.61E-07	4.23E-03
Smart-E	7.85E-03	1.73E-03	6.04E-06	-1.23E-02	6.01E-03	4.00E-02
NYSERDA On-Bill Recovery	1.91E-02	1.65E-03	2.88E-31	6.09E-03	3.84E-03	1.13E-01
NYSERDA Smart-Energy	3.54E-03	1.37E-03	9.50E-03	1.37E-02	2.63E-03	2.13E-07
Keystone	5.00E-04	1.84E-03	7.86E-01	2.06E-03	2.79E-03	4.61E-01

Table A-2. Regression output for all loan portfolios with income (n+36,288)

	30-120 Day Delinquency			Charge-off		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P Value**	**Average Marginal Effects**	**Standard Error**	**P Value**
Credit Score	-1.281E-04	1.054E-05	5.828E-34	-5.264E-04	1.919E-05	1.106E-165
Seasoning (Days)	-4.178E-06	8.405E-07	6.669E-07	1.956E-05	1.202E-06	1.479E-59
Interest Rate	-5.838E-02	5.209E-02	2.624E-01	3.106E-01	8.606E-02	3.068E-04
Principal Amount ($)	8.638E-08	8.786E-08	3.255E-01	4.376E-07	1.587E-07	5.820E-03
60%-80% + AMI	7.537E-04	1.579E-03	6.332E-01	6.521E-04	2.667E-03	8.069E-01
80%-100% + AMI	-1.911E-04	1.505E-03	8.990E-01	-5.883E-03	2.634E-03	2.553E-02

100%-120% + AMI	-4.987E-03	2.061E-03	1.553E-02	-8.617E-03	3.380E-03	1.080E-02
120%+ AMI	-5.030E-03	2.288E-03	2.788E-02	-1.985E-02	4.309E-03	4.075E-06
Smart-E	1.037E-02	2.272E-03	5.065E-06	-9.057E-03	5.632E-03	1.078E-01
NYSERDA On-Bill Recovery	2.469E-02	2.175E-03	7.198E-30	6.040E-03	3.826E-03	1.145E-01
NYSERDA Smart-Energy	4.453E-03	1.783E-03	1.251E-02	1.200E-02	2.740E-03	1.198E-05

Table A-3. Regression output for Michigan Saves (n=14,905)

	30-120 Day Delinquency			**Charge-off**		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P-Value**	**Average Marginal Effects**	**Standard Error**	**P-Value**
Credit Score	-7.445E-05	1.460E-05	0.000E+00	-4.000E-04	3.280E-05	0.000E+00
Seasoning (Days)	-1.933E-06	7.730E-07	1.200E-02	2.092E-05	1.580E-06	0.000E+00
Interest Rate	-5.620E-02	4.400E-02	1.990E-01	1.443E-01	7.400E-02	5.200E-02
Principal Amount ($)	-3.665E-08	1.010E-07	7.160E-01	6.573E-07	1.930E-07	1.000E-03
60%-80% + AMI	-2.400E-03	2.000E-03	1.820E-01	-1.400E-03	4.000E-03	7.100E-01
80%-100% + AMI	-1.500E-03	2.000E-03	3.750E-01	-1.130E-02	4.000E-03	4.000E-03
100%-120% + AMI	-4.100E-03	2.000E-03	6.000E-02	-9.000E-03	4.000E-03	4.400E-02
120%+ AMI	-6.100E-03	3.000E-03	2.500E-02	-2.450E-02	6.000E-03	0.000E+00

Table A-4. Regression output for CT Smart-E (n=3,166)

	30-120 Day Delinquency			**Charge-off**		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P-Value**	**Average Marginal Effects**	**Standard Error**	**P-Value**
Credit Score	-2.133E-04	4.894E-05	1.306E-05	-2.320E-04	4.974E-05	3.093E-06
Seasoning (Days)	-2.126E-06	5.097E-06	6.767E-01	1.337E-05	3.700E-06	3.015E-04
Interest Rate	2.313E-02	1.138E-01	8.389E-01	4.486E-02	9.989E-02	6.534E-01

Principal Amount ($)	5.859E-07	2.801E-07	3.647E-02	1.406E-07	2.904E-07	6.282E-01
60%-80% + AMI	1.413E-02	9.366E-03	1.313E-01	-3.760E-03	6.567E-03	5.670E-01
80%-100% + AMI	1.751E-02	8.914E-03	4.949E-02	5.252E-03	5.460E-03	3.361E-01
100%-120% + AMI	1.052E-02	9.760E-03	2.810E-01	-4.285E-03	6.877E-03	5.332E-01
120%+ AMI	1.103E-02	9.835E-03	2.621E-01	-1.418E-02	1.014E-02	1.622E-01

Table A-5. Regression output for Keystone HELP (n=14,753)

	30-120 Day Delinquency			**Charge-off**		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P-Value**	**Average Marginal Effects**	**Standard Error**	**P-Value**
Credit Score	-5.646E-05	1.320E-05	1.903E-05	-7.247E-04	4.099E-05	5.766E-70
Seasoning (Days)	-8.444E-07	4.786E-07	7.767E-02	2.240E-05	2.110E-06	2.420E-26
Interest Rate	-3.102E-02	2.279E-02	1.736E-01	2.803E-01	1.146E-01	1.442E-02
Principal Amount ($)	7.119E-08	1.331E-07	5.927E-01	1.143E-06	5.896E-07	5.261E-02

Table 5. Regression output for NYSERDA Smart Energy (n=14,176)

	30-120 Day Delinquency			**Charge-off**		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P-Value**	**Average Marginal Effects**	**Standard Error**	**P-Value**
Credit Score	-1.236E-04	1.544E-05	1.205E-15	-6.703E-04	3.265E-05	1.114E-93
Seasoning (Days)	-3.555E-06	1.122E-06	1.535E-03	2.134E-05	2.289E-06	1.132E-20
Interest Rate	-9.784E-02	9.953E-02	3.256E-01	3.829E-02	2.536E-01	8.800E-01
Principal Amount ($)	1.615E-07	1.484E-07	2.764E-01	-1.833E-07	3.359E-07	5.853E-01

Debt-to-Income Ratio (DTI)	1.157E-03	7.455E-04	1.205E-01	1.781E-03	3.402E-03	6.006E-01

Table 6. Regression output for NYSERDA On-Bill Recovery (n=3,849)

	30-120 Day Delinquency			**Charge-off**		
Dependent Variable	**Average Marginal Effects**	**Standard Error**	**P-Value**	**Average Marginal Effects**	**Standard Error**	**P-Value**
Credit Score	-2.773E-04	5.653E-05	9.335E-07	-5.525E-04	5.872E-05	4.939E-21
Seasoning (Days)	-1.094E-05	5.773E-06	5.821E-02	-2.164E-07	6.048E-06	9.715E-01
Interest Rate	-1.994E-01	6.060E-01	7.421E-01	-4.326E-01	7.105E-01	5.426E-01
Principal Amount ($)	-1.972E-07	4.661E-07	6.723E-01	1.414E-06	4.400E-07	1.313E-03
Debt-to-Income Ratio (DTI)	4.248E-03	1.652E-02	7.971E-01	-1.087E-04	1.669E-02	9.948E-01

Appendix B: Participation by Community Reinvestment Act income bin

The Federal Reserve Board, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency (OCC) enforce regulations to implement the Community Reinvestment Act (CRA) of 1977. The CRA "encourages insured depository institutions to help meet the credit needs of the communities in which they are chartered" (FFIEC, 2012), including low- and moderate-income neighborhoods. For purposes of the CRA, the OCC defines low-income as household income that is less than 50% of AMI, moderate-income is 50% to 80% of AMI, middle-income is 80% to 120% of AMI, and upper-income is 120% or more of AMI.[21] Figure 17 shows participation in the studied programs by those CRA bins.

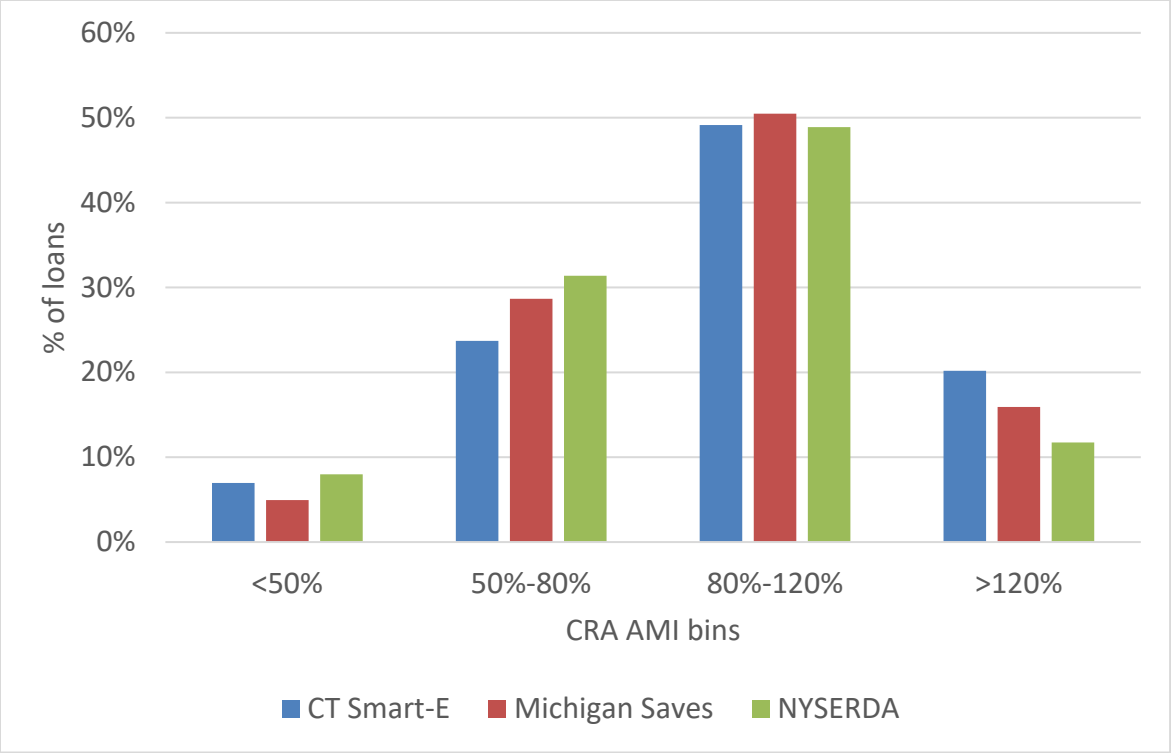

Figure 17. Participation by CRA income bin

[21] See https://www.federalregister.gov/documents/2020/06/05/2020-11220/community-reinvestment-act-regulations.